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Energy poverty and health: Evidence from European countries ☆,☆☆

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ABSTRACT

We estimate the effect of energy poverty on a range of subjective and objective health outcomes among older Europeans using ex-ante harmonized microdata from the Survey of Health, Ageing and Retirement in Europe. To address potential endogeneity concerns, we exploit regional weather-based Eurostat data on Heating Degree Days to construct two instrumental variables for energy poverty.

Our findings indicate that energy poverty has detrimental effects on both physical and mental health. Ordinary Least Squares estimates show that individuals experiencing energy poverty are more likely to report poor health, chronic lung conditions, and score higher on assessments of depressive symptoms and cognitive decline, while also displaying lower grip strength and a higher probability of sarcopenia. Instrumental variable estimates confirm a clinically significant negative effect on physical health, with energy poverty substantially reducing grip strength among older individuals.

From a policy perspective, our results highlight the importance of integrating energy affordability into climate and decarbonization strategies. Policies that increase residential energy costs without adequate compensatory measures may unintentionally worsen heating deprivation and generate adverse health consequences, particularly within ageing societies.

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1. Introduction

Recent increases in residential energy prices, amplified by geopolitical tensions, inflationary pressures, and the transition towards decarbonized energy systems, have renewed concerns about the affordability of domestic energy services among vulnerable households in Europe. In ageing societies, these concerns are particularly relevant, as older individuals spend a larger share of time at home and are therefore more exposed to inadequate indoor thermal conditions. Energy poverty is generally understood as the inability to secure adequate indoor temperatures and essential energy services required for a decent standard of living and the preservation of health and well-being. However, its multidimensional and context-dependent nature makes both its definition and measurement inherently complex (Dubois, 2012; Moore, 2012; Herrero, 2017; Thomson et al., 2017).

A growing empirical literature documents a strong association between energy poverty and adverse health outcomes, including poor self-reported health, respiratory illnesses, depression symptoms, and reduced well-being (Lacroix and Chaton, 2015; Llorca et al., 2020; Ballesteros-Arjona et al., 2022; Katoch et al., 2023). Several mechanisms may explain these relationships, including physiological stress associated with inadequate indoor temperatures and behavioural coping strategies adopted by financially constrained households. In particular, vulnerable individuals may respond to rising energy costs by self-restricting heating consumption, limiting mobility, or reducing other essential expenditures. These behavioural adjustments are likely to be particularly severe among older adults, whose thermoregulation capacity and physical resilience are already compromised and who are therefore especially exposed to the so-called "heat-or-eat" dilemma. Despite the growing literature on energy poverty and health, causal evidence remains limited and focuses predominantly on subjective health indicators. Existing studies mainly rely on energy price variation to identify the effect of energy poverty on self-reported health and well-being (Churchill et al., 2020; Kahouli, 2020; Li et al., 2022; Buchner and Rehm, 2025). Much less is known about the impact of energy deprivation on objectively measured indicators of physical health among older populations.

This paper contributes to the literature in several ways. First, we provide new evidence on the causal effect of energy poverty on health among older Europeans using harmonized microdata from the Survey of Health, Ageing and Retirement in Europe (SHARE). To address the potential endogeneity of energy poverty, we exploit regional variation in Heating Degree Days (HDD) from Eurostat to construct two weather-based instrumental variables. Relative to previous studies relying primarily on energy prices, our approach captures the role of weather-induced heating needs in shaping self-restricting heating behaviour among financially vulnerable households. Second, we extend the analysis beyond subjective health outcomes by focusing on objectively measured and clinically relevant indicators of physical functioning, including grip strength and sarcopenia, alongside respiratory health, depression symptoms, and cognitive abilities. Grip strength is a widely recognized biomarker of overall health, functional decline, and mortality risk. In line with this, Leong et al. (2015) show that lower grip strength is a robust predictor of cardiovascular diseases and mortality risk, yet it has received little attention in the literature on energy poverty. Third, we provide evidence on heterogeneous effects across population groups, identifying particularly vulnerable individuals among older adults living in smaller households. Our findings reveal a significant negative association between energy poverty and all the health outcomes considered. Instrumental variable estimates indicate that energy poverty causes a clinically significant reduction in grip strength among older individuals, corresponding to a substantial deterioration in physical health.

More broadly, our results contribute to the emerging debate on the distributive consequences of climate and decarbonization policies. Policies that increase residential energy costs without adequate compensatory mechanisms may unintentionally intensify heating deprivation among vulnerable households, generating adverse health consequences and increasing pressure on publicly funded healthcare systems. Integrating energy affordability into climate policy design may therefore be crucial not only for equity reasons, but also for the effectiveness and political sustainability of the green transition.

The remainder of the paper is organized as follows. Section 2 reviews the literature on energy poverty and health. Section 3 presents the data. Section 4 illustrates the empirical strategy. Section 5 discusses the results, and Section 6 concludes.

2. Literature review

Energy poverty has increasingly attracted attention in both academic and policy debates, particularly in Europe, where rising residential energy prices, inflationary pressures, and recent geopolitical shocks have intensified concerns about households' ability to afford adequate energy services. Despite growing interest in the topic, there is still no universally accepted definition of energy poverty,[1] largely because the phenomenon is multidimensional and context-dependent, varying across countries, climatic conditions, housing characteristics, social norms, and institutional settings (Dubois, 2012; Moore, 2012; Thomson et al., 2017; Herrero, 2017). More recently, the transition towards decarbonized energy systems has further reinforced the relevance of this issue. While carbon pricing and environmental policies are central tools for reducing emissions, they may also increase household energy costs and disproportionately affect vulnerable groups unless accompanied by adequate compensatory measures (Faiella et al., 2020). As a consequence, understanding the welfare and health implications of energy deprivation has become increasingly important for the design of equitable climate policies.

The literature on energy poverty has initially focused on how to conceptualize and measure the phenomenon. One strand of research adopts an expenditure-based approach, identifying energy-poor households through the share of energy expenditure over

[1] Contributions on energy poverty are initially referenced in studies on fuel poverty. Liddell and Morris (2010) review the different definitions of fuel poverty (e.g., budget shares vs. self-assessments), the variety of health outcomes examined (e.g., physical vs. mental health), and the empirical strategies employed. They also point out several methodological challenges, often related to data limitations.

income or through residual income measures, which assess whether a household's income after housing and energy costs falls below a minimum subsistence threshold (Boardman, 1991; Faiella and Lavecchia, 2021). More recent contributions have attempted to identify "hidden" energy poverty by estimating minimum energy requirements and detecting underconsumption among financially constrained households (Karpinska and Śmiech, 2020; Papada and Kaliampakos, 2020; Barrella et al., 2021). Other studies combine survey and administrative information, including Energy Performance Certificates, to assess fuel poverty risk at detailed geographic levels (Camboni et al., 2021; Fabbri and Gaspari, 2021; Kelly et al., 2020).

Alongside expenditure-based measures, a growing literature relies on consensual or self-reported indicators, typically based on households' inability to keep their homes adequately warm or to pay utility bills on time. These measures are widely used in surveys such as EU-SILC, Eurobarometer, EQLS, and SHARE. Although self-reported indicators may reflect heterogeneous reporting styles and cultural norms (Herrero, 2017), they capture important dimensions of material deprivation that are often missed by expenditure-based approaches, including behavioural adjustments, social exclusion, and self-imposed heating restrictions. In particular, they allow researchers to identify households who consume limited amounts of energy compared to the standards, not because of their preferences, but due to financial constraints.

The growing attention devoted to energy poverty measurement reflects the increasing awareness that inadequate access to domestic energy services may have important consequences for health and well-being (Liddell and Morris, 2010; Ballesteros-Arjona et al., 2022; Katoch et al., 2023). Energy poverty can affect health through multiple and mutually reinforcing mechanisms. Inadequate indoor temperatures may increase physiological stress, worsen respiratory and cardiovascular conditions, impair sleep quality, and reduce physical functioning (World Health Organization, 2018; Liddell and Morris, 2010). At the same time, financially constrained households may adopt behavioural coping strategies – such as reducing heating consumption, limiting mobility, or remaining sedentary for prolonged periods – that may further deteriorate physical health and contribute to frailty among older individuals (Kortebein et al., 2008; Cruz-Jentoft et al., 2019). Energy deprivation may also generate psychological distress and social isolation, while rising utility costs can force households into "heat-or-eat" trade-offs, whereby spending on food and other essential goods is reduced to afford energy expenditures (Bhattacharya et al., 2002; Burlinson et al., 2022; Hashmi et al., 2025). These mechanisms are likely to be particularly severe among older adults, whose thermoregulation capacity, physical resilience, and mobility are often already compromised (Morley, 2001).

Consistent with these mechanisms, a growing empirical literature documents a strong association between energy poverty and adverse health outcomes. Early evidence from the epidemiological and socioeconomic literature focused primarily on the "heat-or-eat" dilemma. Using US data, Bhattacharya et al. (2002) show that low-income households facing unusually cold weather reduce food expenditure to meet heating needs, potentially worsening nutritional outcomes. Cullen (2004) similarly finds that households exposed to unexpected increases in energy costs reduce non-energy consumption, including food expenditure. More recently, Burlinson et al. (2022) show that households relying on prepaid energy meters consume fewer fruits and vegetables than otherwise comparable households. A broader literature further documents significant associations between energy poverty and poor physical and mental health, including respiratory diseases, depression symptoms, reduced well-being, and social exclusion (Lacroix and Chaton, 2015; Llorca et al., 2020; Ballesteros-Arjona et al., 2022).

Despite this growing body of evidence, causal evidence on the health effects of energy poverty remains relatively limited and focuses predominantly on subjective health outcomes. Churchill et al. (2020), using Australian data and energy prices as instruments, find that energy poverty significantly reduces self-assessed health. Kahouli (2020) exploits exogenous increases in residential energy prices in France and documents negative effects on self-perceived health. Li et al. (2022), using Chinese data, instrument energy poverty through municipal energy prices and water resource availability, showing negative effects on subjective well-being among older individuals.

More recently, Buchner and Rehm (2025) use German panel data and energy price variation to show that transitions into energy poverty worsen self-reported health. Recent studies also suggest that the relationship between energy poverty and health may be bidirectional. Fan et al. (2025), for example, show that health shocks may themselves increase the risk of energy poverty by reducing labour supply and household earnings. Complementing this evidence, Hou et al. (2026) document that energy poverty increases physical dependency among older adults in China, highlighting the role of energy deprivation as a social determinant of functional decline.

While the literature on the health consequences of energy deprivation is growing, causal evidence focusing on objective, clinically relevant outcomes among older populations within a multi-country setting remains limited. This paper directly addresses this issue by evaluating both subjective and objective health measures within an instrumental variables framework that exploits regional variation in heating degree days.

3. Data

We use data gathered through SHARE, a multidisciplinary, harmonized and multi-country survey that collects information on demographic and socioeconomic characteristics, as well as health conditions and behaviours of individuals aged 50 or older (and their partners regardless of age) living in Europe (Börsch-Supan, 2019, 2020a,b).

The first regular wave was conducted in 2004, with eleven European countries participating, plus Israel; the last available regular wave (wave 9) refers to 2021/22 and covers the EU-28 fully. In 2008/2009 (wave 3) and 2017 (wave 7), the survey also collected individual retrospective information, such as early-childhood conditions and labour market history, to allow for analysis with a longer-term perspective. Due to the outbreak of COVID-19, SHARE suspended the collection of wave 8 data in March 2020 and started in June 2020 a special COVID-19 survey. The COVID-19 survey was then repeated in 2021.

Table 1
Health by energy poverty.

Outcomes:	(1) Energy poor: NO	(2) Energy poor: YES
Grip strength	34.22	32.07
Sarcopenia	0.100	0.159
Self-reported poor health	0.048	0.139
Diagnosed chronic lung diseases	0.055	0.089
EURO-D scale	2.082	3.476
Memory	9.954	8.804

Notes: Sample size = 44,562 observations. All the t-test of mean equality between the two groups reject the null with p-value < 0.001.

In this study, we are especially interested in energy poverty, which is elicited in waves 5 (2013) and 6 (2015) through a specific question asking whether *the individual has put up with feeling cold to save heating costs, to help keep living costs down (in the last twelve months)*. This question is part of a set of items to identify deprived households.

The energy poverty question is asked of those household respondents[2] who report making ends meet *with some/great difficulties*. Following the design of the questionnaire, we assume that households reporting to make ends meet *easily* are not financially constrained and we recode the binary indicator of energy poverty to zero. In our working sample of about 45000 individuals, about 8% of them live in households that could not keep the house adequately warm to reduce living costs.[3] Fig. 1a shows how this percentage changes among the countries we include in our sample — Austria, Germany, Sweden, Spain, Italy, France, Denmark, Belgium, Poland, Luxembourg and Portugal.[4] Differences among countries might reflect not only differences in socio-demographic characteristics, housing conditions and appliance endowments of households, or related policy interventions, but also different preferences and reporting styles (see Angelini et al., 2014). Fig. 1b compares the share of households – rather than individuals – unable to keep their home adequately warm with official 2015 Eurostat statistics, which are based on a similarly worded question in the harmonized EU Survey on Income and Living Conditions (EU-SILC). Despite all the challenges involved in comparing these statistics, we can observe that SHARE data are reasonably in line with Eurostat statistics.

Our outcomes of interest are self-reported health status, objective health indicators – muscle (or grip) strength and the related binary indicator for sarcopenia –, a dummy for reporting (diagnosed) chronic lung diseases such as chronic bronchitis or emphysema, the EURO-D scale of depressive symptoms and a memory score based on a cognition test. More precisely, self-reported health is a binary variable which takes the value one if the individual reports being in poor or very poor health; it is an overall assessment of well-being, which is a significant predictor of mortality, even after controlling for many objective measures of health (Coe and Zamarro, 2011). We then consider muscle strength, which is an objective physical health indicator measured in SHARE through a harmonized protocol across all countries and waves. In each wave, four grip strength measurements are available for each respondent, two for each hand. The grip strength scale ranges from 0 to 100 kg. Following Andersen-Ranberg et al. (2009), we consider the maximum among the four observations for each respondent. We also define a binary indicator that identifies individuals with very low levels of grip strength at risk of sarcopenia, a muscle disease (or muscle failure) related to aging. We follow the European Working Group on Sarcopenia in Older People (EWGSOP) and use as thresholds 20 kg for women and 30 kg for men (see Cruz-Jentoft et al., 2010). Specifically, this indicator is constructed by applying clinical cut-off points to the continuous grip strength measure, identifying those who fall below the threshold for physical frailty. While the continuous measure captures shifts in muscle strength across the entire distribution, the sarcopenia indicator provides complementary evidence by focusing on the lower tail; it allows us to assess whether energy poverty not only reduces average strength but also increases the probability of entering a state of clinically relevant muscle failure, which is a strong predictor of disability and loss of autonomy.

We do not have information on acute respiratory episodes, but individuals are asked about specific chronic conditions diagnosed by a doctor. We therefore define a binary indicator that takes the value one if the respondent reports chronic lung disease, based on the idea that acute respiratory episodes might become chronic if the individual is exposed to deprived living conditions.

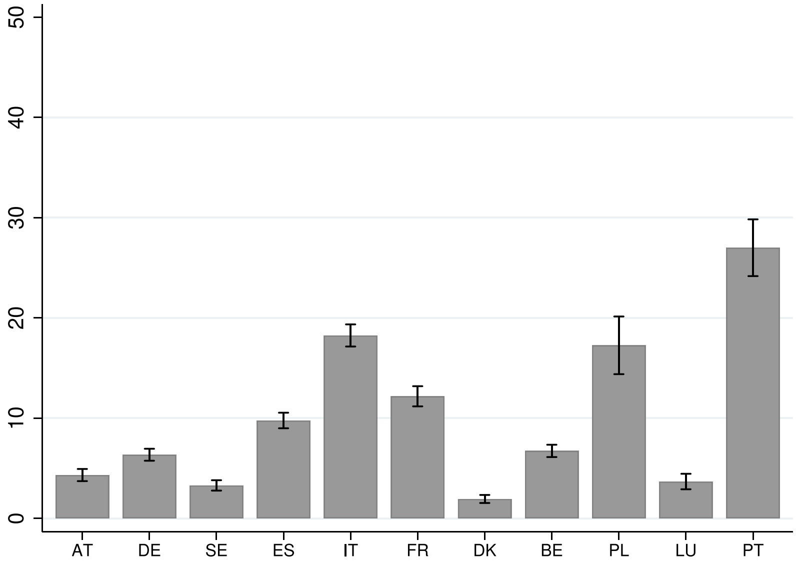
We measure mental health status based on two components: the EURO-D depression scale and a cognitive memory assessment. The EURO-D scale is a depression symptoms scale designed and validated in European countries to measure depression symptoms later in life (Prince et al., 1999). The memory assessment assigns a score based on a word-recall test: the respondent listens to a list of words (10) once and gets tested twice, once immediately after the encoding phase (first trial) and once about five minutes later (delayed recall). The number of words recalled (in the first and second trials) has been used to assess cognitive impairment and dementia (see, for example, Celidoni et al., 2017). Additional details on the health indicators used can be found in Mehrbrodt et al. (2017).

Table 1 shows the differences in health, according to our six health indicators, for the two groups of individuals: those who live in households that tolerate feeling cold to save heating costs and help keep living costs down (*energy poor*), versus all other

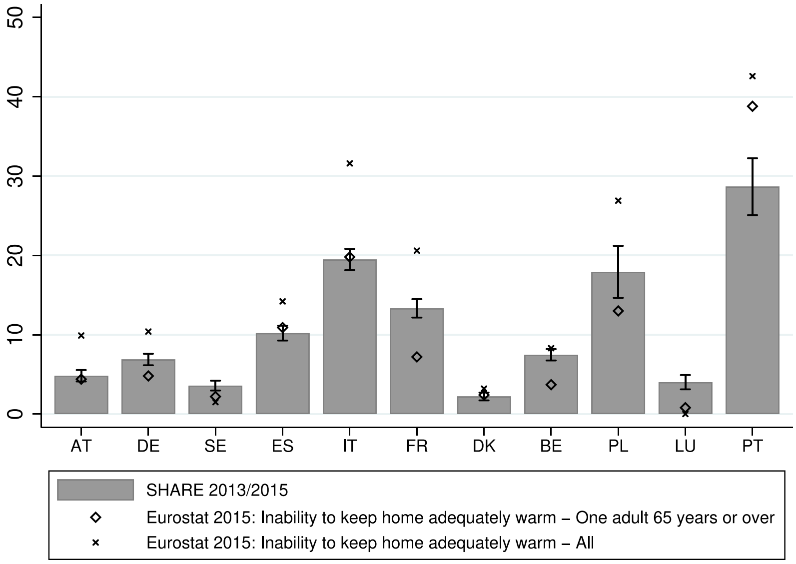
[2] Household respondents answer on behalf of the whole household.

[3] Using design weights, about 13% of individuals live in households that could not keep the house adequately warm to reduce living costs.

[4] The analysis focuses on Austria, Germany, Sweden, Spain, Italy, France, Denmark, Belgium, Poland, Luxembourg, and Portugal, as these are the countries for which both SHARE data and detailed regional information about snow and precipitation from Angelova and Lupio (2020) are available.



(a) Percentage of *individuals* living in households reporting put up with feeling cold to save heating costs, to help keep the living costs down in SHARE (2013/2015).



(b) Percentage of *households* where individuals report they put up with feeling cold to save heating costs, to help keep the living costs down in SHARE and Eurostat Statistics.

Fig. 1. Percentage of Energy Poor individuals and households in SHARE and Eurostat.

households. It can be observed that individuals living in *energy-poor* households report more frequently being in poor health; they have lower grip strength and higher percentages of sarcopenia and chronic lung diseases in all countries, compared to respondents in the other group. *Energy-poor* individuals also report more depression symptoms and recall a lower number of words compared to non-*energy-poor* individuals. For all outcomes, the difference in means is always statistically significant.

Fig. 2 shows the percentages or the average values of the six health indicators by energy poverty status and country. In general, the differences observed in Table 1 are confirmed, although they are not always statistically significant in all countries.

We complement SHARE data with Eurostat statistics about Heating degree days (HDD) and regional characteristics. The HDD index is weather-based and describes the need for the heating energy requirements of buildings in the location considered. It is derived from meteorological data on air temperature, interpolated to regular grids at a resolution of 25 km. The calculated gridded HDD is then aggregated at different regional levels; we use HDD at NUTS 1 or 2 level, depending on the NUTS code available

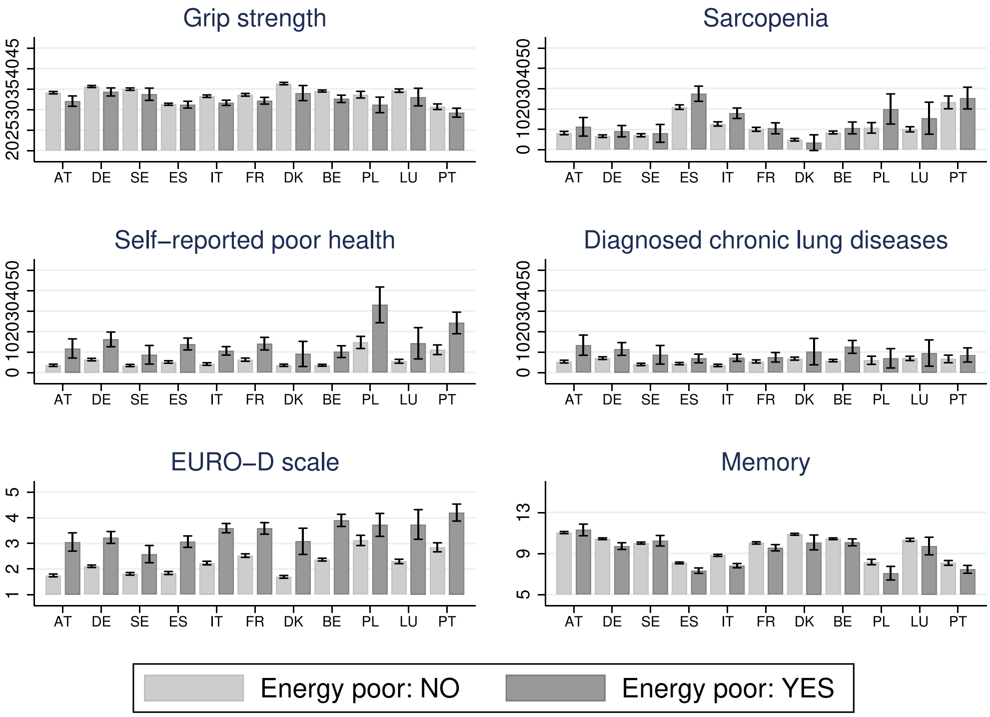


Fig. 2. Health indicators by energy poverty and country.

in SHARE.[5] The monthly value of the HDD index varies between 0 and about 1000. We define two variables based on the HDD information, *hhd_12months* and *hhd_autumnwinter*. The value of the first depends on the region and the month-year in which the interview was carried out, which varies at the individual level.[6] It counts the heating degree days in the past twelve months, as asked specifically in the energy poverty question. The latter, *hhd_autumnwinter*, counts the heating degree days during the cold (autumn/winter) months between September and March in the past twelve months. As explained in the next section, we will use these two weather-based indicators as instruments for energy poverty.

Among the control variables, we also include two indicators derived from Cooling Degree Days (CDD) to account for heat intensity over the past twelve months and specifically during the summer period.

We merge SHARE data with additional regional indicators, also environmental-related, that might be correlated with our instrumental variables and can affect health. We show that our baseline results are also robust to the inclusion of such additional controls. Specifically, the additional regional indicators are the sum of monthly mean precipitation and snow in the 12 months before the interview and during the autumn/winter months, provided by Angelova and Lupio (2020), and two variables capturing economic and health-related regional resources, i.e. the Gross Domestic Product (GDP) per capita and the number of hospital beds per capita, which – according to Eurostat definitions – includes all beds available in both public and private hospitals. We describe our sample in terms of socio-demographic characteristics and other indicators in Table A.1 in the Appendix.

4. Empirical strategy

In this paper, our objective is to estimate the effect of energy poverty ($EnPov$) on health, controlling for individual and household socioeconomic characteristics while taking into account the endogeneity of energy poverty.

We estimate the following model:

$$Y_i = \alpha + \beta EnPov_i + \mathbf{X}_i'\gamma + e_i. \tag{1}$$

where Y_i is the outcome of interest – health – for individual i interviewed either in wave 5 or 6.[7] While muscle (or grip) strength is a continuous variable, for the binary outcomes, i.e. *Sarcopenia*, *Self-reported poor health* and *Diagnosed chronic lung diseases*, we

[5] NUTS is the acronym of Nomenclature of territorial units for statistics in the EU. Following Midões et al. (2024), we exploited the geographical information provided by respondents in all SHARE waves to define NUTS 2 regions for individuals living in Austria, Sweden, Spain, Italy, France, Denmark, Belgium, Poland, Luxembourg and Portugal. For Germany, the dataset allows us to identify NUTS 1 regions.

[6] In the two waves considered, the data collection process covers almost the entire year in all countries.

[7] Although SHARE is a longitudinal survey that follows individuals over time, we do not exploit this temporal variation in our analysis. This is because transitions into and out of energy poverty between waves 5 and 6 are rare, accounting for just 5.5% of the observations in our baseline sample.

estimate a linear probability model: this allows us to account for the potential endogeneity of energy poverty easily.[8] $EnPov_i$ is a binary indicator identifying individuals living in energy poverty (elicited through the direct question on heating cost savings to help keep the living costs down); β is the parameter of interest.

Ordinary-Least-Squares (OLS) estimates of equation (1) might be biased in our framework because of reverse causality and/or omitted variables. Reverse causality can emerge whenever poverty is health-induced: fragile individuals who suffer from bad health conditions are more likely to be out of the labour force, have limited financial resources and, at the same time, *ceteris paribus*, to feel cold because of the health conditions: this is supported by Budría et al. (2025) that, using Australian data, show that ill health might be a stepping stone to energy poverty. Among the omitted variables that might bias the OLS estimates, there could be awareness of energy efficiency that could generate monetary savings and have beneficial effects in terms of health.

To account for the potential endogeneity of $EnPov_i$, we need instruments that are both relevant, i.e. correlated with the endogenous variable, and exogenous, i.e. affecting health only through *energy poverty*. The literature so far has used energy prices as instrumental variables; however, within the time window we consider, there is limited temporal and geographical variability in prices, as public information on prices is available only at the country level. We propose to leverage on weather-based data. Using the HDD information, we define two instruments, *hhd_12months* and *hhd_autumnwinter* as explained above. On the one hand, the HDDs during the coldest seasons (*hhd_autumnwinter*) capture the fact that if autumns and winters are particularly cold, then savings in terms of heating costs might be unlikely, with households choosing other strategies to contain living costs. On the other hand, if low temperatures persist for longer periods, then we expect individuals to be more likely to save heating costs to make ends meet. This effect should be captured through *hhd_12months*, once controlling for *hhd_autumnwinter*.

The identifying assumption of our instrumental variable approach, the exclusion restriction, is that regional HDD affects health outcomes exclusively through the channel of energy poverty. To mitigate potential threats to this assumption, we include a comprehensive set of regional controls, such as Cooling Degree Days, precipitation, snow, regional GDP, and healthcare infrastructure, to isolate heating-related deprivation from other environmental or economic shocks. To provide further empirical support for the validity of the exclusion restriction, we also perform a series of placebo tests aimed at ruling out systematic correlations between our instruments and factors unrelated to energy deprivation that could independently influence health.

In the next section, we will also comment on the relevance of our instruments based on the Kleibergen–Paap rank Wald F-statistics for the excluded instruments (Staiger and Stock, 1997; Lee et al., 2020) and discuss weak identification. Furthermore, given that our standard errors are clustered at the regional level to account for the aggregate variability of our instruments, we complement the standard diagnostics for weak identification with Montiel Olea and Pflueger (2013)'s robust weak instrument test. This test is appropriate in our context as it provides correct critical thresholds in the presence of clustered and non-i.i.d. errors, allowing us to determine whether our instruments exceed the critical values for a specified maximum IV bias.

Our baseline two-stage least squares (TSLS) specification has one endogeneous variable and two instruments; the model is therefore over-identified, and this allows us to run over-identification tests that we report and comment on in the Results section below. We further provide endogeneity test results based on Baum et al. (2003, 2007) to understand whether energy poverty can be treated as exogenous.

It is further important to emphasize that our IV approach identifies a Local Average Treatment Effect (LATE), representing the causal impact of energy poverty specifically for the sub-population of *compliers*, i.e. those individuals whose heating-related behaviour is sensitive to regional HDD variations. This interpretation is entirely consistent with the magnitude of our point estimates, as the health consequences of energy poverty are likely to be more pronounced for households forced to adjust their consumption at the behavioural margin in response to environmental shocks, compared to the general population. This group is particularly relevant for policy, as it represents the population that heating subsidies or energy efficiency programs could most effectively target.

Regarding the model specification, in addition to regional and standard socio-demographic variables (a quadratic polynomial in age, education level, home ownership, gender and the interaction between them, marital and employment status, household size, number of children and grandchildren, indicators for having a car and Wave 6 observations), we also include country and interview month dummies, equivalent household income quartile dummies, a binary indicator equal to one for individuals living in a farmhouse, a detached or semi-detached one- or two-family house (including row houses), and zero for those residing in buildings with three or more housing units. We further control for the number of rooms per capita and its interaction with home ownership and dummies for the type of area where the building is located (a big city – the reference category –, suburbs or outskirts of a big city, large town, small town and rural area or village) and its interaction with home ownership.

In the next section, we comment on our baseline results and present the robustness analysis conducted.

5. Results

Table 2 reports our baseline estimates. More precisely, columns (1) and (2) of panels (a), (b), (c), (d), (e) and (f) show that OLS estimates are in line with what the literature typically documents: there is a highly significant (partial) association between energy poverty and health: individuals in energy poverty have worse health conditions. Based on OLS estimates, experiencing energy poverty increases the chances of reporting being in poor health, reduces grip strength, increases the probability of suffering sarcopenia, increases the probability of being diagnosed with chronic lung diseases, is associated to a higher number of depression symptoms and lower number of words recalled. If we compare the point estimates between columns (1) and (2), we can see that they are

[8] For binary outcomes we report in the Appendix also probit marginal effect estimates.

Table 2
The effect of energy poverty on health. Baseline estimates.

Dep. Var.	(a) Grip strength (std)					(b) Sarcopenia				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	OLS		IV-TSLS		LIML	OLS		IV-TSLS		LIML
EnPov	−0.049***	−0.044***	−1.124**	−0.916*	−0.919*	0.023***	0.021***	0.287*	0.126	0.127
	(0.012)	(0.117)	(0.437)	(0.510)	(0.512)	(0.006)	(0.006)	(0.170)	(0.165)	(0.166)
Obs	44,562	44,562	44,562	44,562	44,562	44,562	44,562	44,562	44,562	44,562
R^2	0.638	0.639	0.560	0.588	0.587	0.100	0.101	0.049	0.093	0.093
Regional variables		x		x	x		x		x	x
Mean Dep.Var.	34.05†	34.05	34.05	34.05	34.05	0.104	0.104	0.104	0.104	0.104
SD Dep.Var.	9.90†	9.90	9.90	9.90	9.90					
Endogeneity test (p-val)			0.030	0.075				0.186	0.474	
Hansen J stat (p-val)			0.792	0.689				0.615	0.449	
Dep. Var.	(c) Self-reported poor health					(d) Diagnosed chronic lung diseases				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	OLS		IV-TSLS		LIML	OLS		IV-TSLS		LIML
EnPov	0.060***	0.059***	0.083	−0.133	−0.136	0.026***	0.026***	0.158**	0.088	0.088
	(0.006)	(0.006)	(0.086)	(0.103)	(0.105)	(0.005)	(0.005)	(0.079)	(0.102)	(0.102)
Obs	44,562	44,562	44,562	44,562	44,562	44,562	44,562	44,562	44,562	44,562
R^2	0.045	0.046	0.044	−0.002	−0.003	0.017	0.017	−0.005	0.012	0.012
Regional variables		x		x	x		x		x	x
Mean Dep.Var.	0.056	0.056	0.056	0.056	0.056	0.059	0.059	0.059	0.059	0.059
SD Dep.Var.										
Endogeneity test (p-val)			0.791	0.040				0.070	0.517	
Hansen J stat (p-val)			0.471	0.286				0.933	0.684	
Dep. Var.	(e) EURO-D scale					(f) Memory				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	OLS		IV-TSLS		LIML	OLS		IV-TSLS		LIML
EnPov	0.453***	0.447***	1.213*	0.025	0.021	−0.057***	−0.056***	−0.652	−0.698	−0.748
	(0.022)	(0.022)	(0.670)	(0.898)	(0.907)	(0.016)	(0.016)	(0.651)	(0.656)	(0.710)
Obs	44,562	44,562	44,562	44,562	44,562	44,562	44,562	44,562	44,562	44,562
R^2	0.110	0.112	0.071	0.100	0.099	0.271	0.271	0.247	0.243	0.239
Regional variables		x		x	x		x		x	x
Mean Dep.Var.	2.20	2.20	2.20	2.20	2.20	9.86	9.86	9.86	9.86	9.86
SD Dep.Var.	2.12	2.12	2.12	2.12	2.12	3.48	3.48	3.48	3.48	3.48
Endogeneity test (p-val)			0.303	0.552				0.368	0.488	
Hansen J stat (p-val)			0.549	0.644				0.858	0.169	
			First-stage (selected coefficients)					First-stage (selected coefficients)		
hhd_12months			0.066**	0.076**				0.066**	0.076**	
			(0.026)	(0.034)				(0.026)	(0.034)	
hhd_autumnwinter			−0.132***	−0.141***				−0.132***	−0.141***	
			(0.041)	(0.044)				(0.041)	(0.044)	
F-test excluded instr.			6.424	8.400				6.424	8.400	
Effective F (Montiel-Pflueger)			9.306	9.303				9.306	9.303	

Notes: Standard errors (in parentheses) are clustered by region. We included the following controls in each specification: a quadratic polynomial in age, education level, home ownership, gender and the interaction between them, the marital and employment status, the household size, the number of children and grandchildren, having a car, an indicator for observations in wave 6, country and interview month dummies, equivalent household income quartile dummies, an indicator for individuals living in a farmhouse, a free-standing one- or two-family house or in a one- or two-family house as row or double house, the number of rooms per capita and its interaction with home ownership, the dummies for type of area where the building is located and its interaction with home ownership. Regional controls are CDD indicators referring to the past 12 months and during the summer months, the sum of monthly mean precipitation and snow in the 12 months before the interview and during the autumn/winter months, GDP per capita and the number of hospital beds per capita. The F-test for the excluded instruments is the Kleibergen- Paap rank Wald F-statistics. The Effective F-statistic is calculated following Montiel Olea and Pflueger (2013). Significance levels: p-value *** ≤ 0.01, ** ≤ 0.05, * ≤ 0.1.

very similar, meaning that including regional controls affects the OLS point estimates only marginally. As discussed in Section 4, however, the OLS parameters might be biased; we, therefore, exploit weather-based data and provide TSLS estimates to account for the potential endogeneity of energy poverty.

Columns (3) and (4) of panels (a), (b), (c), (d), (e) and (f) in Table 2 report TSLS coefficients; selected first-stage information is reported at the bottom of the same table. Looking at first-stage estimates, we can see that the two instruments are highly significant with the expected signs.[9] The instruments' opposing signs reflect distinct behavioural margins: extreme winter cold makes heating restrictions physiologically untenable, whereas prolonged exposure to milder cold facilitates heat-saving strategies as a means of budgetary adjustment.

The F-statistics on the excluded instruments reported in the Table are, however, below the critical values for weak identification testing conventionally used and discussed in Staiger and Stock (1997) and Lee et al. (2020). We also perform the Montiel Olea and Pflueger (2013) robust weak instrument test, which is specifically designed to provide reliable critical values in the presence of clustered standard errors. The effective F-statistic of 9.303 allows us to reject the null hypothesis that the TSLS bias exceeds 20% of the worst-case OLS bias (critical value 7.017) and, importantly, it is close to the 9.997 threshold required to reject a 10% maximal TSLS bias. This test highlights that the potential finite-sample bias quantified through the Montiel Olea and Pflueger (2013) framework is relatively small compared to the overall magnitude of our point estimates. To further mitigate the risk of finite-sample bias, we additionally report limited information maximum likelihood (LIML) estimates given that the LIML estimator is median-unbiased in over-identified models (for a discussion and comparison of the sampling properties of TSLS and LIML estimators, see Angrist and Pischke, 2009). Notably, our effective F-statistic is also essentially at the 9.382 critical value required to reject a 20% maximal bias for the LIML estimator, providing further confidence in our IV estimates. We also report in the Table the p-values of the Sargan–Hansen J test: the p-values indicate that we always do not reject the over-identifying restrictions at the conventional 5% confidence level. Considering the substantial gap between the OLS (−0.044) and TSLS (−0.916) coefficients, even a worst-case relative bias of 20% would imply a minor theoretical distortion that does not alter the clinical significance or the direction of the estimated effect of energy poverty on health.

When taking into account potential endogeneity issues, our results show that energy poverty has a negative effect on grip strength, significant at the 5% level in the specification without regional controls and at the 10% level when including regional controls. The estimated TSLS parameters are −1.124 (s.e. 0.437) and −0.916 (s.e. 0.510), with and without regional controls, respectively. Comparing columns (4) and (5) of panel (a), we can also see that the LIML estimate (−0.919, s.e. 0.512) is very similar to the TSLS coefficient.

The estimated effect on the standardized grip strength outcome corresponds to a decrease of approximately 9 kg , or 25% of the sample mean (34.05 kg), which is clinically significant as it represents a shift of nearly one full standard deviation (SD = 9.90). Such a reduction would move an individual with average muscle strength very close to the clinical thresholds for sarcopenia (Cruz-Jentoft et al., 2019). This implies that energy poverty does not merely cause a marginal weakening but can effectively transition a healthy older adult into a state of physical frailty. This loss is comparable to the functional decline observed during ten days of total bed rest in older populations (Kortebein et al., 2008), underscoring the severe physiological burden of prolonged exposure to cold-induced sedentarism and catabolic stress. Notably, clinical evidence indicates that such a decline is potentially reversible if appropriate interventions are implemented (Cruz-Jentoft et al., 2019; Landi et al., 2012; Fielding et al., 2011). Furthermore, when the body is exposed to intense cold without adequate protection, it can enter a catabolic state (the body consumes reserves, including muscle, to generate heat). Older adults, who have less body fat and impaired thermoregulation, burn energy more quickly, including muscle mass (Morley, 2001). In the presence of malnutrition, this process is exacerbated: with insufficient caloric and protein intake, the body rapidly depletes fat stores and increasingly relies on muscle protein to meet its energy demands (Robinson et al., 2023). Exposure to cold also leads to vasoconstriction, particularly in the limbs, which reduces blood flow and oxygen delivery to the muscles, potentially impairing muscle function and heightening the risk of atrophy in older adults (Greaney et al., 2014).

The fact that TSLS/LIML estimates are larger than OLS coefficients is also consistent with a LATE interpretation. While OLS provides an average association for the entire population, the IV approach identifies the effect for a particularly vulnerable subgroup – the compliers – consisting of households forced to adjust their consumption in response to regional thermal shocks. For these individuals, the physiological and psychological costs of self-restricting heating are likely higher than for the average respondent, explaining the larger magnitude of the causal estimates compared to the population-wide OLS baseline.

Beyond the LATE interpretation, the difference between OLS and TSLS estimates is also consistent with the correction of attenuation bias. This difference is potentially explained by measurement error in energy poverty – which is self-reported – and/or the existence of an omitted variable that is correlated with energy poverty but has a positive effect on muscle strength, such as current or past employment in manual or physically demanding jobs. We also consider the possibility of non-classical measurement error; for instance, if reporting thresholds are systematically correlated with unobserved health determinants. Nevertheless, since our external meteorological instruments (HDD) are unlikely to be correlated with individual reporting biases, the IV approach provides a more reliable identification of the health impact than OLS.

Columns (3) to (5) of Panel (b) report TSLS and LIML estimates when using sarcopenia as an outcome. When controlling for regional variables, the estimated TSLS and LIML parameters are 0.287 – significant at the 10% level – and 0.126 but not statistically significant at the conventional levels. However, the endogeneity test for sarcopenia fails to reject the null hypothesis, suggesting that

[9] Using Australian data, Awaworyi Churchill et al. (2022) investigates the relationship between temperature shocks and energy poverty. They estimate that each additional *cold day* increases the incidence of energy poverty.

energy poverty is exogenous; this supports OLS estimates, which indicate that energy poverty increases the probability of extreme muscle failure by 2.1 percentage points on a baseline of 10.4%, corresponding to about a 20% relative increase.

Moving to Panel (c) in Table 2, Columns (3) to (5) show that energy poverty does not affect the probability of reporting poor health: TSLS and LIML estimates are not statistically significant.

If we focus on diagnosed chronic lung diseases as an outcome and look at Panel (d), we can see that, based on TSLS and LIML estimates, energy poverty has a significant (at the 5% level) positive effect only in column (3) when we do not include regional controls. However, the endogeneity test supports the use of OLS estimates, which indicate a positive effect of energy poverty on the likelihood of being diagnosed with chronic lung disease (2.6 percentage point increase on a baseline of 5.9%, corresponding to about a 44% relative increase).

To summarize the interpretation of our baseline findings, we distinguish between causal and associational evidence based on formal endogeneity tests. For grip strength (p-value=0.075) and self-reported poor health (p-value=0.040), the tests reject the null hypothesis of exogeneity, justifying the use of the IV framework. Provided our identifying assumptions hold, the estimates for grip strength are consistent with a causal interpretation of energy poverty; for self-reported health, however, the preferred IV specification does not reach statistical significance. In contrast, for all other outcomes (sarcopenia, chronic lung disease, depression, and memory) the endogeneity tests fail to reject the null hypothesis. For these variables, we rely on OLS as the preferred estimator. Consequently, for this group of outcomes, we adopt a more cautious, associational interpretation, as the lack of rejection of exogeneity suggests that OLS provides reliable estimates under the assumption of no further unobserved confounding, but without the formal causal leverage provided by the IV framework.

Similarly, in columns (3) to (5) of panel (e), we observe that energy poverty has a significant (at the 10% level) positive effect on depression symptoms (EURO-D scale) in line with recent literature (e.g. Hashmi et al., 2025), but this effect is no more significant when including regional variables among controls. We do not estimate a significant effect of energy poverty on cognition measured through the number of words recalled (columns (3), (4) and (5) of Panel (f)). For depression and memory, the endogeneity tests suggest relying on OLS estimates, which indicate that energy poverty is associated to an increase of about one symptom in the EURO-D scale and a reduction of about 2% of words recalled in the memory test. In the Appendix, we report reduced form estimates, which support the results presented in Table 2 (columns (4) and (5)), and, for completeness, bivariate probit estimates (marginal effects) for our binary outcomes.

Weather conditions and temperatures, which affect the probability of being energy-poor, with consequences in terms of worse physical health, might also affect behaviours such as practising sports or activities typically performed outside. To rule out the possibility that such behavioural factors drive our results, we include, among controls, a binary indicator identifying individuals who practised sport or did social or other kind of club activities in the past twelve months (34% of individuals in our sample reports they practiced sports or activities in the past twelve months).[10] Results are reported in Table 3: OLS, TSLS and LIML parameters align with Table 2 results, considering the full specification, which includes the complete set of regional controls.

We further check the robustness of our estimates when dropping observations from one country at a time, a *leave-one-country-out*, to verify that no single country or climate-zone is driving the results. Estimates – available upon request – are in line with what is reported in Table 2.

Similarly, we explore the *heat or eat* trade-off by incorporating equivalized household food expenditure (at home or away from home) as an additional control. Since energy poverty might force older individuals to reduce their food budget to afford heating costs, omitting this channel could lead to an overestimation of the direct physiological impact of cold exposure. Analogously to our previous check on physical activity, when we control for total food expenditure, acknowledging they might be bad controls, the coefficient for energy poverty on grip strength remains stable in both magnitude and significance, see Table 4. This suggests that while nutritional constraints are a well-documented risk factor for muscle loss, they do not fully account for the observed decline. These results further point towards the direct physiological stress of inadequate indoor temperatures as a primary driver of the identified effects.

To account for both the potential endogeneity of energy poverty and the non-random selection into this condition, we combine Two-Stage Least Squares estimates with Inverse Probability Weighting (IPW) (see Wooldridge, 2007); we weight observations by the (inverse) propensity score of assignment — i.e., the probability of belonging to each group, conditional upon the observed covariates.[11] Results reported in Table 5 are in line with Table 2 estimates. We find a significant negative effect of energy poverty on muscle strength: the IPW estimate for grip strength actually lies between the OLS and the baseline TSLS estimates, and corresponds

[10] Respondents are asked how frequently they engaged in various activities over the past twelve months, including voluntary or charity work, caring for a sick or disabled adult, helping friends or neighbours, attending an educational or training course, participating in a sport, social, or other type of club, engaging in religious activities (e.g., at a church, synagogue, or mosque), taking part in political or community-related organizations, reading books, magazines, or newspapers, solving word or number puzzles (e.g., crosswords or Sudoku), and playing games such as cards or chess. For each activity, individuals can respond with one of the following frequency categories: almost daily, almost every week, almost every month, or less often. Based on these responses, we construct a binary indicator equal to one if the respondent reports having participated in any sport, social, or other type of club during the past twelve months.

[11] The covariates used are those included in **X**: a quadratic polynomial in age, education level, home ownership, gender and the interaction between them, the marital and employment status, the household size, the number of children and grandchildren, having a car, an indicator for observations in wave 6, country and interview month dummies, equivalent household income quartile dummies, an indicator for individuals living in a farmhouse, a free-standing one- or two-family house or in a one- or two-family house as row or double house, the number of rooms per capita and its interaction with home ownership, the dummies for type of area where the building is located and its interaction with home ownership. Regional controls are CDD indicators referring to the past 12 months and during the summer months, the sum of monthly mean precipitation and snow in the 12 months before the interview and during the autumn/winter months, GDP per capita and the number of hospital beds per capita.

Table 3
The effect of energy poverty on health. Robustness analysis, including sports and activities among controls.

Dep. Var.	(a) Grip strength (std)			(b) Sarcopenia		
	(1)	(2)	(3)	(1)	(2)	(3)
	OLS	IV-TSLS	LIML	OLS	IV-TSLS	LIML
EnPov	−0.043***	−0.932*	−0.935*	0.021***	0.128	0.130
	(0.012)	(0.506)	(0.508)	(0.006)	(0.163)	(0.165)
Obs	44,542	44,542	44,542	44,542	44,542	44,542
R-squared	0.640	0.587	0.586	0.102	0.094	0.093
Regional variables	x	x	x	x	x	x
Endogeneity test (p-val)		0.066			0.459	
Hansen J stat (p-val)		0.675			0.440	
Dep. Var.	(c) Self-reported poor health			(d) Diagnosed chronic lung diseases		
	(1)	(2)	(3)	(1)	(2)	(3)
	OLS	IV-TSLS	LIML	OLS	IV-TSLS	LIML
EnPov	0.058***	−0.125	−0.128	0.026***	0.093	0.093
	(0.006)	(0.100)	(0.102)	(0.005)	(0.103)	(0.103)
Obs	44,542	44,542	44,542	44,542	44,542	44,542
R^2	0.049	0.005	0.004	0.017	0.012	0.012
Regional variables	x	x	x	x	x	x
Endogeneity test (p-val)		0.044			0.479	
Hansen J stat (p-val)		0.269			0.703	
Dep. Var.	(e) EURO-D scale			(f) Memory		
	(1)	(2)	(3)	(1)	(2)	(3)
	OLS	IV-TSLS	LIML	OLS	IV-TSLS	LIML
EnPov	0.444***	0.068	0.065	−0.052***	−0.747	−0.800
	(0.022)	(0.885)	(0.892)	(0.016)	(0.659)	(0.712)
Obs	44,542	44,542	44,542	44,542	44,542	44,542
R^2	0.115	0.105	0.105	0.275	0.242	0.237
Regional variables	x	x	x	x	x	x
Endogeneity test (p-val)		0.585			0.431	
Hansen J stat (p-val)		0.652			0.171	
		First-stage (selected coefficients)			First-stage (selected coefficients)	
hhd_12months		0.076**			0.076**	
		(0.034)			(0.034)	
hhd_autumnwinter		−0.141***			−0.141***	
		(0.044)			(0.044)	
F-test of excluded instruments		8.457			8.457	
Effective F (Montiel-Pflueger)		9.397			9.397	

Notes: Standard errors (in parentheses) are clustered by region. We included the following controls in each specification: a quadratic polynomial in age, education level, home ownership, gender and the interaction between them, the marital and employment status, the household size, the number of children and grandchildren, having a car, an indicator for observations in wave 6, country and interview month dummies, equivalent household income quartile dummies, an indicator for individuals living in a farmhouse, a free-standing one- or two-family house or in a one- or two-family house as row or double house, the number of rooms per capita and its interaction with home ownership, the dummies for type of area where the building is located and its interaction with home ownership. Regional controls are CDD indicators referring to the past 12 months and during the summer months, the sum of monthly mean precipitation and snow in the 12 months before the interview and during the autumn/winter months, GDP per capita and the number of hospital beds per capita. The F-test for the excluded instruments is the Kleibergen–Paap rank Wald F-statistics. The Effective F-statistic is calculated following Montiel Olea and Pflueger (2013). Significance levels: p-value *** ≤ 0.01, ** ≤ 0.05, * ≤ 0.1.

to approximately a 7 kg (20%) decline — which is of the same order of magnitude as the baseline TSLS result (9 kg, 25%). The difference reflects the reweighting of observations by the inverse propensity of being energy-poor, which adjusts for selection on observables. The somewhat smaller magnitude under IPW may indicate that part of the baseline TSLS effect was driven by compositional differences between the energy-poor and non-poor groups. Based on OLS estimates, as suggested by endogeneity tests, energy poverty increases the probability of being diagnosed with chronic lung diseases, increases also the number of reported depression symptoms and reduces the number of words recalled in the memory test by a comparable magnitude.

We also performed placebo tests aimed at ruling out systematic correlations between our instruments and factors unrelated to energy deprivation that could independently influence health. In the first falsification test, we use summer temperature shocks (Cooling Degree Days — CDD) as instruments for energy poverty. Since self-reported heating restriction (our measure of energy poverty) should not respond to summer temperature variation, a null first-stage effect is in line with HDDs capturing behavioural responses specifically related to heating needs. As shown in Table A.4 in the Appendix, the first-stage F-statistic for CDD is near

Table 4
The effect of energy poverty on health. Robustness analysis, equivalized household food expenditure (at home or away from home) among controls.

Dep. Var.	(a) Grip strength (std)			(b) Sarcopenia		
	(1) OLS	(2) IV-TSLS	(3) LIML	(1) OLS	(2) IV-TSLS	(3) LIML
EnPov	−0.028**	−1.012*	−1.017*	0.013**	0.118	0.119
	(0.012)	(0.602)	(0.605)	(0.006)	(0.192)	(0.194)
Obs	44,562	44,562	44,562	44,562	44,562	44,562
Regional variables	x	x	x	x	x	x
Endogeneity test (p-val)		0.0833			0.527	
Hansen J stat (p-val)		0.659			0.450	
Dep. Var.	(c) Self-reported poor health			(d) Diagnosed chronic lung diseases		
	(1) OLS	(2) IV-TSLS	(3) LIML	(1) OLS	(2) IV-TSLS	(3) LIML
EnPov	0.044***	−0.206*	−0.209*	0.017***	0.076	0.076
	(0.006)	(0.119)	(0.121)	(0.005)	(0.118)	(0.118)
Obs	44,562	44,562	44,562	44,562	44,562	44,562
Regional variables	x	x	x	x	x	x
Endogeneity test (p-val)		0.0221			0.592	
Hansen J stat (p-val)		0.357			0.666	
Dep. Var.	(e) EURO-D scale			(f) Memory		
	(1) OLS	(2) IV-TSLS	(3) LIML	(1) OLS	(2) IV-TSLS	(3) LIML
EnPov	0.335***	−0.316	−0.326	−0.026	−0.756	−0.829
	(0.022)	(1.032)	(1.048)	(0.017)	(0.772)	(0.853)
Obs	44,562	44,562	44,562	44,562	44,562	44,562
Regional variables	x	x	x	x	x	x
Endogeneity test (p-val)		0.432			0.503	
Hansen J stat (p-val)		0.601			0.171	

	First-stage (selected coefficients)	First-stage (selected coefficients)
hhd_12months	0.062**	0.062**
	(0.033)	(0.033)
hhd_autumnwinter	−0.118***	−0.118***
	(0.041)	(0.041)
F-test of excluded instruments	7.176	7.176
Effective F (Montiel-Pflueger)	7.711	7.711

Notes: Standard errors (in parentheses) are clustered by region. We included the following controls in each specification: a quadratic polynomial in age, education level, home ownership, gender and the interaction between them, the marital and employment status, the household size, the number of children and grandchildren, having a car, an indicator for observations in wave 6, country and interview month dummies, equivalent household income quartile dummies, an indicator for individuals living in a farmhouse, a free-standing one- or two-family house or in a one- or two-family house as row or double house, the number of rooms per capita and its interaction with home ownership, the dummies for type of area where the building is located and its interaction with home ownership. Regional controls are CDD indicators referring to the past 12 months and during the summer months, the sum of monthly mean precipitation and snow in the 12 months before the interview and during the autumn/winter months, GDP per capita and the number of hospital beds per capita. The F-test for the excluded instruments is the Kleibergen–Paap rank Wald F-statistics. The Effective F-statistic is calculated following Montiel Olea and Pflueger (2013). Significance levels: p-value *** ≤ 0.01, ** ≤ 0.05, * ≤ 0.1.

zero, and CDD indicators have no significant effect on the probability of reporting energy poverty. In the second falsification test, we use cataracts as a placebo outcome. Cataracts are a primarily age-related degenerative condition of the eye lens, with an etiology linked to cumulative ultraviolet radiation exposure and metabolic factors, rather than ambient thermal conditions (World Health Organization, 2018). Since there is no established biological mechanism linking indoor temperature to lens opacity (Liddell and Morris, 2010), we expect energy poverty to have no significant impact on this outcome. Any significant finding here would suggest a potential violation of our identifying assumptions or the presence of unobserved confounding. The results reported in Table A.5 in the Appendix show no significant relationship between energy poverty and this outcome, suggesting that the instrument does not capture generic health-weather pathways.

Finally, although our specifications already include equivalized household income quartile dummies, we further tested the sensitivity of our results to broader financial distress. Including the indication of *difficulty in making ends meet* as a covariate leaves our main estimates virtually unchanged. Moreover, using *difficulty in making ends meet* as the endogenous variable yields a weak first stage, confirming that our HDD instrument specifically identifies heating-related deprivation rather than general economic hardship (results are available upon request).

Table 5
The effect of energy poverty on health. Robustness analysis, Two-Stage Least Squares estimates with Inverse Probability Weighting.

Dep. Var.	(a) Grip strength (std)	(b) Sarcopenia	(c) Self-reported poor health
EnPov	−0.754**	0.193	−0.077
	(0.329)	(0.119)	(0.086)
Obs	44,562	44,562	44,562
Regional var.	x	x	x
Endogeneity test (p-val)	0.0180	0.103	0.114
Hansen J stat (p-val)	0.8225	0.6233	0.3927
F-test of excluded instruments	8.222	8.222	8.222
Effective F (Montiel-Pflueger)	15.534	15.534	15.534
Dep. Var.	(d) Diagnosed chronic lung diseases	(e) EURO-D scale	(f) Memory
EnPov	−0.009	−0.483	−0.330
	(0.072)	(0.510)	(0.347)
Obs	44,562	44,562	44,562
Regional var.	x	x	x
Endogeneity test (p-val)	0.950	0.0363	0.244
Hansen J stat (p-val)	0.0423	0.6129	0.0800
F-test of excluded instruments	8.222	8.222	8.222
Effective F (Montiel-Pflueger)	15.534	15.534	15.534

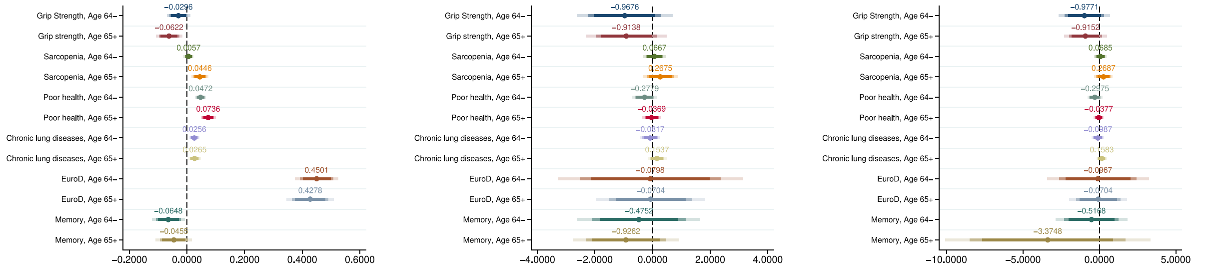
Notes: Standard errors (in parentheses) are clustered by region. To account for both the potential endogeneity of energy poverty and the non-random selection into this condition, estimates combine Two-Stage Least Squares (IV-TSLS) with Inverse Probability Weighting (IPW) following Wooldridge (2007). Observations are weighted by the inverse propensity score of assignment (i.e., the probability of being energy poor), estimated via a logit model conditional upon the full set of observed baseline covariates described below. We included the following controls in each specification (and in the first-step IPW logit estimation): a quadratic polynomial in age, education level, home ownership, gender and the interaction between them, the marital and employment status, the household size, the number of children and grandchildren, having a car, an indicator for observations in wave 6, country and interview month dummies, equivalent household income quartile dummies, an indicator for individuals living in a farmhouse, a free-standing one- or two-family house or in a one- or two-family house as row or double house, the number of rooms per capita and its interaction with home ownership, the dummies for type of area where the building is located and its interaction with home ownership. Regional controls are CDD indicators referring to the past 12 months and during the summer months, the sum of monthly mean precipitation and snow in the 12 months before the interview and during the autumn/winter months, GDP per capita and the number of hospital beds per capita. The F-test for the excluded instruments is the Kleibergen–Paap rank Wald F-statistic. The Effective F-statistic is calculated following Montiel Olea and Pflueger (2013). Significance levels: p-value *** ≤ 0.01, ** ≤ 0.05, * ≤ 0.1.

Figs. 3–5 display heterogeneous effects derived by re-estimating our models on subsamples defined by respondents' age (64 or younger vs. 65 or older), household size (two members or fewer vs. three or more), and area of residence (rural vs. non-rural). This stratified analysis aims to provide insights for more targeted policy interventions. For every subsample, the figures depict the point estimates and their 95% confidence interval of the effects of being in energy poverty on the six outcomes. In Tables A.6-A.8, we report the estimated coefficients alongside several diagnostic checks: endogeneity test results, F-statistics for weak identification, and the p-values of the Hansen J-test for overidentifying restrictions. We also include a Wald test to evaluate whether the differences between the coefficients of the two groups are statistically significant.

TSLS and LIML estimates are less precise; however, we can see that older individuals living in smaller households are a vulnerable group; for them, energy poverty causes a significant reduction in grip strength. The LIML point estimate corresponds to 13 kg less in muscle strength.

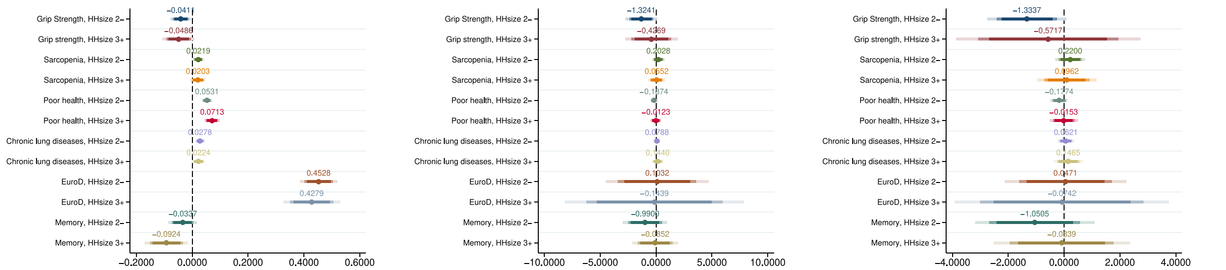
Looking at Wald test results for coefficient homogeneity across the estimated sub-samples, we can see that, in most specifications, the null hypothesis of equal parameters cannot be formally rejected. However, it must be considered that splitting the sample necessarily reduces the number of observations per model, which mechanically inflates the standard errors of the estimates. Since the denominator of the Wald statistic is a direct function of these standard errors, the test becomes highly conservative. This loss of statistical power, typically amplified by weak identification in specific sub-groups, tends to mask structural differences visible in point estimate magnitudes. Notwithstanding the statistical power limitations of the Wald test, several cases are worth mentioning, as they highlight distinct patterns of vulnerability across the sub-samples considered.

Focusing on age-based heterogeneity (Table A.6), the formal Wald test fails to reject the null hypothesis of coefficient equality for the effect of energy poverty on grip strength. According to the TSLS estimates, the effect is estimated with greater precision in the older population. For individuals aged 65 and over, the effect is statistically significant ($\beta = -0.9138^{*}$) and supported by stronger identification ($F = 7.86$) than for the younger cohort. Conversely, for those under 65, the point estimate remains statistically insignificant ($\beta = -0.9676$) despite its similar magnitude; this is largely a consequence of lower precision and weaker instruments ($F = 5.72$), which inflate the standard error. The consistency between TSLS and LIML estimates across both age groups reinforces the stability of the point estimates, suggesting that the Wald test's non-significance is primarily a byproduct of split-sample precision loss rather than a lack of detrimental effects among younger individuals. However, regarding sarcopenia, endogeneity tests consistently fail to reject the null hypothesis of exogeneity. Consequently, based on OLS estimates, a statistically significant difference in parameters emerges, indicating a higher probability of suffering from sarcopenia for the older group. This finding is



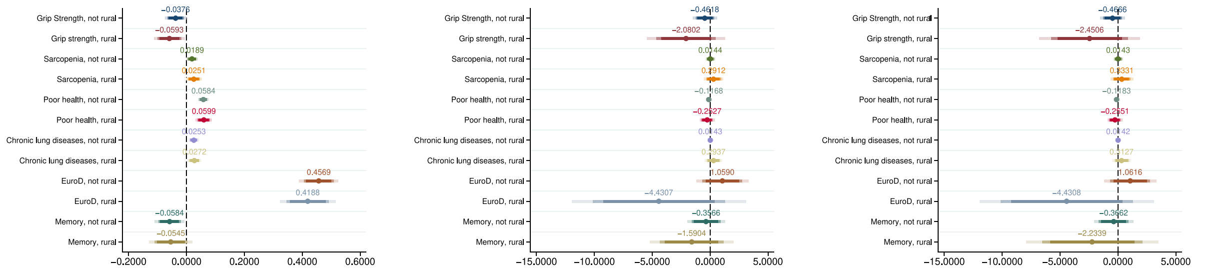
(a) OLS (b) TSLS (c) LIML

Fig. 3. The effect of energy poverty on health. Heterogeneity analysis. Individuals aged 64 or less *versus* 65 or more.



(a) OLS (b) TSLS (c) LIML

Fig. 4. The effect of energy poverty on health. Heterogeneity analysis. Household size lower than or equal to 2 *versus* higher than or equal to 3.



(a) OLS (b) TSLS (c) LIML

Fig. 5. The effect of energy poverty on health. Heterogeneity analysis. Rural *versus* non-rural areas.

clinically consistent with the fact that sarcopenia diagnoses are based on absolute grip strength thresholds. Given the lower baseline physical capacity of older individuals, a marginal reduction of similar magnitude is inherently more likely to drive them below the diagnostic threshold. Finally, regarding subjective health, baseline OLS estimates indicate that the detrimental relation between energy poverty and self-reported poor health is significantly stronger among older individuals (65+), with the Wald test formally rejecting the null of coefficient equality ($p = 0.0325$). However, these OLS patterns must be interpreted with caution for the younger cohort, as endogeneity tests reveal significant endogeneity issues specific to this sub-group.

Looking at Table A.7, which explores heterogeneous effects based on household size, the IV estimates suggest that the detrimental impact of energy poverty on grip strength is predominantly driven by individuals living in smaller households. Although the formal Wald tests fail to reject the null hypothesis of coefficient equality across most outcomes, a result largely attributable to weak identification issues that reduce statistical precision, the divergence in point estimates remains pronounced. The sole exception to this pattern is memory, where the Wald test indicates a borderline significant difference ($p = 0.1010$). For this specific outcome, the negative association between energy poverty and the memory score is stronger among larger households.

Finally, the residence-based analysis reveals that, in general, the point estimates capturing the detrimental effects of energy poverty are larger for individuals residing in rural areas. However, the formal Wald tests generally fail to signal statistically significant differences between the two sub-samples .

6. Conclusions

We estimate the effect of energy poverty on a range of subjective and objective health outcomes among older Europeans using harmonized SHARE data and regional weather-based variation in heating needs. Our analysis documents a robust negative association between energy poverty and health and provides evidence that self-restricting heating behaviour has economically and clinically meaningful consequences for physical health among older individuals.

A key contribution of the paper lies in addressing the potential endogeneity of energy poverty through regional Heating Degree Days (HDD) from Eurostat. Instrumental variable estimates indicate that energy poverty causes a substantial reduction in grip strength, a widely recognized biomarker of functional decline and mortality risk. The large magnitude of the IV coefficients relative to OLS indicates that physical deterioration is particularly severe for households at the behavioural margin, whose heating consumption is highly sensitive to financial and environmental pressures.

More broadly, our findings highlight the severe health costs of behavioural adaptation under financial constraints. When forced to cope with rising energy costs, households trade off thermal comfort and essential expenditures to alleviate budgetary pressure. However, these short-term adjustments result in significant physical deterioration, especially for older individuals with reduced thermoregulatory capacity.

Our heterogeneity analysis further suggests that the health consequences of energy poverty are particularly pronounced among older individuals living in smaller households and, to some extent, in rural areas. These findings point to the importance of targeted interventions aimed at vulnerable population groups rather than uniform energy support policies.

The paper also contributes to the growing debate on the distributive consequences of climate and decarbonization policies. Policies that increase residential energy costs without adequate compensatory mechanisms may unintentionally intensify heating deprivation among vulnerable households. In ageing societies, these effects may translate into additional healthcare burdens and wider welfare losses. Integrating energy affordability into climate policy design may therefore be crucial not only for equity reasons, but also for the effectiveness and political sustainability of the green transition.

A few caveats of the present study deserve discussion. First, while our instrumental variable strategy successfully addresses endogeneity for physical health outcomes, the rejection of exogeneity in some specifications may reflect data constraints, specifically the fact that geographical indicators cannot be disaggregated below the regional level. Nonetheless, this suggests that OLS estimates remain highly informative for specific dimensions of health.

Second, our measure of energy poverty relies on self-reported heating restriction. Although the literature suggests combining both subjective indicators and objective metrics (such as actual energy expenditures or indoor temperature data), our behavioural indicator is critical in its own right. Rather than reflecting mere reporting heterogeneity, it captures the actual financial trade-offs and self-rationing behaviour of vulnerable households, aspects that objective measures often fail to account for.

Finally, our study highlights the importance, for future large-scale surveys, to provide finer spatial identifiers and to include objective data on housing quality, energy efficiency investments, cooling deprivation and adaptive behaviours. While harmonized cross-national surveys like SHARE offer rich data on older populations, they naturally face trade-offs, and such data limitations do not provide sufficient information to fully separate these overlapping components. Access to such comprehensive and disaggregated data would allow future research to investigate the long-term behavioural and health consequences of energy affordability shocks, including the interaction between heating and cooling deprivation in the context of climate change, thereby helping to clarify the mechanisms linking energy deprivation, household decision-making, and health.

Declaration of competing interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

We understand that the Corresponding Author is the sole contact for the Editorial process (including Editorial Manager and direct communications with the office). He/she is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs. We confirm that we have provided a current, correct email address which is accessible by the Corresponding Author.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jebo.2026.107734.

Data availability

SHARE data are available to the scientific community here https://share-eric.eu/data/.

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