UNIVERSITÄT DUISBURG ESSEN

Open-Minded

ifso institute for socio-economics

Martin Buchner
Miriam Rehm

Energy Poverty and Health: Micro-Level Evidence from Germany

uni-due.de/soziooekonomie/wp

ifso working paper *2025* *no.48*

Energy Poverty and Health: Micro-Level Evidence from Germany*

Martin Buchner[†] Miriam Rehm[‡]

October 2024

*We thank Bruno Brinkmeier for excellent assistance in the preparation of this paper, and participants of the IfSO research seminar, the "Political Economy of Inequality" summer school, and the EuHEA PhD Conference for comments and feedback. Naturally, all remaining errors are our own. Martin Buchner gratefully acknowledges PhD funding from the Hans-Böckler Foundation.

[†]RWI – Leibniz Institute for Economic Research & University of Duisburg-Essen, Institute for Socio-Economics, martin.buchner@uni-due.de

[‡]University of Duisburg-Essen, Institute for Socio-Economics, miriam.rehm@uni-due.de

Abstract

This paper aims to understand the health effects of energy poverty in Germany using SOEP panel data from 2010 to 2020. Linear probability models and fixed effects ordered logit models reveal a consistently negative relationship of three expenditures-based energy poverty indicators with general health. The association is stronger for the subjective energy poverty metric: members of households unable to keep the home comfortably warm due to financial reasons have an about 3.23 p.p. lower probability of being in at least satisfactory health. Investigating potential channels shows that mental health is consistently negatively linked to our energy poverty metrics, while physical health is weakly associated with energy poverty in Germany, with the exception of doctor visits. Finally, by instrumenting energy poverty with data on energy price indices and matching energy costs to the heating systems used by households, we show that living in a household that experiences a transition to energy poverty due to rising energy prices is also linked to a lower likelihood of being in good health.

Keywords: energy poverty, health, fixed effects ordered logit models, Germany

JEL Codes: I10, I32, Q41

1 Introduction

Energy poverty of households can make their members sick. When households struggle to attain an adequate level of energy services, leading to energy or fuel poverty (Boardman, 1991; Bouzarovski, 2014), it can result in financial strain on the one hand, and to insufficient heating (and cooling) of living quarters on the other hand (Davillas et al., 2022). Such circumstances can precipitate various physical health problems, including increased risk of hypertension, inflammation, cardiovascular diseases, thrombosis, and respiratory illnesses in children, as well as mental health issues (Gallerani et al., 2004; Fares, 2013; Ballesteros-Arjona et al., 2022). Energy poverty is thus a policy concern both nationally, highlighted by advocacy groups in the United Kingdom since the 1970s, and at the European level, where the European Commission has issued a recommendation on addressing energy poverty (European Commission, 2020). In Germany, recent estimates suggest a prevalence of energy poverty of about 6.6% (Destatis, 2023). With short-run spikes in energy prices and long-term trends stemming from the German energy transition, the financial burden of energy costs on households is likely to increase. This paper aims to investigate whether a robust link exists between energy poverty and mental and physical health in Germany.

While there is ample research on low- and middle-income countries (Banerjee et al., 2021; Jayasinghe et al., 2021; Nawaz, 2021; Nie et al., 2021; Pan et al., 2021), recent studies have uncovered robust relationships between energy poverty and health in several high-income countries. Notably, four key studies using survey panel data for France (Kahouli, 2020; Baudu et al., 2020, EU-SILC), Australia (Churchill and Smyth, 2021, HILDA), and the UK (Davillas et al., 2022, UKHLS) have developed a framework for estimating the causal effect of various energy poverty measures on objective and self-rated health outcomes. Self-reported health serves as a common outcome variable across these studies, with Churchill and Smyth (2021) employing a composite indicator of subjective health and Davillas et al. (2022) in addition accessing objective health data from blood samples. The explanatory variable, energy poverty, is measured through both objective and subjective dimensions, with all three studies employing the low income-high cost measure[1] (Hills, 2012) as an objective measure, along with subjective assessments regarding the ability to adequately heat the home. Churchill and Smyth (2021) and Davillas et al. (2022) also incorporate a composite of objective and subjective measures for energy poverty. To address endogeneity concerns, energy poverty is instrumented with regional energy prices in all three studies, given their correlation with the potentially endogenous explanatory variable, energy poverty, and their presumed lack of direct linkage to health outcomes.

[1] This measure indicates that the share of energy expenditures exceeds 10% of equivalised disposable household income.

Additionally, standard controls include individual and dwelling characteristics, as well as climate factors.

This research yields valuable insights into the relationship between energy poverty and health. In addition to the robust headline correlation of energy poverty and adverse health outcomes (Champagne et al., 2023), it shows consistent findings even when going into more detail. For instance, subjectively measured energy poverty exhibits a stronger negative effect on health compared to measures assessing the financial burden of energy costs, such as the "ten percent rule" (energy costs amounting to more than ten percent of the household budget) or the "low income-high cost" indicator (a composite indicator based on its two namesake concepts). However, some substantial variations persist. Notably, instrumental variable (IV) effect sizes vary considerably across studies (e.g., Baudu et al., 2020; Kahouli, 2020; Davillas et al., 2022; Churchill and Smyth, 2021), emphasizing the significance of the concrete IV specification but also of national institutional characteristics.

Germany is characterised by a more decentralised institutional framework, including the social policy regime, than France or the United Kingdom, and by a less temperate climate than Australia or France. Thus, this study seeks to ascertain whether a robust link between energy poverty and health outcomes exists in the German context.[2] Leveraging representative panel data from the German Socio-Economic Panel (SOEP) spanning from 2010 to 2020, our outcome variable health is measured subjectively using a self-assessed indicator. Self-rated health metrics are recognized as reliable proxies for actual health status, combining both mental and physical health considerations (Schnittker and Bacak, 2014), and are commonly employed in empirical health economics (e.g., Kuehnle and Wunder, 2017) including studies on energy poverty (Llorca et al., 2020). For energy poverty measurement, we employ three expenditure-based metrics that consider the ratio of household income to energy expenditures alongside a subjective indicator, which constitute the most widely used metrics in energy poverty research (Brabo-Catala et al., 2024). The latter may better capture underconsumption of energy due to financial constraints and it avoids labelling high-income, high-energy use households as energy-poor (Thema and Vondung, 2020; Drescher and Janzen, 2021).

Our estimation strategy aims to establish a robust link between energy poverty and health outcomes. Initially, we fit a linear probability model before turning to panel-data ordered logit models with fixed effects using the blow-up and cluster (BUC) estimator proposed by Baetschmann et al. (2020) and Baetschmann et al. (2015). This approach

[2]Reibling and Jutz (2017) present a first quantitative indication for a negative correlation between energy poverty and mental health. Due to data restrictions, however, this study focuses exclusively on heating expenditures (without taking electricity costs into account), uses a single expenditure-based measure of energy poverty, and cannot assess causality.

accommodates the ordered scaling of the dependent variable (self-rated health) and exploits the panel structure of the data by controlling for potential unobserved individual time-invariant confounders. Additionally, we address possible biases in two-way fixed effects models with staggered and intermittent treatment by implementing the innovative Fixed Effects counterfactual estimator proposed by Liu et al. (2024). Across all three approaches, we consistently observe a statistically significant negative association between expenditure-based energy poverty indicators and overall health. Notably, both the linear probability model and the fixed effects ordered logit model show that the link between subjective energy poverty and health is especially strong.

Subsequently, we invesigate potential channels through which energy poverty impacts physical and mental health outcomes. Our findings suggest that the negative association primarily stems from deteriorations in mental rather than physical health in Germany, as evidenced by composite indicators and individual variables.

Furthermore, we adopt an IV approach to address the potential endogeneity between health outcomes and energy poverty. To this end, we instrument energy poverty using data on price indices for oil, gas, district heat, solid fuels, and electricity. Our data permit us to identify the primary energy source households use for heating, which is crucial for instrumenting energy poverty since leveraging the variation in energy prices is the leading approach in instrumenting energy poverty. They are generally assumed to be relevant, since price increases are likely to be correlated with energy poverty. The exclusion restriction is harder to satisfy (Kahouli, 2020; Churchill and Smyth, 2021): An increase in energy prices can affect health status beyond inducing energy poverty. For instance, it may prompt households to reduce direct expenditures on health-related products and services, such as gym memberships or healthy diets, in response to the price surge. However, this substitution effect is less of a concern if energy expenditure changes are small relative to total expenditures or if health expenditures are price inelastic (Davillas et al., 2022). The results of the IV point to a strong negative link between energy poverty and health, and are thus in line both with our multivariate findings and the literature.

Finally, we extensively test the robustness of these results by checking that our findings are not influenced by features of the German welfare state, which covers heating expenditures with some social transfers. Additionally, we restrict the sample to direct survey respondents and non-COVID years, and exclude over-sampled migrants.

The rest of this paper is structured as follows: Section 2 outlines our methodology and the empirical strategy, while Section 3 describes the data and variables. Section 4 presents our findings, commencing with the linear probability models in Section 4.1, followed by fixed-effects ordered logit models in Section 4.2, and two-way fixed effects counterfactual models in Section 4.3. Section 4.4 explores potential channels, and Section 4.5 addresses endogeneity with the IV approach. Section 5 examines the robustness of our results, and Section 6 concludes.

2 Empirical Strategy

To assess the relationship between energy poverty and an individual's overall health status, we first utilize a Linear Probability Model (LPM) for consistency with the existing literature. LPMs offer two key advantages: first, their results afford a simple and intuitive interpretation; and second, they are well-established in the literature and thus facilitate comparability with other studies, such as Kahouli (2020). The estimated equation is as follows:

$$\text{good\_health}_{it} = \beta_1 EP_{it} + \sum_n \beta_n \mathbf{X}_{n,it} + \vartheta_i + \gamma_t + \varepsilon_{it}, \tag{1}$$

where good_health_{it} is the self-rated health of respondent i at time t, which is assigned a value of 1 if the respondent's self-rated health status is "very good", "good" or "satisfactory" and 0 if the response is "poor" or "bad". EP is the respective indicator for energy poverty and $\mathbf{X}$ is a vector of n individual time-varying observed control variables. Individual fixed effects are captured by ϑ_i, while γ_t denotes wave dummies covering time fixed effects.

We proceed by employing fixed-effects ordered logistic regression models, our preferred approach. These models are advantageous as they avoid the need to dichotomize the dependent variable, self-rated health, which is measured on an ordered categorical scale, while still leveraging the panel data structure to account for unobserved time- and individual-invariant factors. However, in order to estimate the fixed effects consistently despite the so-called incidental parameters problem (Lancaster, 2000), Baetschmann et al. (2015) introduce a method leveraging the Conditional Maximum Likelihood (CML) estimator. For ordered categorial dependent variables, the Blow-Up and Cluster estimator (BUC) combines the „information of the CML estimators obtained from dichotomizing samples at different cutoff points“ (Baetschmann et al., 2020) by replacing the sample with copies of itself and applying the CML estimator for the entire enlarged sample.[3] The BUC-approach not only allows for a consistent estimation of fixed effects ordered logit models, but it also does not rely on the assumption that the thresholds are constant across individuals, in contrast to standard ordered logit models for cross-sectional data.

[3]Since the copies of the same units are not independent of each other, standard errors are clustered at the individual level.

We operationalize the fixed-effects ordered logistic models by employing self-rated health as dependent variable, which is scaled from 1 (bad) to 5 (very good health status). The approach can handle the same independent variables, including energy poverty, individual and year fixed effects, and controls, as the linear probability model.

Although the fixed effects ordered logit model is our preferred approach given the data structure, it has been shown that TWFE estimates may suffer from bias stemming from weighting issues, particularly when treatment effects exhibit temporal variation in staggered treatment designs (Chaisemartin and d'Haultfoeuille, 2023; Goodman-Bacon, 2021; Chaisemartin and d'Haultfoeuille, 2020). Our panel data is susceptible to this concern, given that individuals residing in households experience transitions in and out of energy poverty throughout our analysis period.[4] To address this issue, we employ the innovative Fixed Effects counterfactual estimator (FEct) proposed by Liu et al. (2024), which calculates the average treatment effect on the treated by directly imputing counterfactual outcomes for treated observations. This approach treats treated observations as missing during modelling and estimates the counterfactual outcome as a weighted sum of all untreated observations. This method compares the observed outcome of treated observations with the predicted counterfactual for each matched pair, thus removing biases caused by improper weighting that affect conventional TWFE models (Liu et al., 2024). We employ the FEct estimator for our expenditure-based energy poverty indicators, test for the parallel trends assumption, and perform placebo tests by removing pre-treatment observations used at the modelling stage.

Despite controlling for time-invariant heterogeneity and numerous potential time-variant confounding variables in all discussed models, as well as conducting tests for pre-trends and placebo treatments in the FEct models, concerns regarding identification may still arise if energy poverty is correlated with the error term. There are at least three possible sources of endogeneity: First, unobserved time-varying confounding variables not accounted for in the model specifications (see Equation 1) could bias the estimation of the regression coefficients. For instance, individual expectations concerning job loss or income may influence both health and energy poverty (Kahouli, 2020). A second potential source of endogeneity is reverse causation. For instance, individuals in poor health might earn less, thereby increasing the likelihood of being in a state of energy poverty, which could bias the regression estimates upward. Finally, endogeneity may stem from measurement error. Survey respondents might not accurately recall their energy bills, leading to systematic over- or underestimation of their annual energy expenditures.

[4]Figure A5 in the Appendix provides a visual representation of individuals' treatment status in our sample over time.

To tackle these potential endogeneity issues, we adopt instrumental fixed-effects models in our analysis. Household-specific energy prices serve as instruments for our estimation.[5]. Specifically, we employ consumer price indices for the primary energy source used by each household for heating, encompassing gas, oil, electricity, solid fuels, or district heating. The rationale behind instrumenting energy poverty with energy price indices lies in the notion that fluctuations in heating prices impact individual health exclusively through an increase in the probability of experiencing energy poverty. We thus estimate a 2SLS fixed effects equation with the following second stage:

$$\text{good\_health}_{it} = \beta_1 \widehat{EP}_{it} + \sum_n \beta_n \mathbf{X}_{n,it} + \vartheta_{2i} + \gamma_{2t} + \varepsilon_{2it}, \tag{2}$$

where $\mathbf{X}$ are the n controls for individual i at time t, ϑ_{2i} and γ_{2t} are the individual and time fixed effects, and ε is the error terms. $\widehat{EP}_{it}$ indicates the fitted values from the first stage:

$$EP_{it} = \pi_1 Z_{it} + \sum_n \pi_n \mathbf{X}_{n,it} + \vartheta_{1i} + \gamma_{1t} + \varepsilon_{1it}, \tag{3}$$

where Z_{it} indicates the exogenous instrument, that is, household-specific energy prices.

3 Data and Variables

We utilize data from the nationally representative German Socio-Economic Panel (SOEP)[6]. This dataaset is particularly suited for our objectives as it provides detailed longitudinal information on household income, heating and electricity expenditures, individual subjective self-rated health status, and a comprehensive array of additional household and personal characteristics. Our analysis spans the eleven waves from 2010 to 2020, as electricity expenditure data are available from 2010. We restrict the sample to observations of adult respondents with valid information on self-rated health, monthly household net income, household energy expenditure, and all variables used as controls in the main regression model. The resulting sample comprises 255,684 observations from 56,263 individuals.

The outcome variable is respondents' answer to the question: "How would you describe your current health?". Responses are categorized into five options, ranging from bad (1) to very good (5).[7] When investigating the channels, we further distinguish between physical

[5]As discussed in Section 1, instrumental variable approaches are well-established in this literature.

[6]Socio-Economic Panel (SOEP) 2022, core release v37 `doi:10.5684/soep.core.v37eu`.

[7]To align with the dichotomized categories in the LPM model, we invert the scale from the original SOEP data where 1 corresponds to very good and 5 to bad.

and mental health by using the physical component summary scale (PCS) and the mental component summary scale (MCS)[8] which range from 0 (worst) to 100 (best) that are available biennially from 2010 to 2020.

In constructing our main explanatory variable, we employ four distinct measures of energy poverty commonly discussed in the literature (Drescher and Janzen, 2021). These measures are coded as dummy variables, with 1 indicating a household experiencing energy poverty. They include three expenditure-based indicators, considered "objective", and one consensual-based indicator, labeled "subjective".

The expenditure-based metrics rely on the relation between household income and energy expenditures, where the latter are defined as the sum of monthly expenditures on heating and electricity.[9] Both income and energy expenditures are equivalized using the Modified OECD Equivalence Weights Scale[10].

The first objective metric, the Ten Percent Rule (tpr), identifies a household i as energy poor if its energy expenditures (e) constitute at least ten percent of its income (y): $tpr = 1 \mid \frac{e_i}{y_i} > 0.1$. The second objective indicator employed is the Two Times Median Share of Income metric (mtwo), which categorizes households as energy poor if their share of income spent on energy exceeds twice the national median of this ratio: $mtwo = 1 \mid \frac{e_i}{y_i} > 2\overline{(\frac{e}{y})}$. The third objective metric, termed the Low Income High Cost indicator (lihc), classifies households as energy poor if their energy expenditures are above the national median *and* their residual income (i.e. income minus energy costs) falls below the official national income poverty line (60% of median income): $lihc = 1 \mid e_i > \bar{e}$ and $y_i - e_i < 0.6\bar{y}$.[11]

The subjective indicator is based on the question "Do you keep your home comfortably warm in the colder months?" with dichotomous responses of "yes" and "no". If the respondent answers "no" to the initial question, a follow-up question inquires whether this is due to financial constraints. Consequently, our subjective indicator identifies households as energy poor if they respond negatively to the first question and affirmatively to the second.[12] As these questions are available only in the SOEP data from 2016 to 2019, the analysis for this energy poverty indicator is confined to those four panel years.

[8]Both variables are provided by the SOEP and are constructed using explorative factor analysis over a large variety of physical and mental health related SOEP-items (Nübling et al., 2006).

[9]For homeowners, who only provide yearly energy expenditure information, we convert these values to monthly figures by dividing by 12.

[10]Our analysis yields similar results when applying the OECD square root scale.

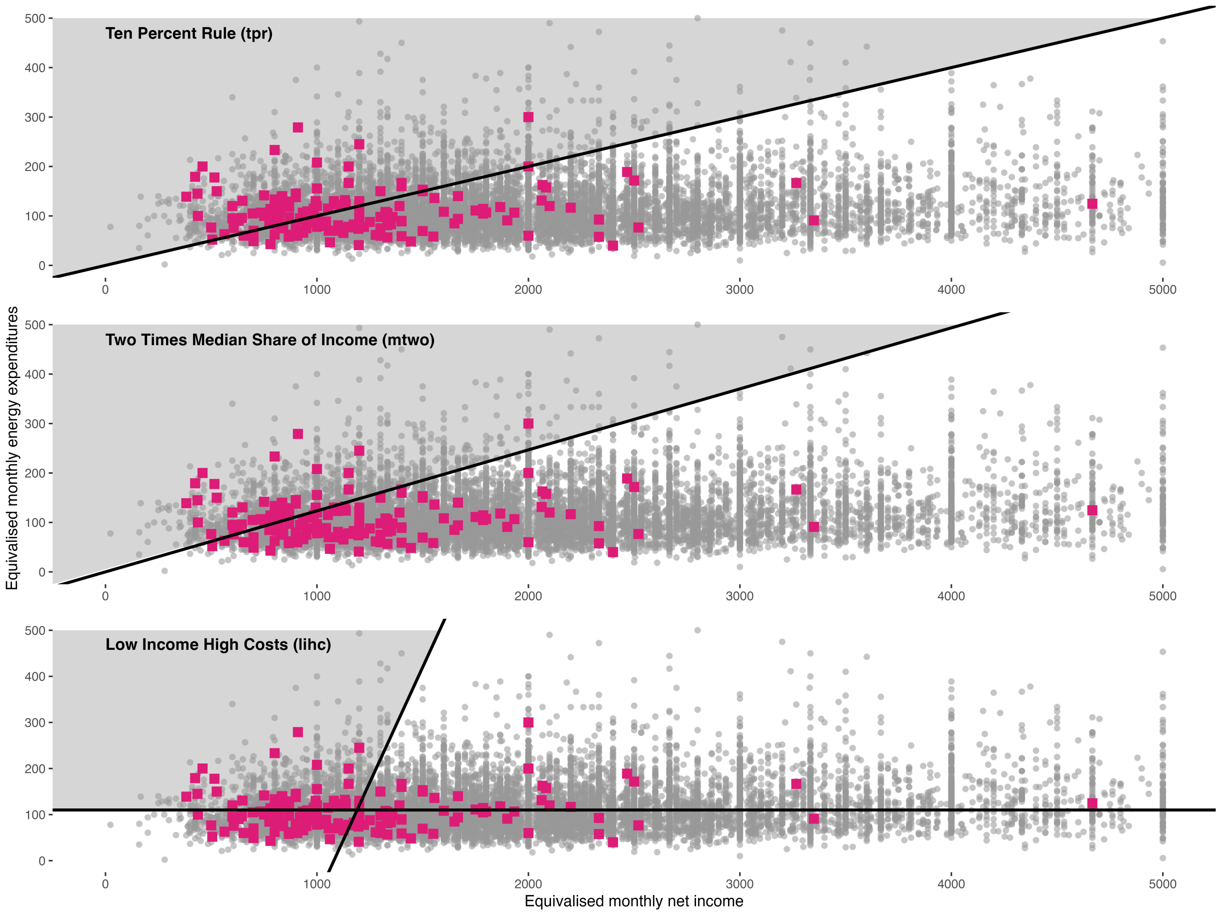
[11]For the calculation of energy poverty indicators that refer to a reference group (Two Times Median Share of Income and Low Income High Cost metric), SOEP data weights are used to calculate the respective median values.

[12]This consensual-based indicator focuses exclusively on heating and thus reflects a narrower definition of energy poverty compared to the expenditure-based metrics (Drescher and Janzen, 2021). Nevertheless, the inability to maintain comfortable warmth at home constitutes a significant pathway through which energy poverty can impact health (Davillas et al., 2022).

Figure 1 shows households categorized as energy poor in 2019 based on our four indicators. Households situated in the shaded areas meet the criteria for energy poverty according to the Ten Percent Rule (top panel), the Two Times Median Share of Income (middle panel), and the Low Income High Cost metric (bottom panel). The pink squares represent households identified as energy poor by the subjective indicator; naturally, they are consistent across panels. Two noteworthy points emerge: First, it visually demonstrates that the Low Income High Cost (lihc) measure is, by construction, particularly associated with low income. Second, there is limited overlap between the subjective indicator and the expenditure-based metrics. For instance, in 2019, only about 3.7% of households classified as energy poor by the Low Income High Cost measure reported not being able to maintain comfortable warmth at home due to financial constraints. Conversely, approximately 24% of subjectively energy poor households also meet the criteria for energy poverty according to the Low Income High Costs indicator. Despite the surprisingly low intersection between the objective and subjective indicators, the objective indicators exhibit a high degree of overlap. This is further illustrated in Figure A1 in the Appendix, where nearly all individuals classified as energy poor by the Two Times Median Share of Income or Low Income High Cost indicators also meet the criteria for energy poverty according to the Ten Percent Rule indicator.

The limited overlap between the objective and subjective indicators underscores the significance of employing a diverse set of energy poverty indicators. By incorporating both objective and subjective assessments, these indicators capture different dimensions of energy poverty. While expenditure-based metrics may effectively gauge the financial burden, the subjective indicator might offer a more nuanced understanding of actual deprivation and, consequently, financial constraints.

Figure 1: Relationship between objective and subjective energy poverty indicators in 2019

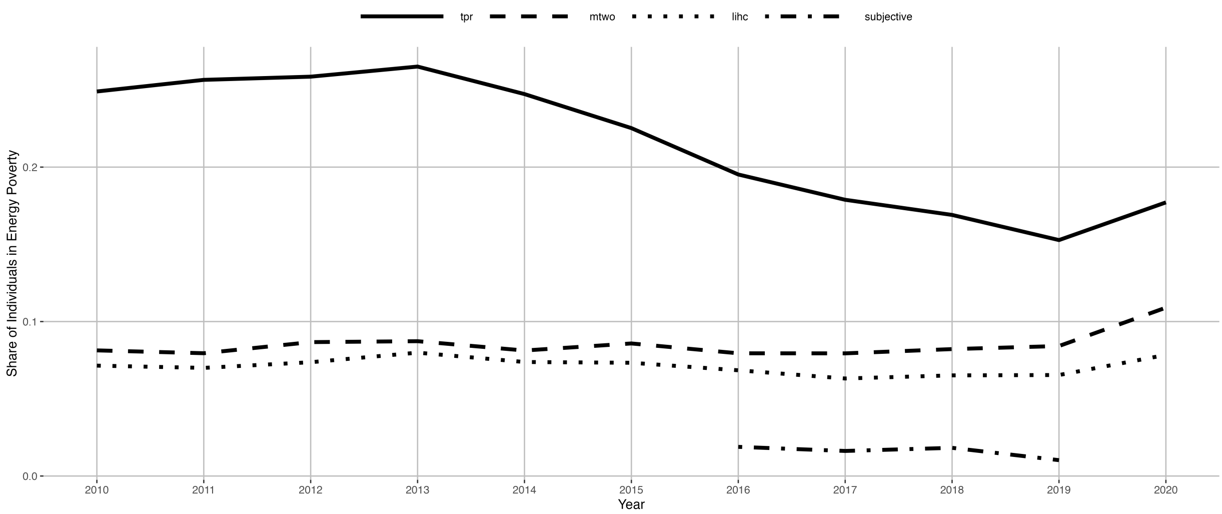


Notes: Each shape represents one household in the dataset in 2019. The pink squares represent households that are energy-poor according to the subjective indicator (i.e., not keeping the home comfortably warm in the colder months due to financial reasons); all other households are represented by grey dots. Upper panel: Relationship between tpr and subjective indicator. All households north of the tpr energy poverty line (indicating households spending more than 10% of household income on energy expenditures) are considered energy poor. Central panel: Relationship between mtwo and subjective indicator. All households north of the mtwo energy poverty line (indicating household with more than two times the median share of energy expenditures in income) are considered energy poor. Lower panel: Relationship between lihc and subjective indicator. All households in the shaded area northwest of the lihc-poverty lines (indicating households whose energy expenditures are above the national median energy expenditures and whose residual income net of energy expenditures is below the national poverty line of 60% of median income) are considered energy poor. Data: SOEP (2022), adopted from Drescher and Janzen (2021).

Figure 2 shows the proportion of individuals classified as energy poor in our sample for each survey year. Notably, in every year, the percentage of individuals identified as energy poor under the Ten Percent Rule significantly exceeds the share identified using the Low Income High Cost, Two Times Median Share of Income, and the subjective indicator. While the proportion of individuals in energy poverty according to the Low Income High Cost and the Two Times Median Share of Income indicators remains relatively stable across most survey years (about 7% and 8.5%, respectively), energy poverty under the Ten

Percent Rule indicator has notably decreased between 2013 and 2019, from about 26.5% to about 15.3%. This decline may be attributable to a reduction in the median share of energy expenditures in household income, which decreased from 7.4% in 2010 to 6% in 2020. The subjective indicator, available only for the survey years between 2016 and 2019, indicates a low incidence, averaging about 1.5%. While the incidence of the energy poverty metrics is relatively stable over time (with the exception of the Ten Percent Rule indicator), there is considerable within-individual variation for each metric (see Table A1 in the Appendix for details).[13]

Figure 2: Evolution of energy poverty rates (2010-2020)



Evolution of energy poverty rates in the sample. Data: SOEP (2022), adopted from Drescher and Janzen (2021).

Finally, our multivariate analysis controls for a host of socio-economic characteristics that may influence both energy poverty and health. These factors encompass age, age squared, education, marital status, the number of dependants in the household (aged below 18 years), labor force status, and equivalized household income. To disentangle the health implications of energy poverty from those of income poverty, we incorporate a control variable for income poverty in all our analyses. This variable is binary, indicating whether an individual's equivalized household income falls below 60% of the median household income for the respective survey year. Summary statistics for all variables that enter the main regression analyses are presented in Table 1.

We employ Germany-wide price indices for electricity, gas, oil, solid fuels, and district heat as instruments for energy poverty. The specific price index matched to each household depends on its primary energy source used for heating. The price index data are sourced

[13]For a comprehensive discussion on the incidence and dynamics of energy poverty in the German SOEP data, see Drescher and Janzen (2021).

Table 1: Summary statistics for the pooled sample (2010-2020)

	Mean	Std. Dev.	Min	Max	n
Main outcome variables					
Self rated health	3.411	0.967	1.00	5.00	255684
Good health	0.829	0.377	0.00	1.00	255684
Energy poverty indicators					
Ten percent rule (tpr)	0.218	0.413	0.00	1.00	255684
Two times median share (mtwo)	0.085	0.279	0.00	1.00	255684
Low income high costs (lihc)	0.071	0.257	0.00	1.00	255684
subjective	0.016	0.125	0.00	1.00	86211
Control variables					
Household income (in Euro)	3238.622	5157.935	1.00	1700000.00	255684
Equivalized household income (in Euro)	1832.627	4179.793	0.67	1700000.00	255684
Log of equivalized household income	7.360	0.520	0.51	14.35	255684
Poverty line	948.745	90.889	840.00	1117.00	255684
Income poverty	0.149	0.356	0.00	1.00	255684
Energy expenditures (in Euro)	189.625	85.649	0.00	1500.00	255684
Equivalized energy expenditures (in Euro)	109.336	51.180	0.00	1400.00	255684
Age	48.986	16.667	17.00	103.00	255684
Age squared	2677.390	1726.530	289.00	10609.00	255684
Number of dependants in hh	0.816	1.142	0.00	11.00	255684
Education					
Less than High School	0.147	0.354	0.00	1.00	255684
High School	0.582	0.493	0.00	1.00	255684
More than High School	0.271	0.445	0.00	1.00	255684
Labor force status					
(Self-)Employed	0.606	0.489	0.00	1.00	255684
Registered Unemployed	0.059	0.236	0.00	1.00	255684
Not employed	0.072	0.258	0.00	1.00	255684
In Education / Apprentice / Community Service	0.049	0.215	0.00	1.00	255684
Pensioner	0.215	0.411	0.00	1.00	255684
Marital status					
Single	0.218	0.413	0.00	1.00	255684
Married	0.610	0.488	0.00	1.00	255684
Separated or divorced	0.120	0.325	0.00	1.00	255684
Widowed	0.052	0.221	0.00	1.00	255684
Alternative health variables					
Number of doctor visits (in last 3 months)	2.351	3.724	0.00	99.00	248713
Number of days off work in survey year	11.025	31.217	0.00	365.00	123568
Dummy indicating any hospital stay in survey year	0.131	0.338	0.00	1.00	196707
Mental Health Summary Scale	50.715	9.905	0.56	80.60	121227
Physical Health Summary Scale	49.237	10.110	8.76	76.42	121227
Frequency of being happy in the last 4 weeks	3.587	0.839	1.00	5.00	227573
Frequency of being sad in the last 4 weeks	2.326	1.011	1.00	5.00	227580
Current Life Satisfaction	7.344	1.706	0.00	10.00	252040
Satisfaction with health	6.735	2.199	0.00	10.00	250495
Worries about own health	1.886	0.686	1.00	3.00	235764

This table shows summary statistics for the data used in the analysis below. Data: SOEP (2022).

from the Federal Statistical Office (Statistisches Bundesamt, 2024). However, it is important to note that due to a methodological change in the calculation of the price indices, data for the district heat price index begins in 2015.

We incorporate one-year lagged energy price index values for our Instrumental Variable (IV) estimates, driven by two considerations: First, in the SOEP dataset, homeowners typically report energy expenditures from the preceding year, while renters, who report current expenditures, are influenced by utility bills based on prior energy prices. Second, given that SOEP interviews predominantly occur during the spring months[14], energy prices from the previous year retain greater salience when respondents report their energy expenditure. Consequently, our instrument comprises 49 unique values, reflecting variations across 5 heating types and 11 time periods (see Figure 3).

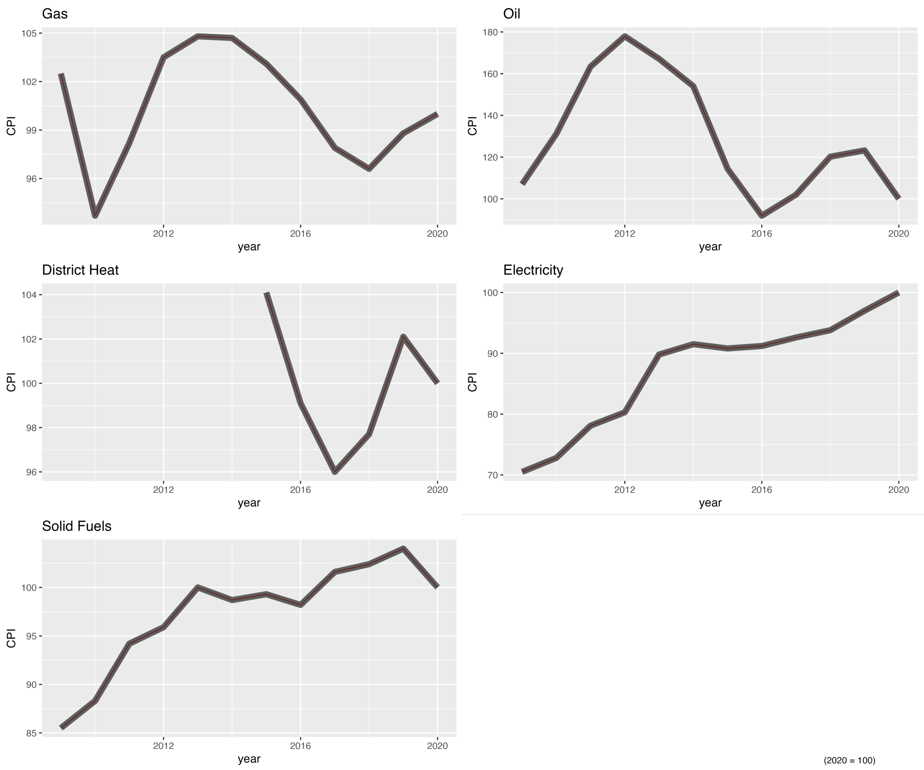
In assigning heating systems to households, we leverage a unique feature of the SOEP dataset. In 2015 and 2020, households were surveyed about their expenditure on heating per energy source[15]. When heating costs are reported for a single energy source, we assign that specific heating system to the household for the respective year. In instances where expenses are incurred for multiple energy sources, we prioritise based on the following hierarchy, reflecting the relative frequency in Germany: gas > oil > district heating > electricity > solid fuels > other (Destatis, 2022). We extend this assigned heating system to all years preceding and succeeding the observed year, provided the household does not report a move. We assume that as long as there is no move, the household's heating system remains unchanged. However, if the heating systems differ between 2015 and 2020, individuals residing in those households are excluded from our instrumental variable (IV) analysis, as we cannot determine the timing of the switch. Our IV analysis thus only includes observations from households that consistently utilize the same energy source for heating over time.

The summary statistics for the reduced subsample, consisting of individuals residing in households where we have successfully assigned a heating system and obtained the corresponding price index from the previous year, are presented in Table A2. Remarkably, no substantial deviations are observed between this reduced sample and our main sample concerning the dependent variable good_health and the energy poverty indicators.

[14]See Figure A4 in the Appendix, which shows that approximately 50% of interviews take place in February and March, and over 75% occur in the first half of the year.

[15]Expenditures can be reported across various categories, including oil, gas, district heating, electricity, environmental, pellets, coal, biomass, liquid gas, and solar. For the analysis presented in this paper, we aggregate these categories into gas, oil, district heating, electricity, solid fuels, and other, as price data are available only for the first five of these energy sources.

Figure 3: Energy price indices



This figure shows the energy price indices for gas, oil, district heat, electricity, and solid fules, indexed to 2020 as 100. We employ the one-year lag of the price indices in our instrumental variable (IV) models. Data: Statistisches Bundesamt (2024).

4 Results

This section first presents the results for energy poverty and health through standard linear probability models, ordered logistic fixed-effects, and two-way fixed effects counterfactual models. It then moves to examining the evidence for potential channels between the two and attempts to address their potential endogeneity using an IV approach. It concludes with robustness checks.

4.1 Linear Probability Models

Table 2 shows linear probability models focusing on the threshold between very good to satisfactory health versus poor to bad health status. The results indicate a negative correlation between health status and energy poverty across all four energy poverty indicators (columns 1-4). Notably, as shown in column 4, the effect size for the subjective energy poverty indicator is substantially larger compared to the expenditure-based indicators. When energy poverty is subjectively measured, it is associated with a 3.2 percentage points lower probability of reporting at least a satisfactory health status.

All four specifications in Table 3 control for other factors potentially related to health as discussed in Section 3, including logarithmized and equivalized household income, income poverty, socio-economic characteristics such as age and age squared, education, labour force status (including being registered as unemployed), marital status, and the number of dependants living in the household. Most relevant for our research question are the covariates capturing income poverty and unemployment, both of which are statistically significantly associated with worse health.

4.2 Ordered Logistic Fixed-Effects Models

Next, we examine whether the negative association between energy poverty and health persists when considering the ordered categorical nature of the dependent variable and the panel data structure. Fixed-effects ordered logistic estimates of the relationship between energy poverty and general health variables are presented in odds ratios in Table 3. Similar to the linear probability model, we incorporate the full set of controls. The exponentiated coefficients for all three expenditure-based energy poverty indicators (columns 1-3) are statistically significant at least at the 5%-level and smaller than one, suggesting that energy poverty is associated with a decrease in the odds ratio for being in better health categories. For instance, the odds ratio of 0.945 in column 1 indicates that living in a household classified as energy poor by the Ten Percent Rule (tpr) decreases the odds ratio of being in a better health category by about 5.5%. In other words, individuals in Ten Percent Rule energy-poor households have 0.945 times the odds of being in better health categories than those in non-energy-poor households. Similarly, the odds ratios for the Two Times Median Share of Income (mtwo) and the Low Income High Cost (lihc) indicators are 0.943 and 0.919, respectively. As shown in column 4, the odds ratio for the subjective energy poverty indicator is substantially larger than those of the expenditure-based indicators. Its point estimate of 0.818 indicates that living in a household unable to keep the home comfortably warm due to financial reasons decreases the odds ratio of being in a better health category by about 18,2%.

Table 4 presents the marginal effects at the sample average, which may be more intuitive to interpret.[16] These indicate that being energy poor according to our four metrics (columns 1-4) is associated with lower probabilities of being in the two best health categories (lines 4-5) and higher probabilities of being in the three lower health categories

[16]Marginal effects at the average use the relative frequencies of the corresponding categories of the outcome variable in the estimation sample to compute the sample average. Note that the *marginal effects at the sample average* differ from the *marginal effects at the average of the regressors* and also differ from the *average marginal effect*. For a more detailed discussion, see Baetschmann et al. (2020).

Table 2: Energy poverty and health – linear probability model

	(1) Good health	(2) Good health	(3) Good health	(4) Good health
Ten percent rule (tpr)	-0.00828***			
	[0.00268]			
Two times median share (mtwo)		-0.00879**		
		[0.00370]		
Low income high costs (lihc)			-0.00892**	
			[0.00396]	
subjective				-0.0323**
				[0.0134]
Income poverty	-0.0108***	-0.0112***	-0.0114***	-0.0119
	[0.00375]	[0.00373]	[0.00372]	[0.00723]
Log of eq. HH income	0.00270	0.00366	0.00448	0.00443
	[0.00364]	[0.00361]	[0.00357]	[0.00681]
Age	0.00215*	0.00218*	0.00213*	0.0179***
	[0.00111]	[0.00111]	[0.00111]	[0.00346]
Age squared	-0.0000812***	-0.0000810***	-0.0000808***	-0.000209***
	[0.0000107]	[0.0000107]	[0.0000107]	[0.0000335]
Registered Unemployed	-0.0551***	-0.0554***	-0.0554***	-0.0542***
	[0.00497]	[0.00497]	[0.00497]	[0.0100]
Not employed	-0.0202***	-0.0203***	-0.0202***	-0.00912
	[0.00399]	[0.00399]	[0.00399]	[0.00836]
In Education / Apprentice / Community Service	-0.00177	-0.00188	-0.00181	-0.0116
	[0.00469]	[0.00469]	[0.00469]	[0.00925]
Pensioner	0.0125**	0.0124**	0.0125**	0.0129
	[0.00569]	[0.00569]	[0.00569]	[0.0111]
High School	0.00338	0.00362	0.00364	-0.0299
	[0.00868]	[0.00867]	[0.00867]	[0.0182]
More than High School	0.00380	0.00404	0.00393	-0.0470*
	[0.0116]	[0.0116]	[0.0116]	[0.0245]
Married	0.00182	0.00180	0.00180	0.00165
	[0.00550]	[0.00550]	[0.00550]	[0.0137]
Separated or divorced	0.0118	0.0115	0.0115	0.0166
	[0.00832]	[0.00832]	[0.00832]	[0.0196]
Widowed	-0.00288	-0.00294	-0.00360	0.00641
	[0.0143]	[0.0144]	[0.0144]	[0.0342]
Number of dependants in hh	0.000885	0.000942	0.00101	-0.00453
	[0.00185]	[0.00185]	[0.00185]	[0.00441]
Constant	0.926***	0.916***	0.912***	0.512***
	[0.0341]	[0.0340]	[0.0338]	[0.0945]
Individual Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
n (total)	255684	255684	255684	86211

This table shows the estimates of a linear probability model for the four energy poverty indicators on the probability of being in good health (dichotomized as 1 for very good, good or satisfactory, and 0 for poor or bad). The reference category for labour force status is (self-)employed, for education is less than high school, and for marital status is single. Cluster robust standard errors in brackets.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Ordered logistic regression

	(1) Self rated health	(2) Self rated health	(3) Self rated health	(4) Self rated health
Ten percent rule (tpr)	0.945***			
	[0.0176]			
Two times median share (mtwo)		0.943**		
		[0.0230]		
Low income high costs (lihc)			0.919***	
			[0.0235]	
subjective				0.818**
				[0.0744]
Socio-econ. controls	Yes	Yes	Yes	Yes
Control for income poverty	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations (total)	255684	255684	255684	86211
Observations (w. variation in outcome)	206662	206662	206662	52671
Panel units (w. variation in outcome)	31797	31797	31797	15581

This table shows the exponentiated coefficients of a fixed-effects ordered logistic regression for the four energy poverty indicators on self-rated health measured on a 5-point scale with 1 = bad and 5 = very good. Cluster robust standard errors in brackets. Data: SOEP (2022).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(lines 1-3). The results suggest that if a household falls into Ten Percent Rule energy poverty, there is a decrease of 1.4 percentage points in the probability of being in good or very good health for its members. These results are consistent across all four indicators; for subjective energy poverty, the association again appears to be the strongest, with a reduction of approximately 5 percentage points in the probability of being in good or very good health.

4.3 Two-way Fixed Effects Counterfactual Models

As a third modeling approach, we employ fixed effects counterfactual models (FEct) to counteract potential weighting issues stemming from our staggered and intermittent treatment. The dependent variable is a dummy variable that captures whether individuals report satisfactory, good, or very good health, as opposed to poor or bad health. The main explanatory variables are the expenditure-based indicators, as the subjective indicator for energy poverty is available for too few periods to adequately test for parallel trends.

Figures A6 to A8 in the Appendix provide a visual assessment of the parallel trends assumption, complemented by an F-test for zero residual averages in the pretreatment periods, where a higher F-test p-value indicates a better fit for pre-trend analysis. The ATT plots and the p-values of the F- Test collectively indicate no substantial presence

Table 4: Marginal effects

	(1) tpr	(2) mtwo	(3) lihc	(4) subjective
self-rated health				
1	0.00192***	0.00200**	0.00285***	0.00712**
	[0.000632]	[0.000827]	[0.000868]	[0.00323]
2	0.00660***	0.00691**	0.00984***	0.0250**
	[0.00218]	[0.00285]	[0.00299]	[0.0113]
3	0.00556***	0.00582**	0.00829***	0.0176**
	[0.00184]	[0.00240]	[0.00252]	[0.00798]
4	-0.00910***	-0.00953**	-0.0136***	-0.0317**
	[0.00300]	[0.00393]	[0.00413]	[0.0144]
5	-0.00498***	-0.00521**	-0.00742***	-0.0180**
	[0.00164]	[0.00215]	[0.00226]	[0.00815]

This table shows the marginal effects of the four energy poverty indicators in a fixed-effect ordered logistic regression, calculated at the sample average of the dependent variable (self-rated health on a 5-point scale with 1 = bad and 5 = very good). The reported standard errors are for effects at the sample average and not for effects at the population average. Data: SOEP (2022).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

of pretreatment differential trends for most models while the p-value of the t-test for the placebo test in the Low Income High Cost model is borderline statistically significant at the 10% level.[17] Furthermore, we conduct a placebo test wherein all observations from periods -2 to 0 relative to the treatment timing are excluded. Instead, the untreated outcomes of these omitted periods are predicted using a model trained with the remaining untreated observations (Liu et al., 2024). The outcomes are depicted in Figures A9-A11 in the Appendix: In the placebo tests, we cannot reject the null hypothesis of an ATT = 0 for the Two Times Median Share of Income and Low Income High Cost models, with p-values of 0.967 and 0.825, respectively. This outcome supports the validity of the underlying assumptions for these models.

[17]This is noteworthy, especially considering that the F-Test is particularly sensitive to deviations from zero: „[W]hen the sample size is large, a small confounder (or a few outliers) that only contributes to a neglectable amount of bias in the causal estimates will almost always cause rejection of the null hypothesis of joint zero means using the F test". (Liu et al., 2024).

Table 5: Fixed effects counterfactual models

EP Indicator	**ATT**	**N**	**sd**	**lower CI**	**upper CI**	**p-value**
tpr	-0.01008	28502	0.003204	-0.01529	-0.005	0.002
mtwo	-0.01268	13842	0.004397	-0.0197	-0.0051	0.004
lihc	-0.01024	11966	0.004931	-0.01844	-0.00223	0.038

This table shows fixed effects counterfactual estimations. Standard errors are obtained through non-parametric bootstrap procedures (500 bootstrap runs). Units must have a minimum of 1 observed period under control to be considered. Data: SOEP (2022)

The average treatment effects of the treated (ATT) are presented in Table 5. We observe similar but somewhat larger negative ATTs compared to the coefficients obtained from the linear probability model. Specifically, being in energy poverty is associated with a decrease in the probability of being in good or very good health by approximately 1 percentage point for the Ten Percent Rule and the Low Income High Cost indicator, and about 1.3 percentages points for the Two Times Median indicator.

Our results thus far demonstrate a robust negative association between energy poverty and health in Germany, aligning with findings from the literature on other high-income countries. As discussed in Section 1, Kahouli (2020), Baudu et al. (2020), and Churchill and Smyth (2021), and Davillas et al. (2022) establish this relationship for France, Australia, and the UK. Moreover, Kahouli (2020) and Churchill and Smyth (2021) also observe stronger effects of consensual-based (i.e., subjective) indicators compared to expenditure-based metrics. In the next section, we explore potential channels through which energy poverty may affect health in Germany.

4.4 Potential Channels

We now turn to exploring the potential channels through which energy poverty may impact health. Table 6 presents the results of fixed-effects regressions for our full model, utilizing mental health (left-hand side panel) and physical health (right-hand side panel) summary scales as dependent variables.[18] The associations with our energy poverty metrics exhibit stark variations: Mental health is negatively associated with energy poverty, statistically significant at least at the 5% level for all our expenditure-based metrics. However, there appears to be no such association for physical health.

While the magnitude of the coefficients for the mental health summary scale associ-

[18]Recall that the dependent variable is available biennially, leading to a reduced number of observations of 121,227. Consequently, we cannot utilize the subjective energy poverty metric due to its limited overlap with the interval censored physical and mental health summary scales.

ated with the three energy poverty metrics may not be directly interpretable due to the composite nature of the outcome variable, the coefficients exhibit consistent sizes. This association persists even after extensive controls for potential confounding factors such as income poverty and unemployment, mirroring the findings from the previous Section.

Table 6: Mental and physical health summary scales – SF12-questionaire

	Mental Summary Scale			**Physical Summary Scale**		
Ten percent rule (tpr)	-0.354***			-0.0438		
	[0.108]			[0.0868]		
Two times median share (mtwo)		-0.401***			0.0460	
		[0.146]			[0.118]	
Low income high costs (lihc)			-0.322**			0.241*
			[0.162]			[0.130]
Socio-econ. controls	Yes	Yes	Yes	Yes	Yes	Yes
Control for income poverty	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
n	121227	121227	121227	121227	121227	121227

This table shows fixed-effects regressions for the three objective energy poverty indicators on mental and on physical health summary scales (ranging from 0 to 100). Due to data availability, this regression covers every other year (2010, 2012, ..., 2020). Individual clustered robust standard errors in parentheses. Data: SOEP (2022).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Next, we explore these two channels further by employing individual items related to mental and physical health. Our data permits us to substitute the dependent variable with three "hard" indicators for physical health and five "soft" indicators for mental health: the logarithmized number of visits to a doctor's office in the previous year, the number of stays at a hospital in the previous year, and the logarithmized number of days off work sick for physical health; and life satisfaction, the frequency of being happy or sad in the last four weeks, health satisfaction, and concerns about health for mental health.

The results are reported in the Appendix. They reinforce the conclusions drawn from the mental and physical health summary scales: Physical health demonstrates a weak, if any, connection to energy poverty after adjusting for income poverty and unemployment. While the number of doctor visits (Table A3) displays some correlation with energy poverty, coefficients for hospital stays (Table A4) and the number of days off work (Table A5) are statistically insignificant.

Conversely, indicators related to mental health consistently substantiate a link with energy poverty even after controlling for other factors. Life satisfaction (Table A6), health satisfaction (to a lesser extent, Table A7), and the frequency of being happy (Table A8) are negatively associated with all four energy poverty indicators, while the frequency of being sad (Table A9) and, less consistently, concerns about one's health (Table A10) tend to increase with energy poverty.

This robust relationship thus supports the hypothesis that, at least within the German context, the negative health impacts of energy poverty may primarily originate from its effects on mental well-being. However, as discussed in Section 2, various potential sources of endogeneity of energy poverty to health necessitate caution in interpreting these findings. Consequently, the next section investigates whether these findings remain robust in an IV analysis.

4.5 Addressing Endogeneity

To assess whether the negative association between energy poverty and health persists while addressing potential endogeneity, we employ 2SLS regressions, instrumenting for energy poverty with household-specific energy prices using energy price data. The results of the IV fixed-effects regression are presented in Table 7. We incorporate the same covariates as in our main specification, including a dummy for income poverty. The Kleibergen-Paap Wald F-statistic of the first stage suggests that the instrument is not weak for the Ten Percent Rule and Two Times Median Share of Income indicators (Stock and Yogo, 2005). However, for the Low Income High Cost indicator, the F-statistic is marginally larger than 10, indicating only a weak correlation between household-specific energy prices and this form of energy poverty. Notably, only the F-statistic for the Ten Percent Rule indicator exceeds the threshold of 104.7, as proposed by Lee et al. (2022). One potential explanation is that the Ten Percent Rule indicator does not rely on a reference population. Consequently, when energy prices rise, the median energy expenditure in the population is likely to rise too, somewhat offsetting the probability of becoming Two Times Median Share of Income or Low Income High Cost energy poor. Therefore, we primarily focus on the results derived from the Ten Percent Rule indicator.

In the second stage of the 2SLS regression, we find a negative and statistically significant coefficient for both the Ten Percent Rule and the Two Times Median Share of Income metric. Living in a household that experiences a transition to Ten Percent Rule energy poverty due to rising energy prices is linked to a decline of being in good health of about 15.5 percentage points. For Two Times Median Share of Income energy poverty, this association is even stronger at about 37.2 percentage points. However, given the strong correlation in the first stage of the 2SLS estimates, we consider the Ten Percent Rule indicator our preferred measure of energy poverty here.

Table 7: Energy poverty and health (IV estimates)

	tpr	**mtwo**	**lihc**
	Second stage		
Energy poverty	-0.1546*	-0.3717*	-0.7364
	[0.0876]	[0.2162]	[0.4656)]
Observations	146,331	146,331	146,331
	First stage		
Energy prices (CPI)	0.0008***	0.0004***	0.0002***
	[0.0000771]	[0.0000561]	[0.0000533]
Kleibergen-Paap Wald F statistic	120.49	39.376	11.114

This table shows the instrumental variable estimates for the three objective energy poverty indicators on the probability of being in good health (dichotomized as 1 for very good, good or satisfactory, and 0 for poor or bad). All regressions include the usual covariates. Individual clustered robust standard errors in parentheses. Data: SOEP (2022).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The endogeneity bias-corrected estimates derived from the 2SLS model appear substantial, a pattern consistent with much of the literature utilizing energy prices as instruments (Churchill and Smyth (2021); Churchill and Smyth (2020) Kahouli (2020); Prakash and Munyanyi (2021)). However, this may indicate lingering concerns regarding the exclusion restriction, urging caution against an overly confident interpretation of causality. Nonetheless, the sign of the coefficients associated with energy poverty in the 2SLS estimates remains consistent with the baseline specification, reinforcing our overall conclusion that energy poverty significantly and detrimentally impacts individuals' health.

5 Robustness Checks

We test the robustness of our findings through several strategies. First, we address a specificity of the German welfare system by excluding households potentially receiving transfers covering energy costs. Second, we restrict the analysis to household heads, since they respond to the SOEP household questionnaire which contains the energy expenditure-related questions. Third, we omit the year 2020 from our analysis to mitigate potential distortions attributable to the COVID-19 pandemic. Finally, we eliminate respondents who were part of the migration samples in the SOEP data to ensure the consistency and reliability of our results.

First, certain households in Germany receive transfers covering housing costs, including heating ("Arbeitslosengeld" or "Wohngeld"). Although our data do not allow for the identification of these households, we are able to exclude potentially eligible households. Specifically, we exclude all observations of individuals in households reporting that at least one member currently receives unemployment benefit II ("Hartz IV", including social benefits and accommodation expenses), monthly subsistence allowance, basic income support for the elderly, or housing allowance (rent and expenses benefit). As shown in Table A11, this affects approximately 14% of our sample. Our results remain qualitatively unchanged.

Second, following Kahouli (2020), we restrict the sample to respondents who completed the survey questionnaire to mitigate subjective bias. Given that the questionnaire contains household-level information such as energy expenditures or energy deprivation (i.e., our subjective indicator), we address this concern by restricting our analysis to household heads. The results for the expenditures-based indicators align closely with those of our baseline specification for the fixed effects ordered logistic regression (see Table A12 in the Appendix), although the odds ratio for the subjective indicator loses statistical significance.

Third, the onset of the COVID-19 pandemic in spring 2020 may distort self-reported health. Thus, we therefore re-run our main specification for the fixed effects ordered logistic regression within the time period 2010 to 2019 (see Table A13 in the Appendix). Once again, the results closely resemble our baseline model.

Finally, between 2013 and 2020, people with migration and/or refugee backgrounds were oversampled in a total of 6 migration samples in the SOEP. To assess whether our results are influenced by this sample peculiarity, we exclude households that are part of these samples. Consistently, we observe qualitatively similar results regarding the magnitude and statistical significance of the coefficients, in line with our main models. These results are displayed in Table A14.

6 Conclusion

This paper aims to understand the health effects of energy poverty in Germany by matching costs to the heating systems used by households in eleven waves of the Socio-Economic Panel (SOEP). It estimates linear probability models, fixed effects ordered logit models, two-way fixed effects counterfactual models, investigates potential channels, and applies an instrumental variable approach.

The panel data analysis reveals a robust negative correlation between three expenditure-based and one consensual-based (subjective) measure of energy poverty, and self-assessed general health. Notably, this correlation remains significant even after adjusting for a host of socio-economic characteristics, including income poverty. Furthermore, it is robust to taking the ordered categorical nature of self-reported health into account by applying a fixed effects ordered logit model. Additionally, innovative two-way fixed effects counterfactual models indicate that potential biases stemming from time-varying treatment effects in our staggered and intermittent treatment roll-out do not influence our results.

In our preferred model, the fixed effects ordered logit model, we observe a decrease in the odds ratio of being in a better health category ranging between 5.5% and 8.1% when using the three expenditures-based energy poverty metrics. Notably, this association is particularly strong for the subjective measure. Specifically, individuals in households unable to keep the home comfortably warm due to financial constraints exhibit an approximately 18.2% lower odds ratio of being in a better health category.

Upon investigating the channels, we find that this association primarily operates through mental health, showcasing a consistent negative correlation with our energy poverty metrics. This connection is evident for a mental component summary scale and for five individual variables. In contrast, the relationship between energy poverty and physical health appears to be weak in Germany, with the exception of doctor visits.

Finally, we attempt to tackle the potential endogeneity of energy poverty and health by employing a 2SLS approach, by instrumenting energy poverty with data on energy prices. Our IV approach bolsters the evidence on the adverse effect of energy poverty on health in Germany. Specifically, it indicates that living in a household that undergoes a transition to energy poverty due to rising energy prices is associated with a decline of being in good health by approximately 18 percentage points.

Our findings are robust to excluding households potentially benefiting from social transfers covering energy costs. Additionally, our results remain consistent when restricting the sample to direct survey respondents, excluding the COVID-19 pandemic years, and omitting the migrant sample.

Our results suggest that economic, social, and environmental policy need to consider the adverse health effects of increasing energy prices. For instance, social transfers should account for the distinct effects of energy poverty beyond solely addressing income poverty. Moreover, given that stress-induced mental health issues may outweigh physical concerns in Germany, there should be a particular emphasis on alleviating these through social and health policies. Such measures could lead to more effective targeting and implementation of policies aimed at mitigating the health effects of energy poverty.

Finally, as our results contribute to a nascent research field, several unanswered questions remain that warrant further exploration. First, given that our findings suggest that energy poverty primarily impacts mental health rather than physical health, future research using more comprehensive health data could answer the question whether mental health is predominantly affected by the financial strain associated with energy poverty or if there are additional factors unique to energy poverty at play. Second, there is a need for closer examination to distinguish the health effects of energy poverty from those of other forms of poverty, particularly income poverty. Third, the relatively stronger coefficients observed with subjective energy poverty indicators throughout our analyses suggest that these indicators capture actual energy deprivation more effectively. Consequently, incorporating corresponding survey items as a standard in panel studies could give a more comprehensive understanding of the health effects of energy poverty.

References

Baetschmann, G., A. Ballantyne, K. E. Staub, and R. Winkelmann (2020). feologit: a new command for fitting fixed-effects ordered logit models. *The Stata Journal* 20 (2), 253–275.

Baetschmann, G., K. E. Staub, and R. Winkelmann (2015). Consistent estimation of the fixed effects ordered logit model. *Journal of the Royal Statistical Society. Series A (Statistics in Society)* 178 (3), 685–703.

Ballesteros-Arjona, V. et al. (2022). What are the effects of energy poverty and interventions to ameliorate it on people's health and well-being?: a scoping review with an equity lens. *Energy Research and Social Science* 87, 102456.

Banerjee, R., V. Mishra, and A. A. Maruta (2021). Energy poverty, health and education outcomes: Evidence from the developing world. *Energy Economics* 101, 105447.

Baudu, R., D. Charlier, and B. Legendre (2020). Fuel poverty and health: a panel data analysis. *FAERE Working Paper* 4, 2274–5556.

Boardman, B. (1991). *Fuel poverty : from cold homes to affordable warmth.* Belhaven Press.

Bouzarovski, S. (2014). Energy poverty in the European Union: landscapes of vulnerability. *WIREs Energy and Environment* 3 (3), 276–289.

Brabo-Catala, L., E. Collins, and B. Barton (2024). Key fuel poverty indicators and variables: a systematic literature review. *Economics of Energy and Environmental Policy* 13 (1), 15–34.

Chaisemartin, C. de and X. d'Haultfoeuille (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review* 110 (9), 2964–2996.

Chaisemartin, C. de and X. d'Haultfoeuille (2023). Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: a survey. *The Econometrics Journal* 26 (3), C1–C30.

Champagne, S. N., E. Phimister, J. Macdiarmid, and A. Guntupalli (2023). Assessing the impact of energy and fuel poverty on health: a European scoping review. *European Journal of Public Health* 33 (5), 764–770.

Churchill, S. A. and R. Smyth (2020). Fuel poverty and subjective wellbeing. *Energy Economics* 86, 104650.

Churchill, S. A. and R. Smyth (2021). Energy poverty and health: Panel data evidence from Australia. *Energy Economics* 97, 105219.

Davillas, A., A. Burlinson, and H.-H. Liu (2022). Getting warmer: Fuel poverty, objective and subjective health and well-being. *Energy Economics* 106, 105794.

Destatis (2022). *Zum Heizen primär verwendete Energieträger 1. Halbjahr 2022.* Accessed on December 20, 2023. URL: https://www.destatis.de/DE/Presse/Pressemitteilungen/Grafiken/Newsroom/2022/_Interaktiv/20221219-heizen-energietraeger.html.

Destatis (2023). *Zahl der Woche: 5,5 Millionen Menschen konnten 2022 aus Geldmangel ihre Wohnung nicht angemessen heizen.* Accessed on March 25, 2024. URL: https://www.destatis.de/DE/Presse/Pressemitteilungen/Zahl-der-Woche/2023/PD23_48_p002.html.

Drescher, K. and B. Janzen (2021). Determinants, persistence, and dynamics of energy poverty: an empirical assessment using German household survey data. *Energy Economics* 102, 105433.

European Commission (2020). COMMISSION RECOMMENDATION (EU) 2020/1563 on energy poverty. *Official Journal of the European Union* L 357/35. Accessed on March 25, 2024. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32020H1563&qid=1606124119302.

Fares, A. (2013). Winter cardiovascular diseases phenomenon. *North American Journal of Medical Sciences* 5 (4), 266–279.

Gallerani, M., B. Boari, D. Toma, R. Salmi, and R. Manfredini (2004). Seasonal variation in the occurrence of deep vein thrombosis. *Medical science monitor : international medical journal of experimental and clinical research* 10, CR191–6.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics* 225 (2), 254–277.

Hills, J. (2012). Getting the measure of fuel poverty: Final Report of the Fuel Poverty Review.

Jayasinghe, M., E. A. Selvanathan, and S. Selvanathan (2021). Energy poverty in Sri Lanka. *Energy Economics* 101, 105450.

Kahouli, S. (2020). An economic approach to the study of the relationship between housing hazards and health: The case of residential fuel poverty in France. *Energy Economics* 85, 104592.

Kuehnle, D. and C. Wunder (2017). The Effects Of Smoking Bans On Self-assessed Health: Evidence From Germany. *Health Economics* 26, 321–337.

Lancaster, T. (2000). The incidental parameter problem since 1948. *Journal of Econometrics* 95 (2), 391–413.

Lee, D. S., J. McCrary, M. J. Moreira, and J. Porter (2022). Valid t-Ratio Inference for IV. *American Economic Review* 112 (10), 3260–3290.

Liu, L., Y. Wang, and Y. Xu (2024). A practical guide to counterfactual estimators for causal inference with time-series cross-sectional data. *American Journal of Political Science* 68 (1), 160–176.

Llorca, M., A. Rodriguez-Alvarez, and T. Jamasb (2020). Objective vs. subjective fuel poverty and self-assessed health. *Energy Economics* 87, 104736.

Nawaz, S. (2021). Energy poverty, climate shocks, and health deprivations. *Energy Economics* 100, 105338.

Nie, P., Q. Li, and A. Sousa-Poza (2021). Energy poverty and subjective well-being in China: New evidence from the China Family Panel Studies. *Energy Economics* 103, 105548.

Nübling, M., H. Andersen, and A. Mühlbacher (2006). Entwicklung eines Verfahrens zur Berechnung der köperlichen und psychischen Summenskalen auf Basis der SOEP-Version des SF 12 (Algorithmus). *DIW Data Documentation* 16. URL: https://www.diw.de/de/diw_01.c.450499.de/publikationen/data_documentation/2006_0016/entwicklung_eines_verfahrens_zur_berechnung_der_koerperliche___menskalen_auf_basis_der_soep-version_des_sf_12__algorithmus.html.

Pan, L., A. Biru, and S. Lettu (2021). Energy poverty and public health: Global evidence. *Energy Economics* 101, 105423.

Prakash, K. and M. E. Munyanyi (2021). Energy poverty and obesity. *Energy Economics* 101, 105428.

Reibling, N. and R. Jutz (2017). "Energiearmut und Gesundheit". *Energie und soziale Ungleichheit: Zur gesellschaftlichen Dimension der Energiewende in Deutschland und Europa.* Ed. by K. Großmann, A. Schaffrin, and C. Smigiel. Wiesbaden: Springer Fachmedien Wiesbaden, 157–184.

Schnittker, J. and V. Bacak (2014). The increasing predictive validity of self-rated health. *PloS one* 9 (1), e84933. URL: `https://doi.org/10.1371/journal.pone.0084933`.

Statistisches Bundesamt (2024). *Genesis-Online, 61111-0003: Verbraucherpreisindex: Deutschland, Jahre, Klassifikation der Verwendungszwecke des Individualkonsums (COICOP 2-5-Steller Hierarchie)*. Downloaded March 1, 2024. URL: `https://www-genesis.destatis.de/datenbank/online/statistic/61111/table/61111-0003`.

Stock, J. and M. Yogo (2005). "Testing for weak instruments in linear IV regression". *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*. Ed. by D. Andrews and J. Stock. Cambridge University Press, 80–108.

Thema, J. and F. Vondung (2020). *EPOV Indicator Dashboard: Methodology Guidebook*. Wuppertal Institut für Klima, Umwelt, Energie GmbH.

A Appendix

A.1 Data Description

Table A1: Between and within variation for energy poverty metrics

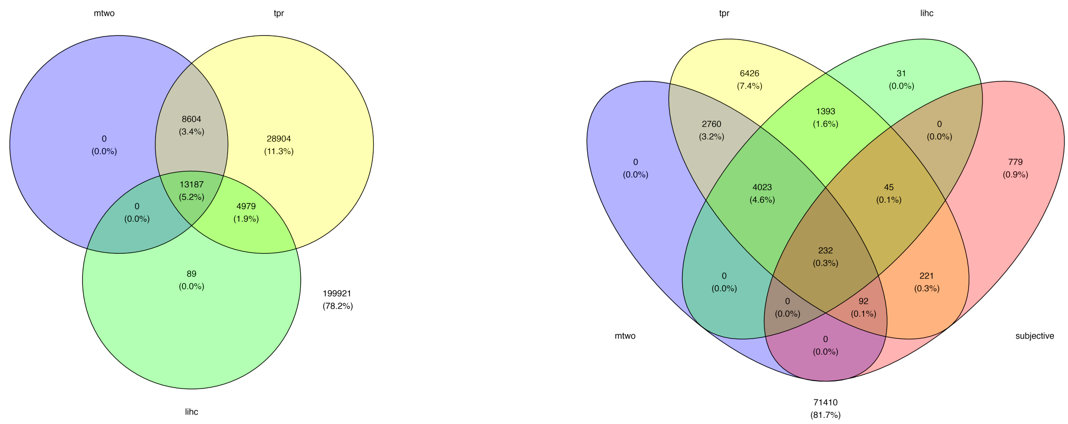
Variable		**Mean**	**Std. dev.**	**Observations**
tpr	overall	.2177453	.4127142	N = 255684
	between		.3631767	n = 56263
	within		.25968	T-bar = 4.54444
mtwo	overall	.0852263	.2792187	N = 255684
	between		.2509484	n = 56263
	within		.1881695	T-bar = 4.54444
lihc	overall	.0713967	.2574869	N = 255684
	between		.2253253	n = 56263
	within		.1758772	T-bar = 4.54444
subjective	overall	.0158796	.1250106	N = 86211
	between		.1039507	n = 31941
	within		.0797766	T-bar = 2.69907

This table shows the variation for the four energy poverty measures between and within individuals. Data: SOEP (2022).

Figure A1: Venn diagrams

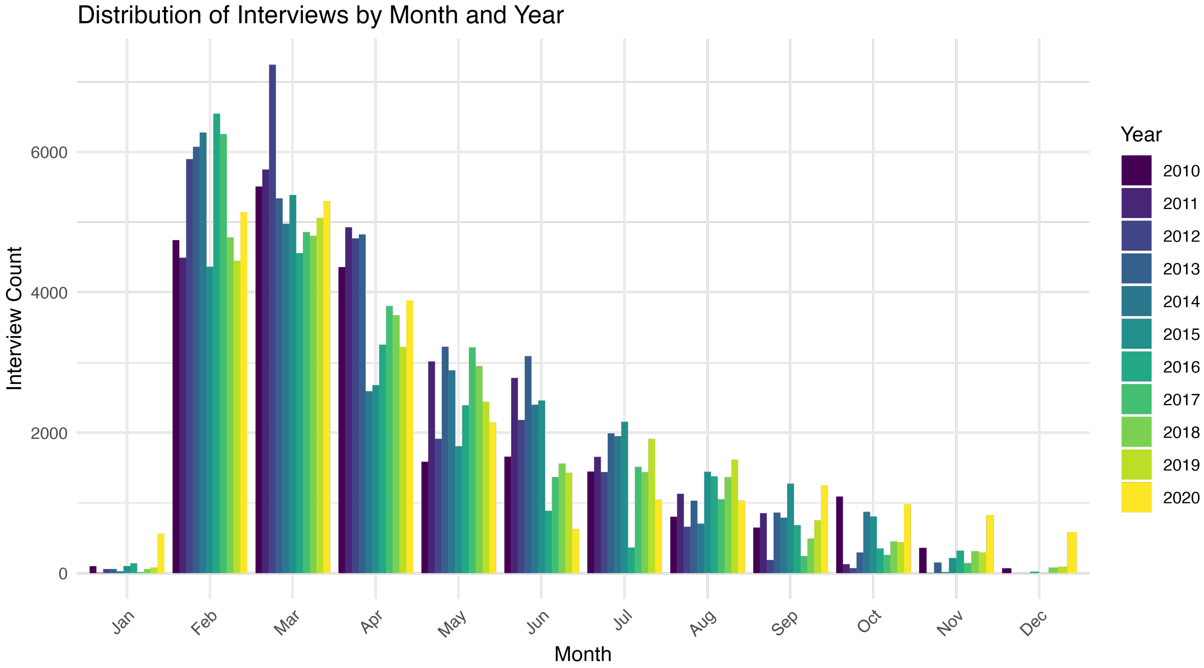
Objective indicator (2010-2020)

Objective and subjective indicator (2016-2019)



Venn diagrams illustrating the intersection of energy poverty indicators within our pooled sample (left panel: 2010-2020; right panel: 2016-2019.). Reading guide for left panel: 13,187 observations (individual-year combinations) in our pooled sample are identified as energy poor by both the tpr and the mtwo indicators. Additionally, 199,921 observations are not classified as energy poor according to any of our objective energy poverty metrics. Data: SOEP (2022).

Figure A4: Month of SOEP interview



Distribution of person interviews in our sample by month and year. 141 observations are excluded due to missing information on the month the interview took place. Data: SOEP (2022).

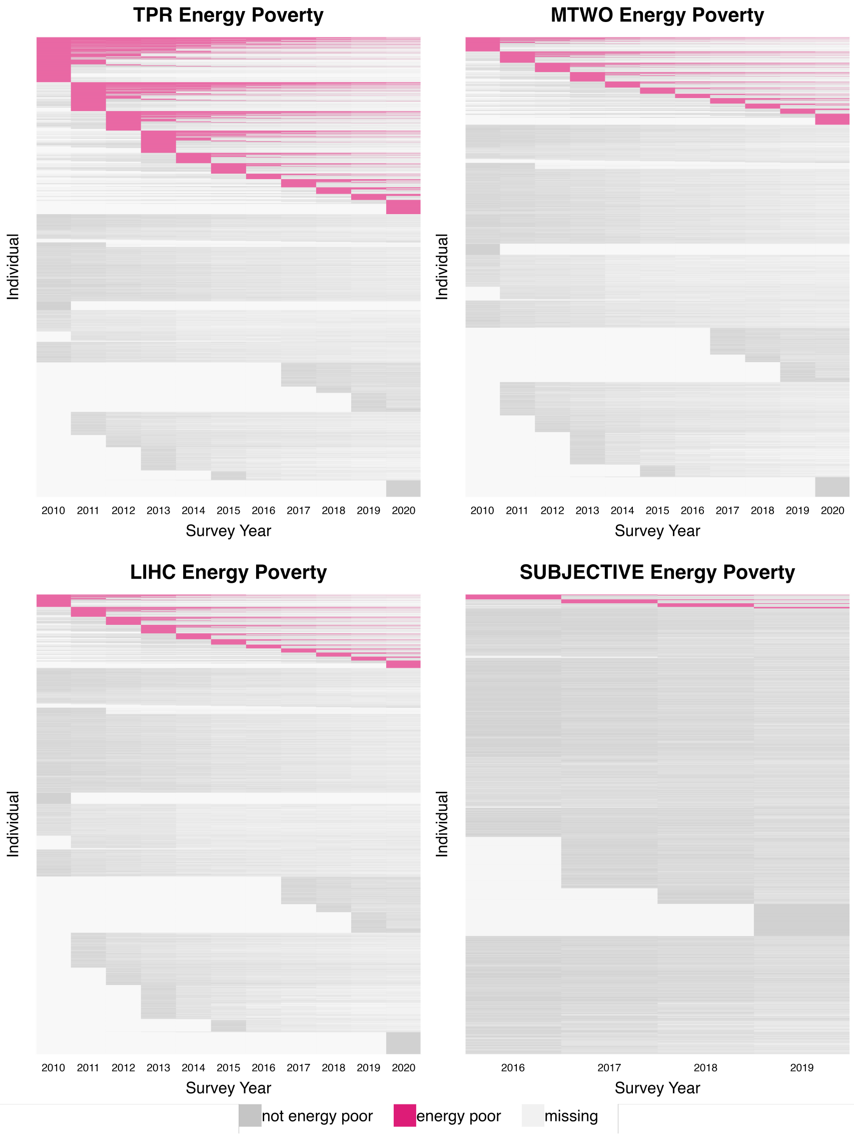
Table A2: Summary Statistics - IV Sample

	Mean	SD	Min	Max	N
self-rated health	3.39	0.95	1.00	5.00	146331
good health	0.83	0.38	0.00	1.00	146331
tpr	0.20	0.40	0.00	1.00	146331
mtwo	0.08	0.27	0.00	1.00	146331
lihc	0.07	0.25	0.00	1.00	146331
subjective	0.02	0.12	0.00	1.00	60417
gas	0.56	0.50	0.00	1.00	146331
oil	0.28	0.45	0.00	1.00	146331
district heat	0.08	0.27	0.00	1.00	146331
electricity	0.04	0.20	0.00	1.00	146331
solid fuels	0.05	0.21	0.00	1.00	146331

Summary statistics for the reduced IV-Sample. Data: SOEP (2022).

A.2 Two-way Fixed Effects Counterfactual (FEct)

Figure A5: Treatment Status Ten Percent Rule Energy Poverty



Visualization of the treatment status for energy poverty (according to the tpr, mtwo, lihc, and subjective indicators, respectively) of all individuals in the sample. Units are sorted based on the timing of receiving the treatment for visualization purposes. Data: SOEP (2022).

Figure A6: FEct – tpr

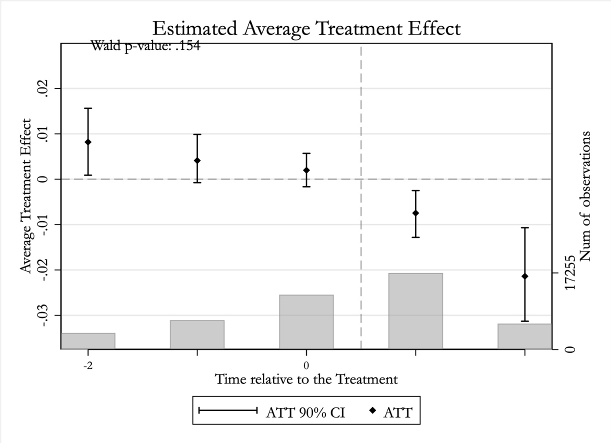


Figure A7: FEct – mtwo

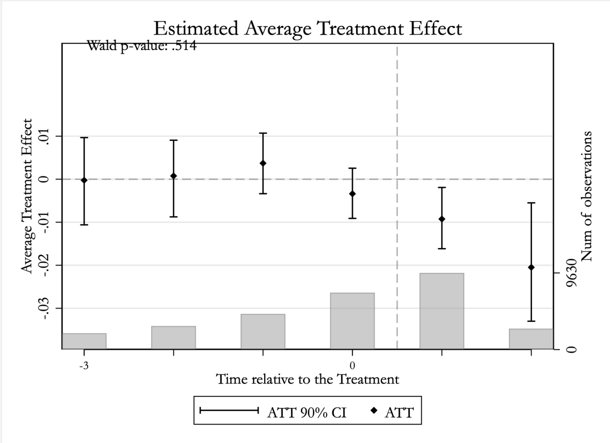
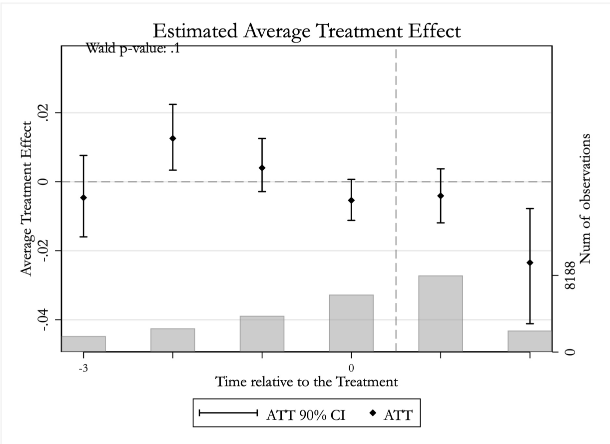


Figure A8: FEct – lihc



Fixed Effects Counterfactual estimations. Standard errors are obtained through non-parametric bootstrap procedures (500 bootstrap runs). Units must have a minimum of 1 observed period under control to be considered. Plot is limited to periods where the number of treated observations exceeds 20 percent of the largest number of treated observations in a period (default is 30 percent; we had to lower this threshold in order to have at least 3 pre-treatment periods). We test for the presence of pretreatment differential trends by using a variant of the F-Test built-in the *fect*-package that tests for zero residual averages in the pretreatment periods (larger F-test p-values suggest better pre-trend fitting). Data: SOEP (2022).

Figure A9: FEct placebo test – tpr

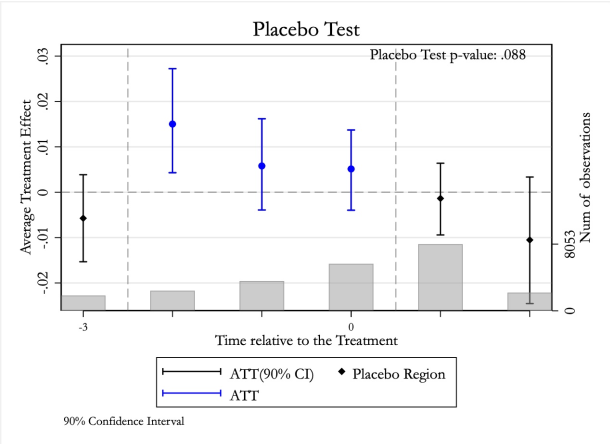


Figure A10: FEct placebo test – mtwo

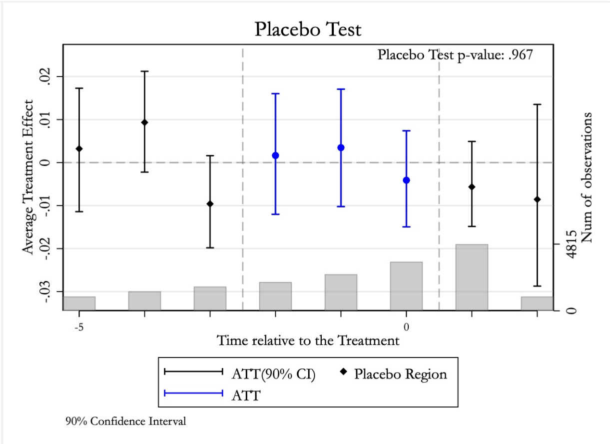
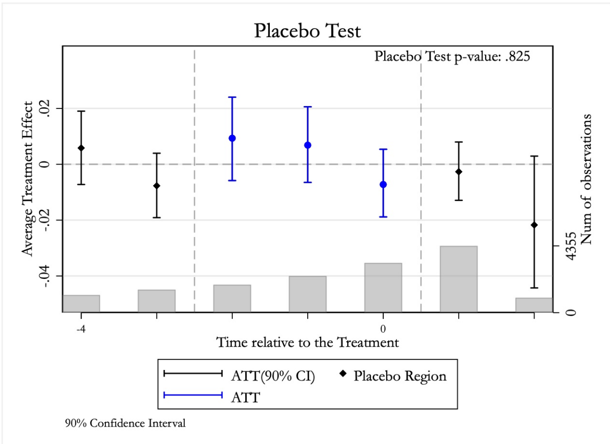


Figure A11: FEct placebo test – lihc



The placebo test is performed by removing all observations from the periods -2 to 0 relative to treatment timing for model fitting. The p-value indicates whether the estimated ATT in this range is significantly different from zero. Standard errors are obtained through non-parametric bootstrap procedures (500 runs). Data: SOEP (2022).

A.3 Robustness Checks

Table A3: Fixed-effects regression - log number of doctor visits

	(1) Log doctor visits	(2) Log doctor visits	(3) Log doctor visits	(4) Log doctor visits
Ten percent rule (tpr)	0.0124**			
	[0.00515]			
Two times median share (mtwo)		0.0116*		
		[0.00700]		
Low income high costs (lihc)			0.00540	
			[0.00740]	
subjective				0.0510**
				[0.0256]
Socio-econ. controls	Yes	Yes	Yes	Yes
Control for income poverty	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
n (total)	248713	248713	248713	85812

Fixed-effects regression. Dependent variable: Log of number of visits to a doctor's office in the previous three months. Cluster robust standard errors in brackets. All regressions include the usual covariates.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Fixed-effects regression - hospital stays

	(1) hospital stays	(2) hospital stays	(3) hospital stays	(4) hospital stays
Ten percent rule (tpr)	-0.00291			
	[0.00309]			
Two times median share (mtwo)		0.00333		
		[0.00446]		
Low income high costs (lihc)			-0.0000771	
			[0.00445]	
subjective				0.00159
				[0.0148]
Socio-econ. controls	Yes	Yes	Yes	Yes
Control for income poverty	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
n (total)	196707	196707	196707	73713

Fixed-effects regression. Dependent variable: Hospital stays in survey year (0=no stay, 1=at least one hospital stay). Cluster robust standard errors in brackets. All regressions include the usual covariates. Data: SOEP (2022).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Fixed-effects regression - number of days off work

	(1) Log days off work	(2) Log days off work	(3) Log days off work	(4) Log days off work
Ten percent rule (tpr)	-0.0245			
	[0.0156]			
Two times median share (mtwo)		0.0259		
		[0.0247]		
Low income high costs (lihc)			0.0145	
			[0.0248]	
subjective				0.0320
				[0.0682]
Socio-econ. controls	Yes	Yes	Yes	Yes
Control for income poverty	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
n (total)	123568	123568	123568	48916

Fixed-effects regression. Dependent variable: Log of number of days off work sick in the respective survey year. Cluster robust standard errors in brackets. All regressions include the usual covariates. Data: SOEP (2022).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Fixed-effects regression - life satisfaction

	(1) Life satisf.	(2) Life satis.	(3) Life satisf.	(4) Life satisf.
Ten percent rule (tpr)	-0.0655***			
	[0.0114]			
Two times median share (mtwo)		-0.0593***		
		[0.0163]		
Low income high costs (lihc)			-0.101***	
			[0.0176]	
subjective				-0.159***
				[0.0607]
Socio-econ. controls	Yes	Yes	Yes	Yes
Control for income poverty	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
n (total)	252040	252040	252040	86037

Fixed-effects regression. Dependent variable: Current life satisfaction (0=Low, 10=High). Cluster robust standard errors in brackets. All regressions include the usual covariates. Data: SOEP (2022).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Fixed-effects Regression - health satisfaction

	(1) Health satisf.	(2) Health satisf.	(3) Health satisf.	(4) Health satisf.
Ten percent rule (tpr)	-0.0153			
	[0.0134]			
Two times median share (mtwo)		-0.0471**		
		[0.0188]		
Low income high costs (lihc)			-0.0335*	
			[0.0200]	
subjective				-0.192***
				[0.0651]
Socio-econ. controls	Yes	Yes	Yes	Yes
Control for income poverty	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
n (total)	250495	250495	250495	85928

Fixed-effects regression. Dependent variable: Current health satisfaction (0= completely dissatisfied, 10=completely satisfied). Cluster robust standard errors in brackets. All regressions include the usual covariates. Data: SOEP (2022).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Ordered logistic regression - frequency of being happy

	(1) Freq. happy	(2) Freq. happy	(3) Freq. happy	(4) Freq. happy
Ten percent rule (tpr)	0.908***			
	[0.0185]			
Two times median share (mtwo)		0.882***		
		[0.0231]		
Low income high costs (lihc)			0.906***	
			[0.0255]	
subjective				0.837**
				[0.0736]
Socio-econ. controls	Yes	Yes	Yes	Yes
Control for income poverty	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations (total)	227573	227573	227573	85873
Observations (w. variation in outcome)	180294	180294	180294	50033
Panel units (w. variation in outcome)	28639	28639	28639	14803

Fixed-effects ordered logit regression. Dependent variable: Frequency of being happy in the last 4 weeks (1=very seldom, 5=very often). Exponentiated coefficients (odds ratios); Cluster robust standard errors in brackets. All regressions include the usual covariates. Data: SOEP (2022).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Ordered logistic regression - frequency of being sad

	(1) Freq. sad	(2) Freq. sad	(3) Freq. sad	(4) Freq. sad
Ten percent rule (tpr)	1.114***			
	[0.0208]			
Two times median share (mtwo)		1.123***		
		[0.0283]		
Low income high costs (lihc)			1.098***	
			[0.0291]	
subjective				1.397***
				[0.122]
Socio-econ. controls	Yes	Yes	Yes	Yes
Control for income poverty	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations (total)	227580	227580	227580	85873
Observations (w. variation in outcome)	198536	198536	198536	61117
Panel units (w. variation in outcome)	32306	32306	32306	18162

Fixed-effects ordered logit regression. Dependent variable: Frequency of being sad in the last 4 weeks (1=very seldom, 5=very often). Exponentiated coefficients (odds ratios); Cluster robust standard errors in brackets. All regressions include the usual covariates. Data: SOEP (2022).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Ordered logistic regression - worries about own health

	(1) Worries health	(2) Worries health	(3) Worries health	(4) Worries health
Ten percent rule (tpr)	1.059***			
	[0.0225]			
Two times median share (mtwo)		1.045		
		[0.0294]		
Low income high costs (lihc)			1.058*	
			[0.0318]	
subjective				1.386***
				[0.146]
Socio-econ. controls	Yes	Yes	Yes	Yes
Control for income poverty	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations (total)	235764	235764	235764	86019
Observations (w. variation in outcome)	164916	164916	164916	41858
Panel units (w. variation in outcome)	25983	25983	25983	12394

Fixed-effects ordered logit regression. Dependent variable: Worries about own health (1=not concerned at all, 3=very concerned). Exponentiated coefficients (odds ratios); Cluster robust standard errors in brackets. All regressions include the usual covariates. Data: SOEP (2022).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A11: Ordered logistic regression excluding unemployment benefit recipients

	(1) Self rated health	(2) Self rated health	(3) Self rated health	(4) Self rated health
Ten percent rule (tpr)	0.956**			
	[0.0206]			
Two times median share (mtwo)		0.940**		
		[0.0289]		
Low income high costs (lihc)			0.912***	
			[0.0306]	
subjective				0.799*
				[0.0958]
Socio-econ. controls	Yes	Yes	Yes	Yes
Control for income poverty	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations (total)	220922	220922	220922	76975
Observations (w. variation in outcome)	174942	174942	174942	45489
Panel units (w. variation in outcome)	28178	28178	28178	13662

Fixed-effects ordered logit regression. Dependent variable: self rated health (5-point scale with 1=bad, 5=very good). Exponentiated coefficients (odds ratios); Cluster robust standard errors in brackets. Excluded are observations of individuals in households where at least one member receives unemployment benefit II (Hartz IV, including social benefits and accommodation expenses), monthly subsistence allowance, basic income support for the elderly, or housing allowance (rent and expense benefits). Data: SOEP (2022).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A12: Ordered logistic regression (only household heads)

	(1) Self rated health	(2) Self rated health	(3) Self rated health	(4) Self rated health
Ten percent rule (tpr)	0.951**			
	[0.0221]			
Two times median share (mtwo)		0.931**		
		[0.0279]		
Low income high costs (lihc)			0.913***	
			[0.0281]	
subjective				0.879
				[0.0953]
Socio-econ. controls	Yes	Yes	Yes	Yes
Control for income poverty	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations (total)	155005	155005	155005	52609
Observations (w. variation in outcome)	124665	124665	124665	32001
Panel units (w. variation in outcome)	19092	19092	19092	9437

Fixed-effects ordered logit regression. Dependent variable: self rated health (5-point scale with 1=bad, 5=very good). Exponentiated coefficients (odds ratios); Cluster robust standard errors in brackets. The sample is restricted to observations from household heads. Data: SOEP (2022).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A13: Ordered logistic regression (2010-2019)

	(1) Self rated health	(2) Self rated health	(3) Self rated health	(4) Self rated health
Ten percent rule (tpr)	0.949***			
	[0.0183]			
Two times median share (mtwo)		0.941**		
		[0.0241]		
Low income high costs (lihc)			0.914***	
			[0.0243]	
subjective				0.818**
				[0.0744]
Socio-econ. controls	Yes	Yes	Yes	Yes
Control for income poverty	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations (total)	232151	232151	232151	86211
Observations (w. variation in outcome)	186493	186493	186493	52671
Panel units (w. variation in outcome)	30003	30003	30003	15581

Fixed-effects ordered logit regression. Dependent variable: self rated health (5-point scale with 1=bad, 5=very good). Exponentiated coefficients (odds ratios); Cluster robust standard errors in brackets. Observations from the year 2020 are excluded. Data: SOEP (2022).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A14: Ordered logistic regression excluding migration samples

	(1) Self rated health	(2) Self rated health	(3) Self rated health	(4) Self rated health
Ten percent rule (tpr)	0.938***			
	[0.0184]			
Two times median share (mtwo)		0.936**		
		[0.0244]		
Low income high costs (lihc)			0.914***	
			[0.0251]	
subjective				0.818**
				[0.0744]
Socio-econ. controls	Yes	Yes	Yes	Yes
Control for income poverty	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations (total)	229388	229388	229388	76393
Observations (w. variation in outcome)	189159	189159	189159	52671
Panel units (w. variation in outcome)	28168	28168	28168	15581

Fixed-effects ordered logit regression. Dependent variable: self rated health (5-point scale with 1=bad, 5=very good). Exponentiated coefficients (odds ratios); Cluster robust standard errors in brackets. Sample restricted to households not part of the SOEP migration samples. Data: SOEP (2022).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

ifso working paper

ifso working papers are preliminary scholarly papers emerging from research at and around the Institute for Socio-Economics at the University of Duisburg-Essen.

All **ifso working papers** at uni-due.de/soziooekonomie/wp

ISSN 2699-7207

UNIVERSITÄT DUISBURG ESSEN

Open-Minded

ifso institute for socio-economics

Institute for Socio-Economics
University of Duisburg-Essen

Lotharstr. 65
47057 Duisburg
Germany

uni-due.de/soziooekonomie
wp.ifso@uni-due.de