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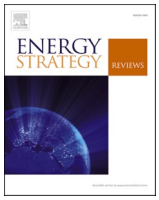

Household energy burdens in Europe at times of geopolitical energy price volatility

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ABSTRACT

Understanding how energy price volatility affects European households is essential for designing effective and equitable energy policies. This work assesses the distributional impacts of energy price changes across EU countries, intensified by recent geopolitical events. We employ microdata from the European Household Budget Surveys (HBS) to estimate heterogeneous household energy price elasticities across distinct income levels and EU countries using Causal Forests, a robust non-parametric method. Drawing on HBS waves from 2010, 2015, and 2020, we evaluate how elasticities vary across income and nation and project resulting energy burdens under 2022 price conditions. We also integrate objective expenditure-based energy poverty indicators from HBS with subjective measures from the European Union Statistics on Income and Living Conditions (EU-SILC) survey, such as households' perceived ability to keep their homes adequately warm and manage financial burdens, by systematically applying three advanced data fusion methods (including a hybrid kNN-lightGBM model, Gaussian Copula Synthesizer, and Wasserstein Generative Adversarial Networks) to further explore the multidimensional nature of energy poverty.

Our results show strong heterogeneity in the impacts of energy price increases for gas and electricity, with lower-income households facing higher energy burdens. Gas price elasticities decrease with income, confirming the regressive nature of gas price shocks. Back-projecting or hindcasting for 2022 also indicates that the poorest households are the ones that are likely to experience notable increases in energy burdens under such shocks, although the magnitude varies considerably based on countries' dependence on Russian fossil fuel imports. The fused datasets suggest limited sensitivity of subjective energy deprivation measures to price changes, though this may reflect fusion uncertainty.

These findings highlight both the potential and limitations of combining multiple EU microdata sources. They point to the need for targeted short-term financial support for vulnerable populations alongside sustained long-term policy investments in energy efficiency improvements and renewable energy development to effectively alleviate energy poverty across the EU.

1. Introduction

Household energy poverty in the European Union (EU) has emerged as a critical socioeconomic challenge. The concept has gained increased scholarly and policy attention in recent years, particularly as energy prices have exhibited significant volatility following geopolitical developments. The Energy Poverty Advisory Hub (EPAH), launched by the European Commission in 2021, aims to alleviate energy poverty in Europe. The Fit for 55 package, adopted by the EU in July 2021, also clearly mentions measures to identify fundamental drivers of energy poverty risks for households, including high energy prices, low household incomes, and inefficient buildings and appliances. Despite increased policy attention, recent estimates suggest that 10.6% of EU citizens were unable to keep their homes adequately warm in Refs. [1, 2]. Both recent estimates are substantially higher than the estimated 7% of the population in 2020.

This study addresses three interrelated objectives: (1) estimating heterogeneous energy price elasticities across EU households using micro survey data that accounts for variation in income levels and geography; (2) assessing distributional differences in vulnerability to

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energy poverty among countries with differential exposure to fossil fuel import dependencies; and (3) evaluating multidimensional energy poverty through integration of objective expenditure measures with subjective well-being indicators via innovative data fusion methods across two distinct surveys.

Our work extends beyond previous research in several key dimensions, as highlighted also in the literature review section below. We build on insights from an earlier study, where we have examined appliance adoption patterns and their relationship to energy poverty in low and middle income countries [3]. In this study, we use Causal Forests to estimate consumption-based price elasticities across households in the EU with explicit treatment of unobserved heterogeneity. In addition, we combine subjective well-being indicators from the European Union Statistics on Income and Living Conditions (EU-SILC) survey with expenditure data from Household Budget Surveys (HBS) through three modern data fusion approaches, which is a novel methodological contribution of this work. This integration addresses a persistent limitation in energy poverty research, namely the inability to jointly examine objective expenditure burdens and subjective perceptions of affordability within a single analytical framework.

Our analysis employs microdata from the Household Budget Surveys (HBS) for the years 2010, 2015 and 2020, which are the most recent comprehensive EU-wide data available including energy expenditures. Specifically, we employ an objective measure of energy burden defined as the ratio of energy expenditures to overall household expenditures from these surveys. We first estimate heterogeneous household prices elasticities accounting for differences in income levels and geography across households in the EU, employing a Causal Forest [4] approach for the estimation. We then construct counterfactual simulations to back-project or hindcast these structural elasticities, using only information available up to 2020, and evaluate potential impacts under 2022 price levels. This approach allows us to characterize underlying vulnerabilities in the household energy consumption structure conditional on pre-shock data, while acknowledging that we do not directly observe 2022 household behavior.

The motivation for examining these structural vulnerabilities has intensified following recent geopolitical developments. Gas prices reached an unprecedented peak of €346 per MWh in August 2022, exacerbating a trend that had begun in 2021, following Russia's full-scale invasion of Ukraine. This price shock has disproportionately affected vulnerable populations, with experts projecting that elevated energy prices will persist throughout the remainder of the decade due to geopolitical instability and the ongoing transition to low-carbon energy sources [5]. Understanding how different households are affected and how they respond to such price shocks can help identify how and where policy interventions might be effectively targeted, which requires characterizing variation in price responsiveness and exploring multiple dimensions of energy deprivation. This is particularly relevant considering that, as a consequence of the Russian invasion, the EU pivoted towards importing gas from the USA [6], and therefore, is still dependent on external actors and prone to suffer supply shocks.

To this end, we also apply and compare three data fusion approaches to merge EU-SILC with HBS microdata. This enables assessment of whether energy prices affect subjective measures of energy poverty, such as the ability to keep the dwelling warm, the ability to make ends meet, and financial burden perceptions, which are dimensions not captured by expenditure data alone.

In the following, we first review relevant recent literature on energy poverty in the EU. We then describe the methods and data employed in our analysis. Following this, we present our results, and finally conclude with a brief discussion of the implications of these results for policy along with caveats and limitations of our analysis. Finally, we conclude with an outlook for future research.

2. Literature review

Energy poverty has been conceptualized as the inability of households to secure essential energy services required for a decent life. In developing regions, it is largely a question of access, while in the European context it concerns affordability. The condition arises from the interaction of low incomes, high energy costs, and poor housing efficiency, making it a multidimensional issue that is difficult to measure consistently.

The literature on energy poverty has evolved substantially in its conceptualization and measurement approaches. Researchers have developed multiple indicators to capture different dimensions of energy poverty. Energy poverty in the EU has been defined and measured in terms of absolute expenditure thresholds (expenditure approach), subjective perceptions of affordability and access (consensual approach), and to a lesser extent measures of indoor air temperature [7] (direct measurement) [3]. The Energy Community Secretariat recommends monitoring energy poverty through a comprehensive set of indicators, including energy burden (share of energy costs in household disposable income), the 2M indicator (proportion of households spending more than twice the national median share on energy), and the inability to keep homes adequately warm [8]. These indicators provide different perspectives on the multidimensional nature of energy poverty, though their application remains inconsistent across EU member states. The metrics also often identify different population segments, offering contrasting pictures of who is affected [9,10]. Studies show little overlap between subjective and expenditure-based measures, implying that much energy poverty remains undetected when relying on a single dataset or indicator.

To capture its multidimensional nature, researchers have also developed composite indices that combine information on income, expenditure burden, self-reported constraints, and housing quality. Statistical techniques such as Principal Component Analysis, factor analysis, and the Alkire and Foster method have been employed to improve analytical robustness, but these methods also raise questions about weighting and aggregation. Despite these advances, consensus on how best to integrate diverse indicators remains limited [4,11–13].

The literature reveals methodological challenges in studying energy poverty, particularly regarding data sources. Most analyses of energy poverty in the EU rely on either the European Union Statistics on Income and Living Conditions (EU-SILC) or Household Budget Surveys (HBS), each with distinct advantages and limitations [11]. EU-SILC provides rich information on living conditions but is limited by its predominantly qualitative variables. Conversely, HBS offers detailed numerical data on household expenditures but lacks certain building characteristics relevant to energy poverty analyses. Because these surveys sample different populations, direct integration is impossible without statistical matching. Recent methodological innovations have focused on integrating these datasets to overcome their individual limitations. There have been recent pioneering efforts at applying statistical matching techniques between HBS and EU-SILC, though these approaches remain underutilized in energy poverty research [12,13]. Only a single study for Hungary has matched these datasets to study energy poverty [9]. This integration allows for more comprehensive analyses that combine qualitative insights on living conditions with quantitative data on energy expenditures.

Across approaches, income, prices, and household building characteristics and efficiency consistently explain household vulnerability to energy poverty in the EU. Higher income reduces exposure to energy poverty, while increases in energy prices and poor dwelling performance raise it [14]. Since energy demand appears largely inelastic to price changes, particularly among lower-income households for whom energy represents a necessity good, price shocks translate directly to welfare loss. The JRC has estimated that inflation has increased material and social deprivation in the EU by approximately 2 percentage points, while energy poverty specifically may have increased by 5 percentage points

[6].

Literature also highlights the heterogeneous impact of energy price shocks across different population segments and regions. The burden of higher energy prices is not evenly distributed, with low-income households in poorly insulated dwellings being particularly vulnerable. Furthermore, substantial geographical disparities exist in energy poverty rates across the EU. Recent price shocks have had particularly severe effects in Central and Eastern European Member States [15]. Recent studies suggest that wealthier countries and households experience differential impacts as compared to poorer countries and households [16]. A range of policy options, ranging from mitigating the price pass-through on the supply side, to directly supporting households through cash transfers on the demand side, have been suggested as ways to address the effects of recent price rises [17]. To balance heterogeneous effects of fuel prices with the need to maintain price signals motivating conservation of gas, targeted direct transfers to poorer gas-users in Europe appears to be emerging as a promising policy [17–19]. However, existing subsidies reach only a fraction of those in need, reflecting wide disparities in coverage and efficiency across member states [20–22].

Despite substantial progress, significant gaps persist in the literature. First, while numerous studies document the prevalence of energy poverty, the heterogeneous effects of energy prices across different household types, dwelling characteristics, and geographical contexts remain insufficiently explored. Second, methodological approaches to data integration between HBS and EU-SILC specifically for energy poverty analysis require further development. Third, interactions between structural vulnerabilities and exposure to external shocks in countries with different energy import dependencies warrant deeper analysis. Our research addresses these gaps by combining estimation and analysis of heterogenous elasticities and modern data integration techniques to illuminate factors that relate to energy poverty and guide more precise policy interventions [23].

3. Methods and data

3.1. Data sources

We use microdata from the European Household Budget Surveys (HBS) (EUROSTAT, 2023). This is a rich quinquennial meta-dataset of micro-level household budget surveys from 26 countries in the European Union. We use the last three available waves, corresponding to the years 2010,2015 and 2020 for different parts of the analysis. Specifically, we use the first two waves of 2010 and 2015 for the estimation, and the newest wave of 2020 for testing the model fit. We opted to not use the year 2020 as part of our estimation sample as the overall disruptions caused by the COVID pandemic may not make it representative for this estimation sample. Due to missing data, we remove some of the countries for the analysis, ending up with 16, 16 and 14 countries in the 2010, 2015 and the 2020 sample, respectively. Some descriptive statistics of both samples can be found in Table 1.

We also employ the EU-SILC survey, which is a harmonized, cross-sectional, and longitudinal dataset that provides detailed microdata on income, poverty, social exclusion and living conditions across European countries. Conducted every year by Eurostat in collaboration with national statistical offices, EU-SILC collects information on household and individual socio-economic characteristics, including employment status, education, housing conditions, and social transfers. The dataset is widely used for policy evaluation and research on inequality and welfare dynamics, as it offers high comparability across countries due to standardized data collection methodologies.

3.2. Estimating an objective measure of energy poverty and fuel price elasticities

In previous studies, we have shown that individuals at different levels of income respond differently to changes in fuel prices [3]. Here, based on a similar premise, but following a different methodological approach, we apply Causal Forests [23] to estimate heterogeneous energy price elasticities of individuals at different income levels. We follow this approach because in this work we are mainly concerned with understanding the effects of prices on household fuel expenditures.

Causal forests provide a robust and flexible method for estimating varying fuel price elasticities by explicitly capturing heterogeneity in individual responses across different income levels. Unlike traditional parametric approaches that impose specific functional forms on the relationships between variables of interest (e.g., price and household income) or the remaining controls, causal forests operate within a non-parametric, data driven framework. This is particularly suited for detecting complex, nonlinear interactions between fuel prices and consumer responses without restrictive model assumptions.

Specifically, we consider the Causal Forests assume the following structural form [24]:

$$Y = \theta(X) \times T + g(X, W) + \varepsilon, E[\varepsilon|X, W] = 0$$

$$T = f(X, W) + \eta, E[\eta|X, W] = 0$$

$$E[\eta \times \varepsilon|X, W] = 0$$

where Y is the outcome variable, X is a feature variable, T is a treatment variable, and W is a set of additional covariates. We are, specifically, interested in estimating $\theta(X)$, the heterogeneous treatment effect function. This is done by solving the local moment equation:

Table 1
Descriptive statistics of key variables from the 2010, 2015 and 2020 HBS.

Year	Gas Consumption	Electricity Consumption	Gas Price	Electricity Price	Household Size	Net income	Total Expenditure
2010	23.3	2948.3	22.7	0.3	2.4	24,866.6	24,215.0
	(2.00)	(181.38)	(0.37)	(0.01)	(0.07)	(1348.68)	(1160.20)
2015	15.7	3061.8	24.3	0.2	2.5	21,724	2,0592.4
	(1.57)	(192.02)	(0.57)	(0.01)	(0.08)	(1432.85)	(1148.15)
2020	24.1	2718.5	21.4	0.3	2.3	27,210.3	24,324.1
	(2.01)	(155.38)	(0.49)	(0.01)	(0.08)	(1523.28)	(1189.19)
Year	Percentage Urban	Percentage Female Heads	Percentage Married Head	Percentage Less than High School Heads	Percentage Head Working	Percentage Head Working Full Time	
2010	63.6	38.5	52.2	56.6	58	37.9	
	(2.70)	(2.73)	(2.80)	(2.78)	(2.77)	(2.72)	
2015	61	39.9	53.7	64.1	57.2	49.1	
	(2.99)	(3.00)	(3.05)	(2.94)	(3.03)	(3.06)	
2020	72.2	40.3	50.9	54.2	56.2	49.1	
	(2.67)	(2.92)	(2.98)	(2.97)	(2.96)	(2.98)	

$$\hat{\theta}(x) = \underset{\theta}{\operatorname{argmin}} \sum_{i=1}^{n} K_x(X_i) \times \left(Y_i - \hat{q}(X_i, W_i) - \theta \times \left(T_i - \hat{f}(X_i, W_i) \right) \right)^2$$

with nuisance functions $\hat{q}(X_i, W_i)$ and $\hat{f}(X_i, W_i)$ being global estimators of $q(X, W) = E[Y|X, W]$ and $f(X, W) = E[T|X, W]$ respectively, and $K_x(X_i)$ a similarity metric. The method does not force any strong functional form assumptions on any of the functions, save from Lipschitz continuity of $\theta(.)$.

In our case, Y is (log) fuel consumption, X is (log) net income, T is (log) fuel price and W is a set of household characteristics including total household expenditure, household size, gender, marital status, education level, working status of household head, and whether the household is in a particular country and in an urban area.

The estimation of Causal Forests was made on a random sample of 90% of the households available in each country-year combination, and tested in the remaining 10% of the households, as well as in the households available for the year 2020. The model performs comparably in all samples, showing an MSE of 0.814, 0.690 and 0.640 in the estimation, test, and 2020 samples for the causal effects of prices on gas consumption, and of 0.080, 0.066 and 0.100 respectively for the causal effects on electricity, showing that the model does not overfit and predicts with relatively equal accuracy within and outside the estimation sample.

3.3. Fusing datasets to relate objective to subjective measures of energy poverty

Energy burden objectively estimated in terms of the share of total household budget spent on energy or a particular fuel is not the only measure of energy poverty, there are other behaviors that may reflect the effect of rising energy prices on well-being. Obtaining such measures, however, remains problematic, and in many cases, we cannot find appropriate data sources that include all this information. In our case, the EU-SILC survey provides interesting subjective measures that can be associated to energy poverty and well-being but does not provide information on energy consumption or expenditures.

We therefore apply data fusion methods to merge variables from the HBS to the corresponding years of the EU-SILC to explore associations between objective and subjective measures of energy poverty. Several methodologies are available to fuse data that retain several important features of the data relevant for causal analyses [25,26]. In the absence of a method that provides a clear advantage, we propose the use of various independent alternatives and compare the results.

We test three different modern data fusion methods. The first method we apply is the kNN + lightGBM-based fusion model [27]. This hybrid approach leverages kNN's ability to capture local dependencies and LightGBM's predictive power, making it effective for high-dimensional, heterogeneous datasets [28]. We test this method against two alternative fusion methods, which we present in the Appendix. The second method we apply is the Wasserstein Generative Adversarial Networks (WGAN) for the Design of Monte Carlo Simulations [27]. The WGAN framework enhances Monte Carlo simulations by generating high-fidelity synthetic samples that closely resemble real-world data distributions. By minimizing the Wasserstein distance between the real and synthetic distributions, WGAN improves sample diversity and stability. Finally, we apply the Gaussian Copula Synthesizer, as implemented by the Synthetic Data Vault [26]. This method captures complex dependencies between variables while allowing flexible marginal distributions, making it well-suited for preserving statistical properties [29].

We screen the following variables in EU SILC as potentially relevant for our study: the ability to keep the dwelling warm, the ability to make ends meet, the financial burden, and the lowest income needed to make ends meet. To simplify the process, we recode the categorical variables as binary. We fuse these variables to our main HBS-sample using the three proposed algorithms and use Causal Forests to see whether fuel prices have any effect on any of these. Specifically, we use the following variables available both in HBS and SILC to perform the statistical matching: net income, rent avoided by homeowners, monthly rent, monthly housing cost, household size, marital status, and employment status. Note that it is not necessary for the data fusion that all these variables have a causal relationship with either our treatment or outcome variables. Finally, to minimize biases, we do 100 rounds of imputation for each of the variables for each of the households. Table 2 shows the mean and standard deviation of the variables in the EU SILC sample and in the fused datasets.

4. Results

4.1. Heterogeneity in fuel price elasticities

We estimate causal forests independently for gas and electricity expenditures. The results can be seen in Fig. 1, with blue lines and areas representing the estimated effects and their confidence interval, and red lines showing the net income distribution. On the left panel, we can see a continuous decrease in the elasticity of gas consumption to price changes as income increases, whereas on the right panel, for electricity we observe a rapid decrease up to around 20,000 EUR, followed by a stabilization/slow increase in the price elasticity of electricity consumption beyond this income level.

Having estimated causal effects, we then estimate the energy burdens of the households in the HBS sample projected to the year 2022, the year with the highest price increases as the consequence of the war. To do that, first, we adjust the income distributions of households in the sample to reflect the levels of 2022 by using median of disposable income and Gini values for the year 2022. Next, we apply fuel prices (gas and electricity) for the year 2022 to all relevant values obtained from EUROSTAT (see Table 3).

Table 2 presents an analysis of household energy burdens across different income levels (quintiles) and projects these burdens to 2022, distinguishing between countries where Russia is the largest source of fossil imports and those where this is not the case. For the overall sample, only the lowest income households (1st quintile) had a noticeably higher projected energy burden, and this was primarily observed in the years before the COVID-19 pandemic. Households in other income quintiles saw only marginal changes in their energy burden. Interestingly, the distributional impacts in the COVID-19 year (2020) appear similar to the projections for 2022. This may possibly be because the increase in fossil prices affected not only residential energy prices, but also overall inflation, which could have obscured the specific impact of fossil fuel prices on household energy burdens. The importance of indirect effects is also supported by recent literature [30].

When looking at different groups of countries based on their main source of fossil imports interesting differences can be observed. In countries where Russia was the major source of imports, our analysis

Table 2
Mean and standard deviation of the subjective measures of energy poverty in the original (EU-SILC) data and the corresponding synthetic datasets following each of the 3 methods.

	Able to keep house warm	Able to make ends meet	Financial burden	Lowest income to make ends meet
EU-SILC	0.884 (0.320)	0.406 (0.491)	0.804 (0.397)	1589.629 (31,954.3)
SDV	0.909 (0.287)	0.437 (0.496)	0.801 (0.399)	2631.586 (2076.778)
WGAN	0.856 (0.351)	0.410 (0.492)	0.821 (0.383)	6215.141 (226,838.422)
Fusion	0.890 (0.313)	0.431 (0.495)	0.816 (0.387)	1846.285 (5604.143)

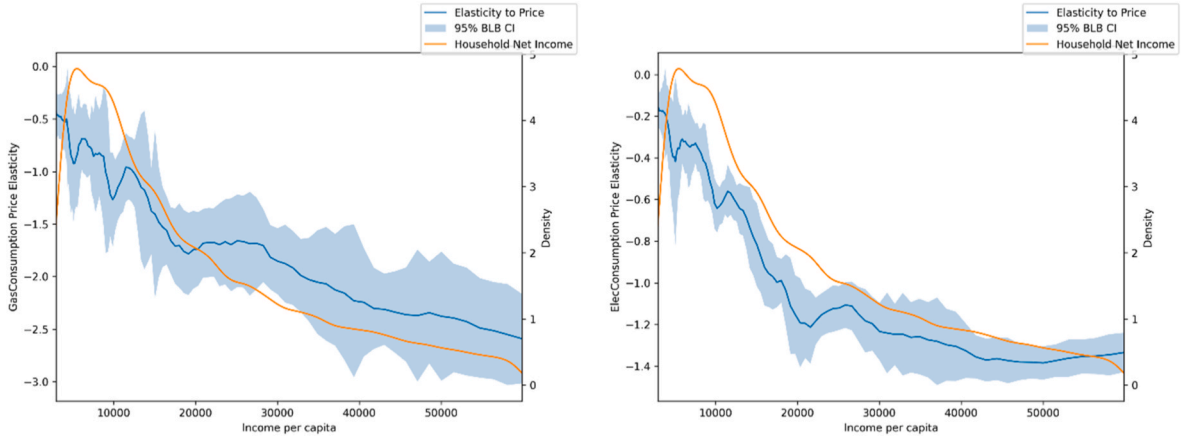

Fig. 1. Distribution of household income (orange line) and estimated elasticity to fuel prices at different income levels (blue).

Table 3
Average energy burdens of households in different income quintiles in the observed data at different years and the projected burdens in 2022.

		All countries		Countries with majority oil imports not from Russia		Countries with majority oil imports from Russia	
Year	Quintile	Observed	2022 Projected	Observed	2022 Projected	Observed	2022 Projected
2010	1	11,7%	12,8%	11,3%	14,4%	12,2%	11,2%
2010	2	7,4%	7,1%	6,5%	6,4%	7,8%	7,5%
2010	3	5,3%	5,4%	5,2%	4,9%	5,4%	5,6%
2010	4	3,8%	3,8%	3,9%	3,6%	3,8%	3,9%
2010	5	2,7%	2,4%	2,4%	2,1%	2,8%	2,7%
2015	1	11,4%	12,2%	12,6%	15,4%	10,5%	9,6%
2015	2	7,3%	7,1%	7,3%	7,4%	7,3%	6,9%
2015	3	5,7%	5,6%	6,0%	5,9%	5,5%	5,5%
2015	4	4,3%	4,3%	4,5%	4,5%	4,1%	4,2%
2015	5	2,7%	2,7%	2,7%	2,6%	2,7%	2,9%
2020	1	9,0%	9,2%	9,4%	11,1%	8,9%	8,6%
2020	2	5,2%	5,2%	5,3%	5,6%	5,2%	5,1%
2020	3	4,1%	4,1%	4,3%	4,2%	4,1%	4,0%
2020	4	3,4%	3,3%	3,3%	3,2%	3,4%	3,3%
2020	5	2,4%	2,3%	2,2%	2,0%	2,5%	2,4%

suggests that overall inflation seemed to have a more dominant effect, leading to a decrease in energy burdens. Conversely, in countries where Russia was not the major source of imports, energy burdens appeared to increase (Table 2). However, only two countries seem to drive the results in each group, Hungary and Romania (Fig. 2), with the remaining countries only showing minor changes. This may be due to the distinct energy import structures and policy responses to the energy crises in these two countries. Hungary, which traditionally relied heavily on Russian fossil fuel imports, secured exemptions from EU sanctions and maintained discounted gas prices through long-term contracts with Gazprom. Additionally, Hungary's government implemented price caps and subsidies to shield consumers, which helped stabilize energy costs. In contrast, Romania, with its significant domestic energy production, particularly in natural gas and coal, was less dependent on Russian imports. However, exposure to rising European market prices led to increased energy burdens, despite its domestic resources.

Relationship between objective and subjective measures of fuel poverty.

The results of the experiments applying different methods for data fusion on the selected measures related to energy poverty can be seen in Fig. 3, for the fusionModel. In Figure A1 in the Appendix, we present results for the WGAN and SDV models. We find the results to be consistent among models. However, they imply a statistically insensitive response to prices (i.e. statistically indistinct from zero) for all levels of income for the subjective measures of energy poverty (ability to keep warm, make ends meet, financial burden, lowest income needed to make ends meet) after applying data fusion methods. This is not a negative result, as it implies that these subjective measures are not affected by changes in fuel prices in households across all income levels, potentially shielding households to the volatile effects of fossil price inflation. Nevertheless, these results should be taken with caution. Although we apply three completely independent methodologies and obtain similar results, we cannot ascertain that these results are not a consequence of the fusion processes themselves.

At an aggregate level, results derived from the three data fusion methods are broadly consistent and support the robustness and validity of our methodological approach in assessing the general sensitivity of subjective energy poverty indicators to fuel price shocks. However, a closer look at a more granular level reveals important differences across models. Fig. 4 here and Figure A2 in the Appendix illustrate the heterogenous treatment effects on subjective energy poverty measures by country and their dependence on Russian fossil fuel imports (pink-labeled for high-dependency, blue-labeled for low dependency). The figures show how the three different data fusion models (fusionModel, SDV, WGAN) capture household responses to fuel prices changes across selected EU countries, further subdivided into lower-income households (Q12), and middle-to-higher-income households (Q345). Specifically, the fusionModel (Fig. 4) method captures greater variability and more pronounced differences between countries and income groups, clearly illustrating stronger adverse effects of energy price increases on lower-income households, especially in Hungary and Bulgaria, both countries that are heavily reliant on Russian fossil fuels. In contrast, the SDV and WGAN methods (Figure A2) produce results showing less variability and smaller estimated impacts, underscoring that methodological choices can substantially influence findings, particularly at detailed levels of analysis. Thus, our comprehensive use of multiple fusion

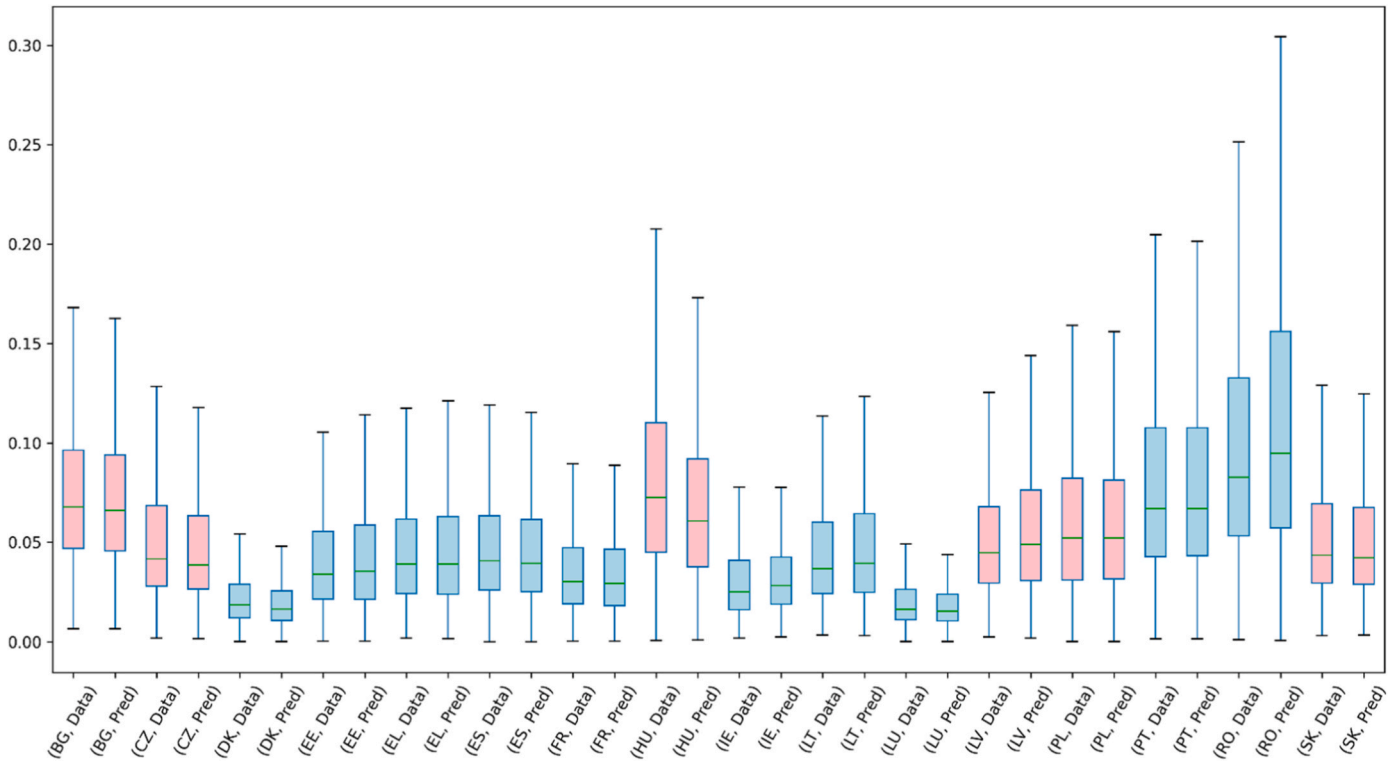

Fig. 2. Energy burden distribution by country for the year 2015 (Data) and projected in 2022 (Pred) (pink, countries whose major source of oil imports is Russia).

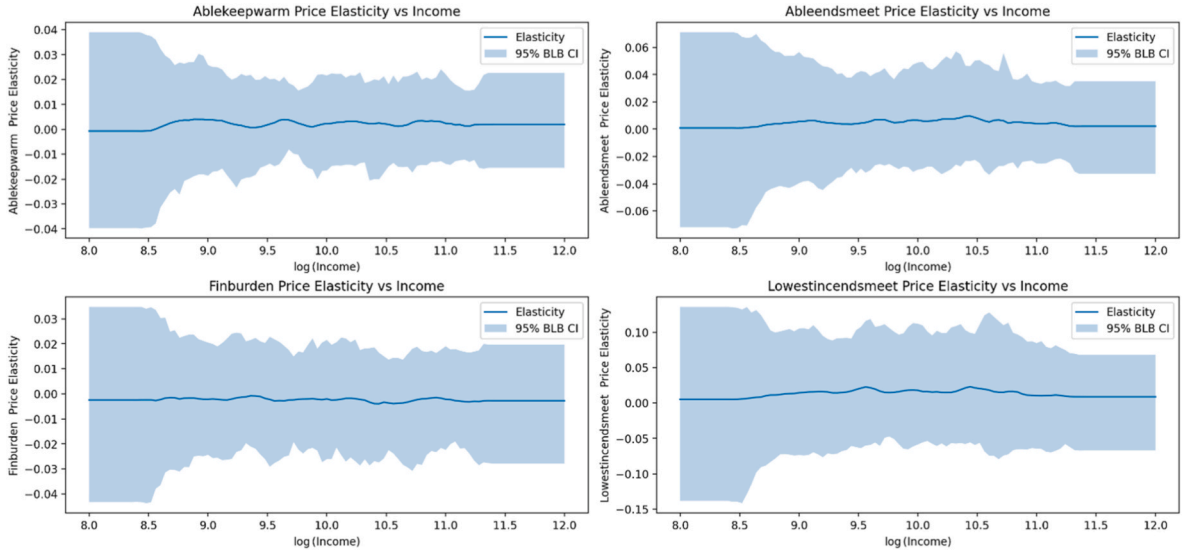

Fig. 3. Elasticity to prices of the subjective measures at different income levels estimated on the fusionModel synthetic dataset.

methods provides confidence in our overall conclusions while emphasizing the necessity for careful interpretation when considering nuanced, country-specific, or income-specific outcomes.

5. Discussion

Efforts to reduce energy poverty have gained increasing attention within the EU, particularly as high and volatile energy prices place additional strain on vulnerable households. As recent geopolitical events have heightened concern about affordability, this study focuses specifically on analyzing the heterogeneous impacts of recent energy price increases across different population segments and nations in the region using recent data from the HBS and EU-SILC surveys.

Our research also seeks to advance the conceptualization and measurement of energy poverty in the EU by combining objective expenditure-based metrics with subjective assessments of deprivation. A major contribution is the application of Causal Forests to estimate heterogeneous energy price elasticities to evaluate how price responsiveness varies across income brackets and across countries. In addition, we apply three distinct data fusion techniques to link HBS and EU-SILC data on objective and subjective measures of energy poverty, including Gaussian Copula Synthesizer, WGAN, and kNN + lightGBM. Finally, our research provides valuable insights into the geopolitical dimensions of energy poverty by comparing the impact of energy price shocks on

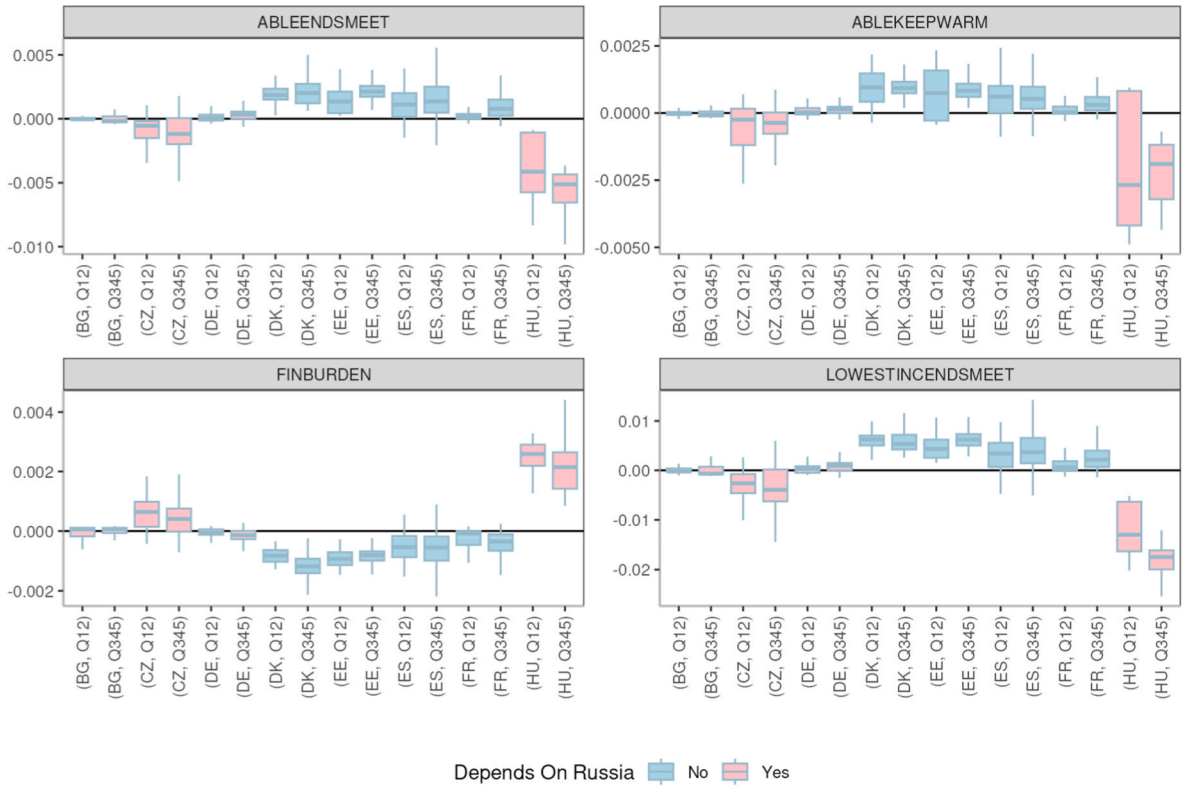

Fig. 4. Distribution of Heterogeneous Treatment Effects on Subjective Energy Poverty Measures Across Selected EU Countries on the fusionModel synthetic dataset, by National Dependency on Russian Oil Imports

Notes:

(1) Seven European countries are included in the analysis based on data availability: Bulgaria (BG), Czechia (CZ), Denmark (DK), Estonia (EE), Spain (ES), France (FR), and Hungary (HU).

(2) Country color coding reflects dependency on Russian fossil fuel imports: **Pink** presents countries primarily reliant on fossil fuel imports from Russia while **Blue** indicates countries with limited reliance on Russian fossil fuel imports

(3) Countries are disaggregated by household income quantiles: **Q12** presents Lower-income households (bottom 40% of the income distribution); **Q345** presents Middle-to higher-income households (top 60% of the income distribution)

(4) Each facet corresponds to a different subjective energy poverty measure: Perceived ability to make ends meet (**ABLEENDSMEET**); Ability to keep the home adequately warm (**ABLEKEEPWARM**); Perceived financial burden due to energy costs (**FINBURDEN**); Self-reported minimum income required to make ends meet (**LOWESTINCOMEENDMEETS**).

countries with differing levels of reliance on Russian oil imports.

Our findings align with recent literature on this topic that suggest that the effect of energy prices is heterogeneous across nations and households with lower-income households particularly affected [16,31]. Our key findings suggest a decreasing elasticity of gas consumption with rising income, and significant heterogeneity in energy burden impacts across countries (particularly those with different reliance on Russian oil imports). EU-focused analyses reveal substantial cross- and within-country variation in energy affordability following the 2021–2022 surge, with lower-income and energy-inefficient households disproportionately affected [32]. These studies further show that impacts depend on pre-shock consumption patterns and national energy system characteristics, underscoring that vulnerability reflects both household-level traits and country-specific exposure [32,33]. Our findings are also broadly consistent with recent IMF analyses examining the distributional impacts of the energy price surge and policy responses, which emphasize that energy and food price shocks disproportionately affect lower-income households requiring targeted, temporary support measures to mitigate welfare losses, a conclusion that aligns closely with our evidence of declining price elasticities and higher energy burdens among poorer households [17,18]. Using pre-2020 microdata to project impacts under 2022 price conditions, our approach complements this literature by offering a structural perspective on vulnerabilities embedded in pre-shock consumption patterns, offering additional insights into how future price shocks may propagate unevenly across households and countries.

Our data fusion results, applying three different methodologies to combine the HBS with EU-SILC data, suggest a statistically insensitive response of subjective well-being measures to fuel price changes after data fusion. However, this insensitivity may be partly due to the inherent limitations of current data integration techniques. The consistent results across three fusion methods, however, strengthen the reliability of the findings and help bound overall uncertainty.

We also recognize several methodological limitations of this work. Regarding the data used, we had to remove some countries from the analysis due to missing data in the HBS dataset for certain years. This reduction limited in the sample size and geographical coverage and could potentially affect the generalizability of our findings to the entire EU. Our results of energy burdens in 2022 rely on projections based on our estimations using data up to 2020. This adds uncertainty, particularly given recent market fluctuations post 2020. While we employed three innovative data fusion techniques to integrate EU-SILC and HBS data, our analysis of the relationship between objective and subjective energy poverty measures suggests a statistically insensitive response to prices. However, this result could be a consequence of the fusion processes themselves, suggesting a potential limitation in the reliability of these specific findings. These issues highlight the pressing need for more harmonized and timely EU-wide microdata for future research.

Despite these challenges, our study offers useful insights for policymakers. Addressing energy poverty will likely require a combination of targeted short-term financial assistance for vulnerable households and long-term investments to strengthen building efficiency, promote the electrification of heating, and enhance energy system resilience. Our results also support continued methodological development and investment in more robust monitoring tools to track the evolving distribution of household energy vulnerability.

6. Conclusions

This study provides an integrated assessment of household energy burdens in Europe by combining heterogeneous price elasticity estimation with advanced data fusion approaches to link objective and subjective indicators of energy poverty. Across multiple HBS waves, our results show robust evidence of regressive energy price impacts and substantial cross-country heterogeneity. Although data fusion suggests limited sensitivity of subjective deprivation indicators to price changes, this finding warrants cautious interpretation given methodological uncertainties.

Projecting these insights to 2022 price levels highlights the extent to which sudden price increases are likely to disproportionately affect lower-income groups and countries with structural vulnerabilities, emphasizing also that the geopolitical dimensions of energy supply cannot be ignored. While several countries in the region have taken measures to counteract the recent energy price increases and shield households from price volatility, this has impacted national budgets. In the longer term, efforts to improve the efficiency of the European building stock and heating systems, as well as to enhance energy security are needed. A shift to more renewable energy can be a means to enhance energy security and meet the climate goals of lower emissions in the region, but if such a transition is accompanied by increased volatility in the energy markets in the short-term, increased budget allocations will be required to ensure adequate energy services at affordable prices for households. Policies aimed at enhancing energy security and diversifying energy sources can play a crucial role in mitigating future vulnerabilities to external price shocks and their disproportionate effects on the energy poor.

Future research should focus on improving data integration across European surveys, developing fusion methods that better preserve complex household attributes, and incorporating behavioral and technological adaptation into projections of energy burdens. Efforts should also be expanded to integrate more detailed data on building features, heating technologies, and appliance use characteristics to improve modelling of household energy requirements and adaptation strategies. Using longitudinal panel datasets can provide insight into how vulnerability and household responses change over time. Additionally, systematic review of recent national policy efforts, alongside the harmonization of survey tools, could strengthen the evaluation of interventions and refine measurement of energy poverty. Strengthening the evidence base in these areas can support more effective and equitable EU energy policy design.

CRediT_author_statement

Miguel Poblete Cazenave: Conceptualization, Methodology, Data curation, Software, Writing. Setu Pelz.: Data curation, Software, Writing. Shonali Pachauri: Conceptualization, Writing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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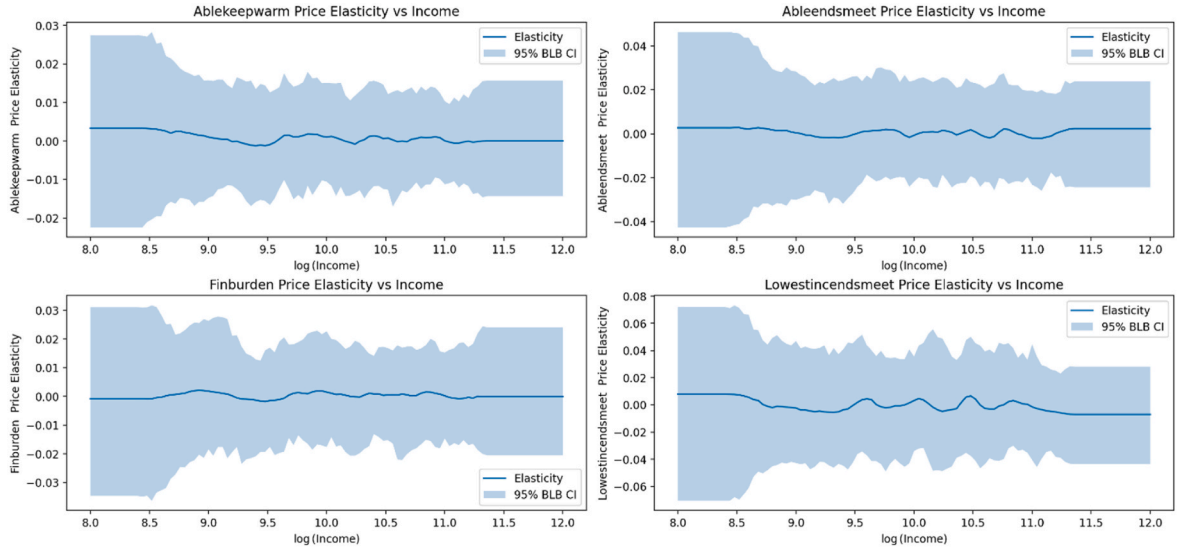
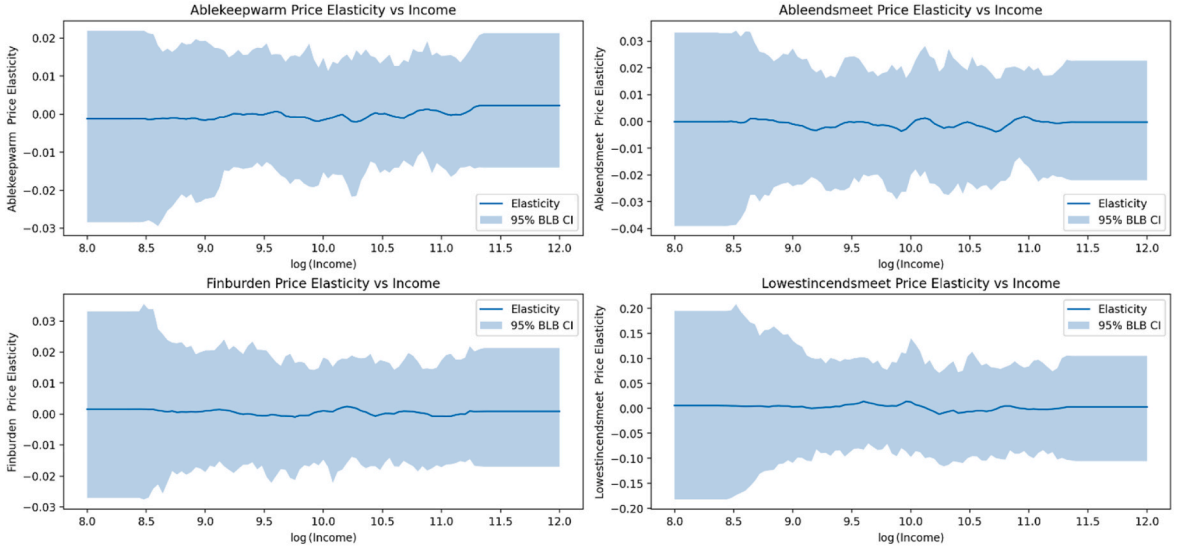
APPENDIX

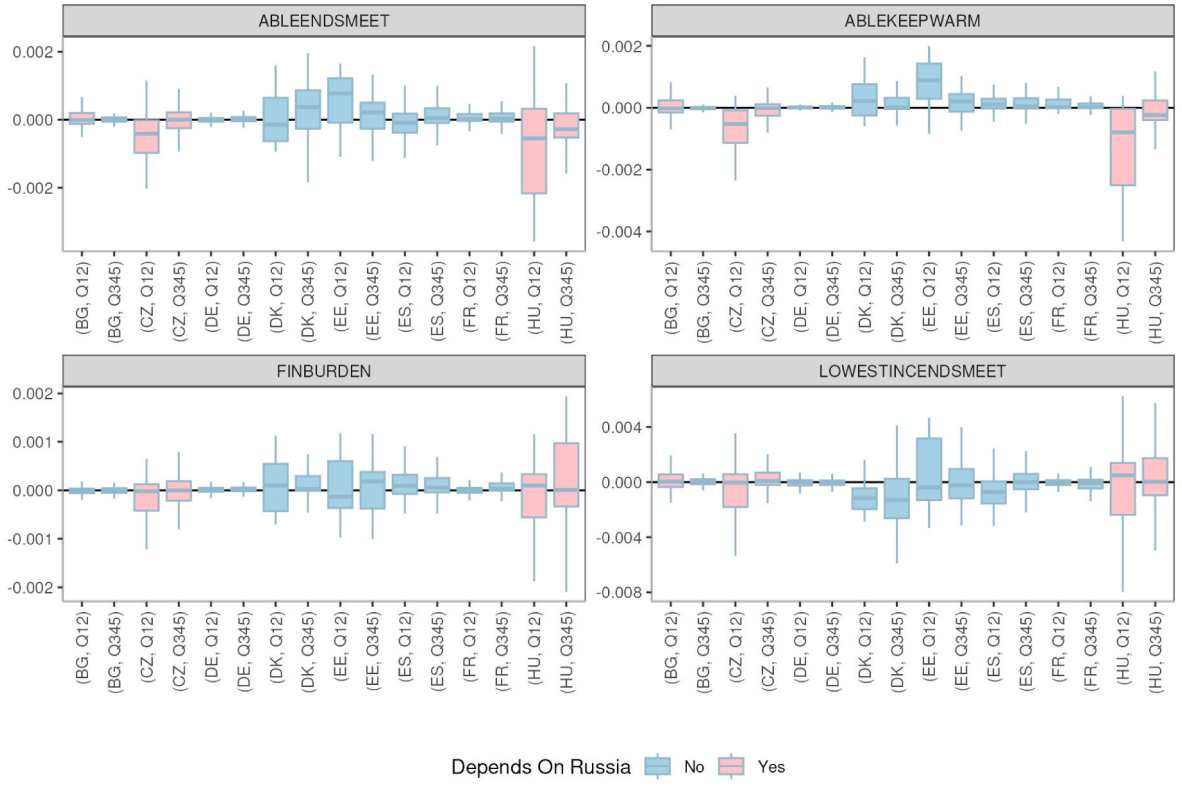


(a) SDV

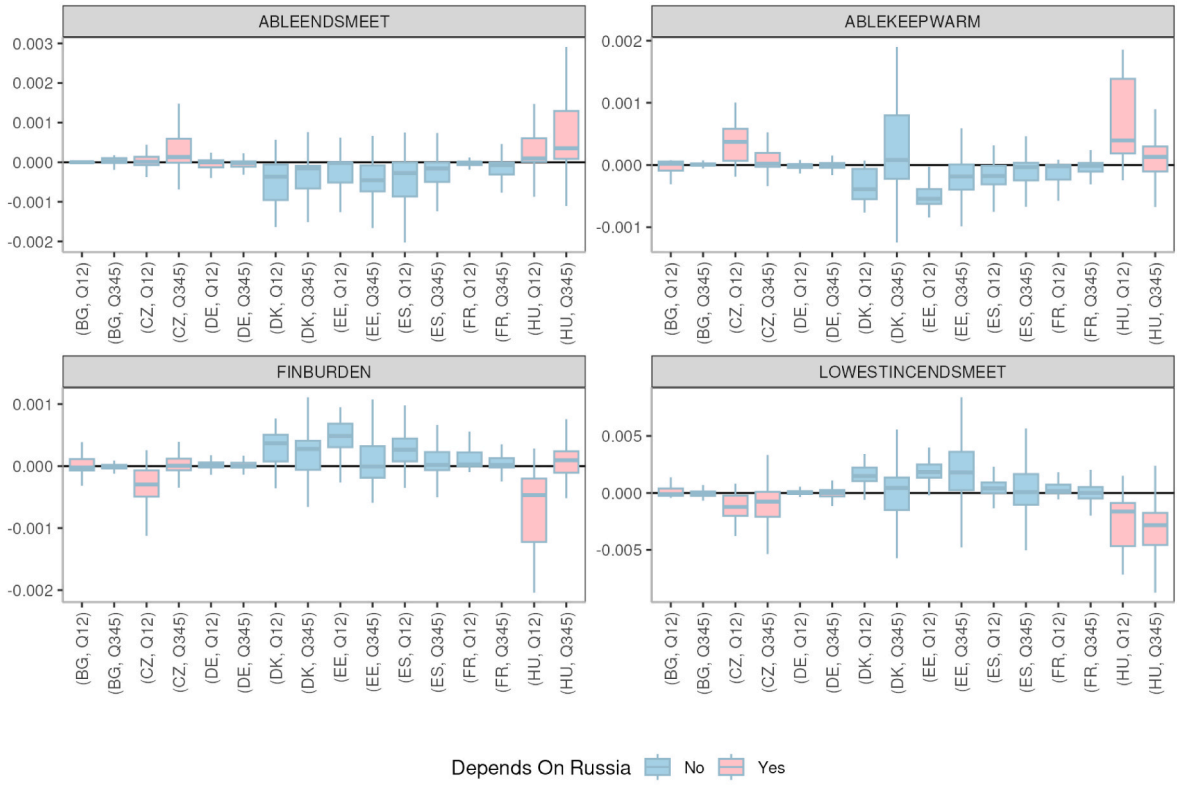


(b) WGAN

Fig. A1. Elasticity to prices of the subjective measures at different income levels estimated on the SDV and WGAN synthetic datasets.



(a) SDV



(a) WGAN

Fig. A2. Distribution of Heterogeneous Treatment Effects on Subjective Energy Poverty Measures Across Selected EU Countries on the SDV and WGAN synthetic datasets, by National Dependency on Russian Oil Imports

Notes:

(5) Seven European countries are included in the analysis based on data availability: Bulgaria (BG), Czechia (CZ), Denmark (DK), Estonia (EE), Spain (ES), France (FR), and Hungary (HU).

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(8) Each facet corresponds to a different subjective energy poverty measure: Perceived ability to make ends meet (**ABLEENDSMEET**); Ability to keep the home adequately warm (**ABLEKEEPWARM**); Perceived financial burden due to energy costs (**FINBURDEN**); Self-reported minimum income required to make ends meet (**LOWESTINCOMEENDMEETS**).

Data availability

The authors do not have permission to share data.

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