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Research article

A comprehensive study to estimate income and price elasticities of household electricity consumption using Auto-metrics

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A R T I C L E I N F O

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A B S T R A C T

This study focuses on understanding family electricity consumption behaviors in response to income and price changes from 1994 to 2022 across 12 prominent European countries. We employ a unique econometric approach, Auto-selection Models, to analyze the nuances of energy demand elasticity. Our methodology includes the use of saturation techniques, which are highly effective in identifying anomalies and discontinuities in the data, ensuring the reliability of our results. The Auto-metrics method streamlines the model selection process and enhances the accuracy of elasticity predictions. We use Error Correction Models (ECMs) for each country to examine the long-term equilibrium relationships among key variables such as energy consumption, household income, electricity prices, and weather patterns, taking into account any observed anomalies and significant structural changes. The findings reveal varying levels of income and price elasticity across the countries, reflecting their unique economic and climatic conditions. The study's results hold significant implications for policymaking. By recognizing and adapting to the varied characteristics of electricity demand elasticity, energy policies can be more accurately tailored at both the national and European Union levels.

1. Introduction

Accurately estimating home electricity demand elasticities poses a significant challenge in achieving sustainable development and energy security. European households face diverse income levels and fluctuating electricity prices due to market liberalization, renewable energy integration, and policy reforms. These factors contribute to complex consumption patterns that are difficult to measure accurately. The variability across European states, with their different economic standings, energy infrastructures, and climates, exacerbates this issue. Traditional econometric models often struggle to capture these complexities, leading to oversimplified and potentially misleading elasticity estimates. This limitation hampers policymakers who rely on these estimates to forecast demand, set tariffs, and devise conservation incentives. Household electricity consumption is a pivotal component of total energy demand, influencing economic policy, environmental sustainability, and energy security significantly. Amidst the energy transition and climate policy challenges in European countries, understanding the factors that drive household electricity consumption becomes increasingly crucial. The demand's income and price elasticities reveal how sensitive consumers are to changes in income and electricity prices, affecting energy conservation efforts and policy effectiveness.

Previous research has largely depended on macro data at national, regional, or state levels, with only a fraction using household

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survey data. Quantitative methods, including time series, cooperation models, fundamental time-series modeling (FTSM), and panel data methods, are prevalent. However, most studies incorporate control variables like income, electricity price, alternative costs, climate indicators, population density, urbanization, and household characteristics in survey-based studies. Some research accounts for changes in preferences, behavior, regulation, and energy efficiency improvements [1]. Their approach, estimating a stochastic threshold system model (STSM) for power demand, models unknown factors with a stochastic trend (the Underground Power Demand Trend or UPDT), incorporating extremes and structural breaks. Yet, this method only partially addresses outliers and breaks modeling, lacking comprehensive tests for potential extremes and breaks during the estimation period, unlike the literature on time-series analysis [2]. Thus, further research on this topic is necessary.

This work introduces a novel econometric strategy to identify outliers and structural breaks for estimating electricity consumption's income and price elasticity. We use the Auto-metrics search method on annual data covering electricity usage, income, price, and weather variables to define an unencumbered error correction model for household electricity consumption. This model is then refined with phase predictor models that account for anomalies and structural breaks. Auto-metrics enables automatic model selection in scenarios with more variables than observations, providing reliable elasticity estimates that are robust, accurate, and simplified.

Significant contributions of this study include:

1. Employing annual data from 1994 to 2022 for 12 key European countries, where in 2019, the residential sector accounted for over 82% of the EU's total domestic consumption. This may be the first study to use this econometric approach for calculating income and price elasticity of electricity consumer demand.
2. Utilizing a unique econometric methodology of Auto-selection Models, saturation techniques for identifying outliers and structural breaks, and the Auto-metrics algorithm. Error correction models are used for each country to identify co-integrating relationships among key variables, assuming outliers and breaks are addressed.
3. Findings suggest that long-run income elasticities are consistently below one, and long-run price elasticities are also below one in total value across all countries, indicating electricity is treated as a conventional good and consumption is not highly sensitive to price changes. Elasticity predictions, however, vary by country, attributable to differences in GDP per capita and energy consumption.

The remaining sections of this paper are structured as follows: Section 3 briefly reviews significant research on modeling household electricity consumption. Section 4 introduces and describes the analysis information and econometric approach, while Section 5 presents estimation results and discussions. Section 6 concludes with policy implications.

2. Literature review

The power industry and policymakers stand to benefit significantly from accurate projections of future electricity demands and understanding how fluctuations in price and income affect electricity consumption. Optimal management and strategic investments in electricity production and distribution are crucial for the sector's efficiency. In recent decades, numerous research and policy articles have explored power demand forecasting, and the elasticities of price and income. Researchers have developed various methods to estimate and forecast power demand over extended periods, categorized into four distinct classes according to Ref. [3]. Load forecasting encompasses four timeframes: (a) extremely short-term load estimation, covering periods from minutes to an hour in advance, crucial for real-time load management; (b) short-term load estimation, which daily measures and predicts load for scheduling electricity generation and maintaining the transmission system; (c) medium-term estimation, spanning from a week to a year in advance, used for fuel requirement forecasts and system maintenance. A wide range of techniques, both statistical (e.g., multivariate regression, semi-parametric combined designs, autoregressive models) and computational (e.g., machine learning, fuzzy regression algorithms), are utilized for modeling and estimation. Umair & Dilanchiev [4] focus on methods like estimate combination, multilevel estimation, and probabilistic load estimation, incorporating automated learning and AI, though recent research on these last two approaches is limited.

The majority of research utilizes aggregated data on electricity usage, revenue, cost, and variables like alternative goods prices, climate indices, housing stock, population, and urbanization levels. A smaller segment relies on microdata from surveys on household attributes, residence characteristics, and appliance usage. The rise of co-integration evaluation in economics has made unpredictable time series simulations the standard for electricity demand estimation in the 2000s and early 2010s. The two-stage estimating technique and the maximum likelihood method for multi-dimensional co-integration evaluation have been established and used by researchers like Y. Li & Umair [5] and CUI et al. [6]. They've introduced methods such as the autoregressive distributed lag (ARDL) bounds approach, enhancing the estimation of short- and long-term elasticities without outliers and discontinuities. However, if outliers and breaks are present, economic evaluations may suffer from omitted variable biases.

Only time-series estimation studies and research based on the STSM method have addressed outliers in electricity consumption modeling. The STSM method, as first proposed by Yu et al. [7], allows for breaking down a time series into unobserved components (trend, seasonality, cycle, irregularity) for independent estimation. Incorporating external variables like revenue and price into an STSM enables associated elasticity predictions, transforming the STSM into a behavioral model. One significant limitation of this approach is its failure to consider all potential outliers, such as breakdowns that might have occurred during observation. In cases where variables outnumber observations, a machine-learning model selection process is required, a step not taken in the studies mentioned above.

Recent literature reviews show inconsistent findings on the short- and long-term income and cost elasticities of household energy demand. The discrepancies in elasticity estimates can be attributed to various factors, as systematic review studies [8] have highlighted. Notably, Christopoulos & Tsionas [9] found that cost elasticity from panel-based studies is significantly higher than that from time-series research, and elasticity tends to be lower in studies conducted during energy shortages. Yuan et al. [10] observed that both revenue and cost elasticities of energy consumption in Romania have decreased over time, likely as incomes have risen.

Our work introduces a novel econometric strategy for estimating income and cost elasticities for household electricity demand, addressing the challenges posed by unaccounted outliers and structural changes in the data. By specifying a generic unconstrained error correction model for household electricity consumption and augmenting it with dummies for potential structural aberrations and breakdowns, we aim to provide more reliable elasticity estimates. Employing the Auto-metrics search method allows for automatic model selection in scenarios with more parameters than available data, ensuring accurate and robust findings.

3. Theoretical framework

The European Union is currently transitioning from fossil fuels to higher quality alternative energy sources [11]. This shift is transforming the continent's generation and connectivity landscapes, necessitating significant investment in the electrical sector in the coming years, as projected by the European Commission (2014). The European transmission network consists of over 300,000 km of transmission lines, with 355 crossing international borders [12]. According to Ishaque [13], the total capacity in the EU expanded by 59% from approximately 619 GW in 1996 to nearly 978 GW by 2014, while gross electricity generation increased by 17%, from 2745 TWh to 3190 TWh. This discrepancy arises because the newly added capacity predominantly consists of renewable energy sources, which generally have lower capacity utilization rates compared to conventional power plants. Despite a 10% decrease in gross energy consumption per person in the EU during this period, total electricity consumption rose by 15%, indicating a clear trend towards greater electrical power use and improved energy efficiency across all economic sectors. However, there are significant variations between countries; for example, per capita electrical consumption in some countries is seven times that of Romania.

Since the 1990s, the EU power market's wholesale and some retail aspects have gradually been liberalized. Auray et al. [14] describe this as "the world's largest cross-jurisdiction transformation of the electricity sector," resulting from integrating different state-level or national electrical markets and liberalizing the European Union's electricity market. However, they note skepticism regarding the consumer benefits of liberalization. Researchers like Zeng et al. [15] have observed that energy market reform has led to different outcomes for former and new member states, with electricity rates in the new member states converging more rapidly to the EU average, causing residents to face rapidly increasing expenses. In several newly joined member states, electricity cost accessibility has been a challenge, with governments controlling final prices for households.

The estimation process utilizes data from the 2003 Statewide Residential Appliance Saturation Study (RASS) in California, supported by the state's principal investor-owned utilities and conducted by the California Energy Commission [16]. The sample frame comprises the general population of utility customers who use electricity. The 2002 California Energy Survey collected data on residential energy use and appliance ownership from a statistically representative sample of the state's population across various utility service locations and temperature zones. We employ a unique econometric methodology in our modeling exercise, including Auto-selection Models, saturation techniques for identifying outliers and structural breaks, and the Auto-metrics algorithm. Error correction models are used for each country to identify a co-integrating link among explanatory variables such as energy use, income, and electricity price. To analyze the trade-offs between short-term fuel uses and long-term technological choices, we included only households that consume both natural gas and electricity in the subsample, allowing us to consider households capable of switching fuel sources without significant initial costs. The analysis covers the years 1990–2003 for all technologies except space heating, analyzed from 1980 to 2003 due to outdated cost information [17]. The significant price fluctuations during the energy crisis provide a unique natural experiment for measuring short-term energy flexibility, long-term conservation responses, and the widespread adoption of energy-efficient technologies. The data used in our research captures a wide range of variance in fuel prices, usage, household variables, and equipment choice, enabling insightful analysis. By examining income and price elasticities, we can gain insights into consumer behaviors, preferences, and motivations regarding energy consumption. This information is crucial for market participants, regulators, and policymakers to make informed decisions and effectively respond to changing conditions.

4. Methodology and data sources

4.1. Advantages of vector error correction model selection

In this study, we forecast domestic electricity consumption for each of the 12 countries using an autonomous model selection, saturation techniques, and Auto-metrics. The autonomous model selection is implemented through the "Hendry" or "LSE" general-to-specific method [18], facilitated by the search technique Auto-metrics, utilized in the econometric software OxMetrics81. This approach starts with a comprehensive model encompassing all potentially influential factors (i.e., variables, dynamic effects, breaks, deviations, irregularities, and trends). It then proceeds to systematically eliminate statistically insignificant factors to derive a simplified yet comprehensive model that uses the General Unrestricted Model (GUM) to delineate the relationship under investigation. As the GUM becomes more complex with an increasing number of variables, manual simplification may become impractical or even impossible. This necessitates the use of automated selection methods. This section provides a concise overview of Auto-metrics, with a more detailed explanation available in Ref. [19].

Table 1
Summarizes the research on modeling household electricity consumption utilizing aggregate data, including both long- and short-term elasticities.

Research	Country & Duration	Procedure	Predictor factors	Short-run revenue flexibility	Short-run cost flexibility	Long-run cost flexibility	Long-run cost flexibility
[26]	Romania 1950–1994	Long-term relationship analysis	Revenue, fuel oil and electricity costs, hard disk and CD-ROM storage costs, plus interest rates.	0.40	−0.64	0.53	−0.49
[27]	Ireland 1975–1996	Long-term relationship analysis	Consumer spending, electricity price, HDD and CDD.			1.0 to 1.08	−0.59 to −0.22
[28]	Belgium (30 cities) 1988–1991	Balanced panel data methods	Income tax collected at the local level, power rates, family sizes, population counts, hard disk capacities, and dummy variables to account for tariff variations.			0.34	−0.31
[29]	Slovenia 1961–2000	Long-term relationship Analysis	Considerations of cash, electricity prices, population, weather, and the proportion of government taxes to income	0.25 to 0.47	−0.25 to −0.19	0.82 to 1.25	−0.60 to −0.45
[24]	Latvia 1960–2000	Long-term relationship analysis	Economic growth, urbanization, income, oil prices, and CDD.	0.24	−0.16	1.58	−0.16
[30]	Germany 1991–2005	Long-term relationship Analysis	Income, electricity price, temperature.	0.3	Not important statistically	1.56	−0.41
[31]	Estonia 1975–2005	Long-term relationship Analysis	Analysis of salary, electricity cost, natural gas cost, and climate.	Not important statistically	−0.27	0.33	−0.55
[32]	Luxembourg 1970–2007	Long-term relationship Analysis	Analysis of salary, electricity cost, natural gas cost, and climate.	0.38 to 0.45	−0.47 to −0.34	0.50 to 0.72	−0.64 to −0.53
[33]	Spain 1980–2005	Long-term relationship analysis	Income, electricity price, natural gas price.	Not important statistically	−0.12	0.26 to 0.32	−1.57 to −1.46
[34])	Bulgaria 1972–2005	Long-term relationship analysis and Short-term scientific mission	Revenue, electricity cost.	From 1.83 to 1.97	Not important statistically	0.1 to 1.97	−0.07 to −0.03
[35]	30 European countries 1975–2005	Long-term relationship analysis	Revenue, electricity cost, heating oil cost, home occupancy rates, HDD, and CDD.	0.2	−0.40	0.28	−1.08
[36]	USA (35-Countries) 1990–2005	Fixed panel data methods	Income, electricity price, HDD and CDD.			0.82	−0.21
[37]	USA (38 states) 1995–2007	Long-term relationship Analysis	Income, electricity price, HDD and CDD.			0.34 to 1.20	−0.35 to −0.13
[38]	USA (39 states) 1996–2008	Analysis of panel data in real time	Electricity cost, heating oil cost, home occupancy rates, HDD, and CDD.		−0.16 to −0.09		−0.74 to −0.45
[39]	Turkey 1992–2007	Static panel data methods	Budget, electrical cost, and hard disk space are all discussed.			Not important statistically	−0.26 to −0.22
[40]	Greece (20 cities) 1995–2005	Analysis of panel data in real time.	Factors such as GDP, electricity costs, population size, CDD, and HDD.		−0.836 to −0.653		−2.267 to −1.274
[41]	USA and EU 1962–2009	Short-term scientific missions	Income, electricity price.	0.39	−0.1	1.58	−0.39
[42]	Pakistan 1965–2009	Long-term relationship Analysis	Analysis of salary, electricity cost, natural gas cost, and climate.	Not important statistically	Not important statistically	1.97	−1.22\
[43]	Finland (35 provinces) 2002–2007	Analysis of panel data in real time	Income tax collected at the local level, power rates, family sizes, population counts, hard disk capacities, and dummy variables to account for tariff variations.	0.24	−0.08	0.62	−0.20
[44])	China 1987–2014	Short-term scientific missions	Considerations including GDP, energy costs, the number of people, and even CDD and HDD.			0.44 to 0.72	−0.17 to 0.01

(continued on next page)

Table 1 (*continued*)

Research	Country & Duration	Procedure	Predictor factors	Short-run revenue flexibility	Short-run cost flexibility	Long-run cost flexibility	Long-run cost flexibility
[45]	USA (45 cities) 1990–2012	Analysis of panel data in real time	Considerations of cash, electricity prices, population, weather, and the proportion of government taxes to income		−0.20 to −0.10		−0.32 to −0.22
[46]	28 European countries 1998–2016	Analysis of panel data in real time	Considerations including GDP, energy costs, the number of people, and even CDD and HDD.	0.14 to 0.20	−0.045 to −0.042	0.88 to 0.93	−0.32 to −0.20
[34]	USA (40 states) 1997–2013	Balanced and dynamic time series panel data methods	Money, electricity costs, population, climate, and the social taxes to earnings ratio	0.15	−0.09	0.62	

4.2. Vector error correction model

The Auto-metrics algorithm conducts a tree search with the GUM at its root and each branch representing a potential reduction path. This means that the GUM is the most complex model in the framework and that there is always a model with fewer variables at each node and sub node. The search procedure commences with removing the least essential GUM variable and proceeds along that branch until it reaches its endpoint. After the reduction process, the created model is known as a terminal, and Auto-metrics continues to investigate the next possible fork. The modeler determines the "target size," or the fraction of extra variables that will be kept after the elimination procedure. Auto-metrics will go backward until a viable model is identified if a terminal fails all diagnostic tests. There are several diagnostic procedures available, including the error autocorrelation analysis, the ARCH analysis [20] the normality evaluation [21], the tests for heteroscedasticity [22], and the Resetting test [23]. Auto-metrics enables the incorporation of urge and phase indices for each sample data point into the autonomous choice of models, enabling the detection of outliers and breakdowns in the data. Both Urge-Indicator Saturation (IIS) and Step-Indicator Saturation (SIS) are clarified in literature, with paperwork conveying their conceptual properties and studies providing attractive scientific services [24]. The Artist IIS employs dummies with definitions of $I_{i,t} = 1$ for $t = i$ and zero else for model saturation. In a broad, unconstrained model, the T of these dummies will represent the T occurrences in the sample. SIS employs temporary placeholders known as dummies $S_{i,t} = 1$ for $t \leq i$; otherwise, a value of zero. Step variables help capture permanent modifications that would otherwise be overlooked when constructing a scientific model.

When there are more parameters in the model than there are assessments, like when T urge dummies and T phase dummies are added to the sample of T assessments, first making sections of dummies can still do an automatic estimation for groups of observations, then adding a single collection of dummies into the framework, picking the most important ones, repeating the process for another collection of dummies, and then re-estimating the mo. We can also choose to have particular variables "fixed" in Auto-metrics, meaning that they remain in the final model despite the algorithm's efforts to remove them since they are not considered statistically notable.

We prescribe an unrestrained error correction framework including both IIS and SIS for modeling household power use. The formula is as follows:

$$\Delta ln\ C_t = \alpha_0 + \alpha_1 \Delta ln\ C_{t-1} + \alpha_2 \Delta lnGDP_t + \alpha_3 \Delta lnGDP_{t-1} + \alpha_4 \Delta ln\ P_t + \alpha_5 \Delta ln\ P_{t-1} + \alpha_6 \Delta lnHDD_t + \alpha_7 \Delta lnHDD_{t-1} + \alpha_8 \Delta lnCDD_t + \alpha_9 \Delta lnCDD_{t-1} + \beta_1\ ln\ C_{t-1} + \beta_2 lnGDP_{t-1} + \beta_3\ ln\ P_{t-1} + \beta_4 lnHDD_{t-1} + \beta_5 lnCDD_{t-1} + \sum_{i=1}^{T} \gamma_i I_{i,t} + \sum_{i=1}^{T} \delta_i S_{i,t} + \varepsilon_t \tag{1}$$

Where ($\Delta ln\ C_t$) is the one-year slowed rate of evolution of the associated factors, ($\Delta lnGDP_t$) is the one-year and older slowed rate of evolution of homeowners' electrical usage per individual, ($\Delta lnHDD_t$) is the power source one-year slowed rate of evolution of GDP per individual, ($\Delta lnCDD_t$) is the single year slowed rate of evolution of homeowners electrical power price, ($ln\ C_{t-1}$) is the single-year slowed rate of evolution of HDD, ($lnGDP_{t-1}$) is the single-year slowed rate of evolution of CDD, ($ln\ P_{t-1}$), (HDD_{t-1}) and ($lnCDD_{t-1}$). We use the last four parameters as "fixed" in these regression analyses.

To ensure that an essential long-term connection exists, we must first ensure that the value of the coefficient connected with the missed factor in log levels ($\hat{\beta_1}$) is highly significant with an unfavorable value [25]. The correct specifications of the chosen model are assessed using these several diagnostic methods. Ultimately, we determine the revenue and cost elasticities in the long term.

4.3. Data sources

This paper utilizes data sets covering the years 1994–2022 for 12 central European countries: Ireland, Belgium, Slovenia, Latvia, Germany, Estonia, Luxembourg, Spain, Bulgaria, Greece, Finland, and Romania. The data are sourced from two reputable organizations: the International Energy Agency (IEA, 2019) and Eurostat (2020). The data include:

Table 2
Observation results Belgium, Romania, Slovenia, Latvia, Germany and Estonia.

Belgium		Romania		Slovenia		Latvia		Germany		Estonia	
Variables	ΔlnC_at_t	Variables	ΔlnC_be_t	Variables	ΔlnC_de_t	Variables	ΔlnC_dk_t	Variables	ΔlnC_fr_t	Variables	ΔlnC_ie_t
I1982	−0.179** (0.0 19)	S11985	−0.036*** (0.008)	S11991	0.156*** (0.013)	I1981	−0.059** (0.018)	I1996	−0.049*** (0.007)	I1991	−0.070*** (0.013)
I1988	0.237*** (0.018)	S11987	−0.017** (0.008)	S11992	−0.136*** (0.014)	S11983	−0.082*** (0.015)	I2004	0.039*** (0.006)	I1998	0.049** (0.013)
S12003	0.032*** (0.010)	S12002	−0.045*** (0.009)			S12017	0.042*** (0.013)	I2006	−0.069*** (0.006)	I2010	−0.044*** (0.013)
		S12003	0.067*** (0.009)					I2012	−0.025*** (0.009)	S11983	−0.040*** (0.010)
		S12006	0.145** (0.009)					I2015	−0.047*** (0.008)	S12002	0.046*** (0.014)
		S12007	−0.061*** (0.012)					I2018	−0.023*** (0.007)	S12003	−0.079*** (0.015)
		S12008	0.083*** (0.011)					S11982	−0.076*** (0.007)		
		S12009	−0.092*** (0.011)					S11990	−0.024*** (0.007)		
		S12010	0.050*** (0.011)					S11991	0.035*** (0.009)		
		S12011	−0.022** (0.010)					S11992	−0.037*** (0.007)		
		S12015	0.030*** (0.007)					S12010	−0.042*** (0.005)		
		S12018	−0.045*** (0.010)								
								ΔlnC_fr_{t-1}	−0.431*** (0.035)		
								ΔlnP_fr_t	−0.388*** (0.034)	ΔlnP_ie_t	−0.295*** (0.036)
ΔlnC_at_{t-1}	0.193*** (0.055)	$\Delta lnGDP\_be_{t-1}$	−0.302** (0.110)					$\Delta lnHDD\_fr_t$	0.317*** (0.014)	$\Delta lnP\_ ie_{t-1}$	0.155*** (0.034)
$\Delta lnHDD\_at_t$	0.186*** (0.041)	$\Delta lnHDD\_be_t$	0.176*** (0.017)	$\Delta lnHDD\_de_t$	0.188*** (0.022)	$\Delta lnHDD\_dk_t$	0.168*** (0.029)	$\Delta lnHDD\_fr_{t-1}$	0.188*** (0.017)	$\Delta lnHDD\_ie_t$	0.212*** (0.034)
lnC_at_{t-1}	−0.110*** (0.037)	lnC_be_{t-1}	−0.270*** (0.031)	lnC_de_{t-1}	−0.122*** (0.032)	lnC_dk_{t-1}	−0.256*** (0.047)	lnC_fr_{t-1}	−0.325*** (0.017)	lnC_at_{t-1}	−0.244*** (0.042)
$lnGDP\_at_{t-1}$	0.102** (0.045)	$lnGDP\_be_{t-1}$	0.160*** (0.029)	$lnGDP\_de_{t-1}$	0.021 (0.025)	$lnGDP\_dk_{t-1}$	0.050* (0.030)	$lnGDP\_fr_{t-1}$	0.130*** (0.018)	$lnGDP\_ie_{t-1}$	0.060*** (0.018)
lnP_at_{t-1}	−0.084** (0.037)	lnP_be_{t-1}	−0.080*** (0.025)	lnP_de_{t-1}	−0.044*** (0.016)	lnP_dk_{t-1}	−0.090** (0.036)	lnP_fr_{t-1}	−0.087*** (0.016)	lnP_ie_{t-1}	−0.196*** (0.023)
$lnHDD\_at_{t-1}$	−0.049 (0.033)	$lnHDD\_be_{t-1}$	0.026 (0.018)	$lnHDD\_de_{t-1}$	0.077*** (0.021)	$lnHDD\_dk_{t-1}$	0.155*** (0.026)	$lnHDD\_fr_{t-1}$	0.133*** (0.018)	$lnHDD\_ie_{t-1}$	0.120*** (0.019)
$lnCDD\_at_{t-1}$	0.002 (0.004)	$lnCDD\_be_{t-1}$	0.003*** (0.002)	$lnCDD\_de_{t-1}$	0.004* (0.003)	$lnCDD\_dk_{t-1}$	−0.002 (0.002)	$lnCDD\_fr_{t-1}$	−0.003 (0.002)	$lnCDD\_ie_{t-1}$	−0.002 (0.003)
Perception	44	Perception	44	Perception	44	Perception	44	Perception	44	Perception	42
R-squared	0.938	R-squared	0.990	R-squared	0.913	R-squared	0.812	R-squared	0.998	R-squared	0.946

Note: Standard errors in parentheses.
***p0.02, **p0.06, *p0.2.

Table 3
Observation results Ireland, Luxembourg, Spain, Bulgaria, Greece and Finland.

Ireland		Luxembourg		Spain		Bulgaria		Greece		Finland	
Variables	ΔlnC_it_t	Variables	ΔlnC_nl_t	Variables	ΔlnC_es_t	Variables	ΔlnC_pt_t	Variables	ΔlnC_sw_t	Variables	ΔlnC_uk_t
I1983	0.029***	I1978	−0.040***	I1978	−0.051***	I2017	0.069**	I1986	0.138***	S11999	0.048***
	(0.0010)		(0.010)		(0.012)		(0.029)		(0.035)		(0.010)
I2012	0.037***	I1982	−0.028***	I1980	0.040***	S11984	−0.103***	I2011	0.130***	S12003	−0.033***
	(0.010)		(0.009)		(0.010)		(0.025)		(0.035)		(0.010)
I2014	−0.028***	I1983	−0.032***	I1983	−0.055***	S12011	0.053***			S12015	0.036***
	(0.010)		(0.009)		(0.009)		(0.016)				(0.012)
I2015	−0.052***	S11988	0.098***	I1985	0.053***	S12015	−0.061***				
	(0.010)		(0.009)		(0.009)		(0.021)				
S11980	−0.027***	S11989	−0.071***	I1986	−0.029***						
	(0.010)		(0.012)		(0.010)						
S11984	−0.065***	S11990	0.056***	I1988	−0.040***						
	(0.009)		(0.011)		(0.009)						
		S11991	−0.037***	I2000	−0.112***						
			(0.009)		(0.009)						
		S12014	0.032***	S11993	−0.040***						
			(0.005)		(0.007)						
				S12007	0.031***						
					(0.008)						
				S12009	−0.087***						
					(0.007)						
				S12012	0.078***						
					(0.006)						
				S12017	−0.085***						
					(0.010)						
				Constant	−0.704**						
					(0.327)						
				ΔlnC_es_{t-1}	−0.484***					ΔlnP_uk_t	−0.239***
					(0.043)						(0.050)
$\Delta lnGDP\_it_{t-1}$	−0.549***			$\Delta lnGDP\_es_t$	1.412***					$\Delta lnHDD\_uk_t$	0.263***
	(0.098)				(0.090)						(0.028)
lnC_it_{t-1}	−0.464***	lnC_nl_{t-1}	−0.341***	lnC_es_{t-1}	−0.170***	lnC_pt_{t-1}	−0.152***	lnC_sw_{t-1}	−0.168***	$lnGDP\_uk_{t-1}$	−0.405***
	(0.055)		(0.071)		(0.024)		(0.032)		(0.041)		(0.071)
$lnGDP\_it_{t-1}$	0.355***	$lnGDP\_nl_{t-1}$	0.217***	$lnGDP\_es_{t-1}$ 1	0.121***	$lnGDP\_pt_{t-1}$	0.113***	$lnGDP\_sw_{t-1}$	0.135**	$lnGDP\_uk_{t-1}$	0.206***
	(0.046)		(0.043)		(0.040)		(0.040)		(0.054)		(0.037)
lnP_it_{t-1}	−0.073***	lnP_nl_{t-1}	−0.028**	lnP_es_{t-1}	−0.119***	lnP_pt_{t-1}	−0.115***	lnP_sw_{t-1}	−0.113***	lnP_uk_{t-1}	−0.247***
	(0.020)		(0.012)		(0.012)		(0.037)		(0.037)		(0.031)
$lnHDD\_it_{t-1}$	−0.078***	$lnHDD\_nl_{t-1}$	0.006	$lnHDD\_es_{t-1}$ 1	0.064***	$lnHDD\_pt_{t-1}$	−0.047	$lnHDD\_sw_{t-1}$	−0.031	$lnHDD\_uk_{t-1}$	0.056**
	(0.018)		(0.015)		(0.021)		(0.033)		(0.052)		(0.025)
$lnCDD\_it_{t-1}$	−0.002	$lnCDD\_nl_{t-1}$	0.001	$lnCDD\_es_{t-1}$	0.020**	$lnCDD\_pt_{t-1}$	0.019	$lnCDD\_sw_{t-1}$	−0.002	$lnCDD\_uk_{t-1}$	−0.002
	(0.006)		(0.001)		(0.008)		(0.013)		(0.003)		(0.002)
Observations	44	Observations	44	Observations	44	Observations	44	Observations	44	Observations	44
R-squared	0.960	R-squared	0.925	R-squared	0.985	R-squared	0.864	R-squared	0.663	R-squared	0.875

Note: Error standards enclosed in brackets.
***p0.02, **p0.06, *p0.2.

1. Household electricity consumption per capita in kWh (C_t), calculated by dividing the total household electricity consumption figures from the IEA (2020) by population numbers from Eurostat (2020). The 2019 household electricity consumption values are based on data from Eurostat (2020).
2. GDP per capita in real terms (2015 US. dollars) (GDP_t), derived by dividing the GDP figures from the IEA (2019) by the population data from Eurostat (2020).
3. The price of electricity for households, as reported by the IEA in 2019, in USD per kilowatt-hour (P_t) (see Table 1).

5. Results and discussion

The suggested models picked using Auto-metrics measurement systems to represent 12 European countries are listed in Tables 2 and 3, respectively. We chose the most consistent and efficient error-correcting model for all countries under consideration. The chosen urge and step indicator factors highlight demand anomalies, such as aberrations and breaks, in a given year or time.

Electricity use, revenue (as determined by GDP), cost, and climate factors such as HDD and CDD are all found to have a long-run correlation with the calculated value of the term for error correction $\hat{\beta}_1$, which is harmful and highly valuable to the 1% importance level in all models. Revenue and cost log-level the estimations of coefficients are $\hat{\beta}_2$ and $\hat{\beta}_3$, respectively are highly significant at the 96% confidence level for all countries except Austria due to an underestimate of the predicted factor on the log level of revenue. $lnHDD_{t-1}$ Statistical significance is found for the coefficient of variation (which symbolizes the effect of winter temperatures on the consumption of electricity for heating purposes) for Belgium, Germany, Ireland, Latvia, Bulgaria, and Estonia but not for the majority of other countries (the exceptions being Latvia, Germany, and Bulgaria, where the values of the coefficients $lnCDD_{t-1}$ are minimal).

The short-run effect factors on revenue $\hat{\alpha}_2$ and $\hat{\alpha}_3$ costs $\hat{\alpha}_4$ and $\hat{\alpha}_5$ are not significant in the majority of the countries since the parameters in the initial variation are not kept in the final analyses. For the countries of Romania, Germany, Belgium, Estonia, Slovenia, Spain, and Finland, the values of the coefficients $\Delta lnHDD_t$ (which represent the predicted short-run effect of winter conditions on electrical energy usage) are highly significant. In contrast, we find a highly significant value $\Delta lnCDD_t$ for none of the countries (which represent the short-run effect of warm weather). According to Ref. [47], the longer warmer durations in Europe than cooling periods help explain why wintertime significantly impacts power demand more than warm weather.

Table 4 shows each selected model's long-term revenue and cost flexibility, which were determined by dividing the $\hat{\beta}_2$ (value of GDP) by the $\hat{\beta}_3$ (value of cost) by the appropriate $\hat{\beta}_1$ (t-1 time period usage of electricity factor). We also include 96% confidence ranges to illustrate the range of possible values for revenue and cost elasticities. Except for Romania's revenue elasticity (which is not essential) and Slovenia's revenue elasticity (11% significance), the future price and revenue flexibility are deemed significant at the typical 2% and 6% standards. Additionally, the signs of all long-run elasticities are as predicted, being favorable for revenue and unfavorable for prices. Various point estimates have standard errors, which are reflected in the range of the guarantee interval. Germany has a wide range of confidence in the income elasticity due to the significant average error of the calculated coefficient on GDP. In contrast, France has a narrow assurance interval for income elasticity because the average errors of the calculated coefficients on GDP and electrical usage are small relative to the dimensions of the coefficients. Looking at long-term revenue elasticities, all European countries are below 1, indicating that electricity is a needy good instead of a luxury item. Several country-specific factors contribute to the observed range of earnings elasticities. The first is the wide range in GDP per person across countries. More specifically, countries with a lower per-individual GDP (averaged during 1994–2022) have better financial elasticity than those with a higher per-capita GDP. The long-run revenue elasticity in Finland is 0.20 (with a GDP per individual of $40,463 in 2016 US dollars), and in Spain, it is 0.75 (with a GDP per capita of $25 in 2016 US dollars). As seen in Fig. 1, except in Germany and Slovenia, there is an adverse correlation among long-term elasticities of income and per-individual GDP. This result accords with research of Fouquet (2015), who found that the coefficient of income elasticity of demand decreases with more money due to the oversupply effect.

The various levels of energy conservation attained by countries are a second consideration. Households' average "ODYSSEE-MURE" consumption ratings are shown in Fig. 2 for 2005–2012. The overall score of a nation can quickly determine its level of energy conservation. Three energy efficiency measures (current efficiency, growth in efficiency, and policy support) are used to get overall ratings. Each country is given a score from zero to one over all three requirements based on a wide range of signs (taken from the

Table 4
Shows 96% probability ranges for the long-run revenue and cost elasticities that were estimated.

	Long-run revenue elasticity	[96% Conf. Interval]	Long-run cost elasticity	[96% Conf. Interval]
Ireland	0.530	[0.0645 5.376]	−0.761	[−0.858 −0.258]
Belgium	0.592	[0.306 1.052]	−0.296	[−0.389 −0.144]
Slovenia	0.195	[−0.027 0.672]	−0.348	[−0.462 −0.097]
Latvia	0.410	[0.266 0.566]	−0.267	[−0.326 −0.192]
Germany	0.165	[−0.162 1.220]	−0.355	[−0.391 −0.231]
Estonia	0.244	[0.075 0.587]	−0.804	[−0.937 −0.737]
Luxembourg	0.766	[0.460 1.261]	−0.156	[−0.191 −0.095]
Spain	0.638	[0.267 1.560]	−0.082	[−0.108 −0.014]
Bulgaria	0.740	[0.153 2.179]	−0.756	[−0.874 −0.465]
Greece	0.709	[0.181 1.665]	−0.700	[−0.785 −0.651]
Finland	0.810	[0.113 2.820]	−0.669	[−0.748 −0.439]
Romania	0.906	[0.242 1.058]	−0.608	[−0.703 −0.562]

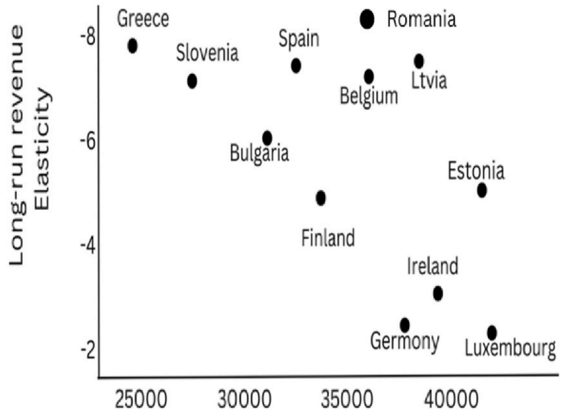

Fig. 1. Shows the correlation among long-term revenue flexibility and GDP per person (mean value 1994–2022 in 2018 US dollars).

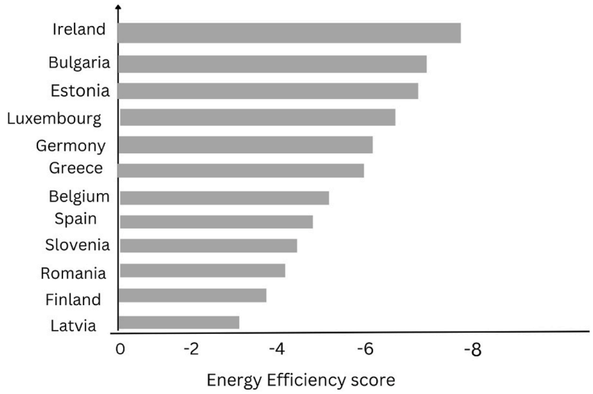

Fig. 2. Shows the average residential energy efficiency ratings for 12 European countries between the years 2005 and 2022.

ODYSSEE Data) and its energy regulations (taken from the MURE Data), with the ultimate energy efficiency rating being the weighted mean of all the individual criteria scores. Ireland, the United Kingdom, and France, which scored the highest, have a long-run elasticity of income smaller than 0.6, as shown in Fig. 3. Germany, Spain, Romania, and Finland, which scored the lowest, have the most significant long-run revenue elasticity. As income rises, the proportion of electricity used to power appliances may increase only slightly in countries that are successfully implementing conservation of energy regulations and have an incredible stock of equipment.

The long-term cost elasticities estimated for all countries vary less than one, indicating that residential electricity consumption is inflexible to price in the short and long term. This makes sense, as electricity is a necessity that can only be replaced by natural gas for heating and cooking. Long-term cost elasticities vary from country to country due to unavoidable circumstances, among the most significant of which is the inability to replace the use of electricity with another fuel source for certain services.

Even though many changes have been made at the EU level to create a regular market and improve energy efficiency requirements,

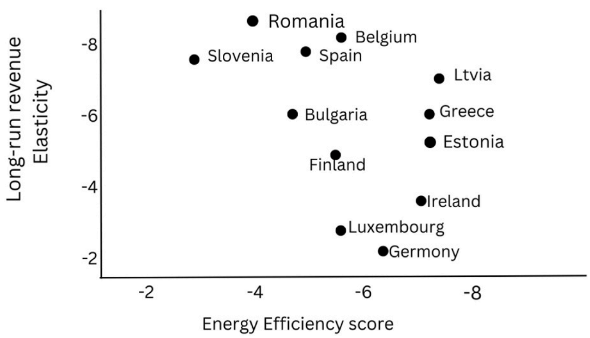

Fig. 3. Shows the correlation between income elasticity and the energy-efficiency levels over the long term.

unique factors like different per-capita incomes and energy efficiency capacities are still the most important. The fact that long-term revenue and cost elasticities vary between countries demonstrates this.

The calculated elasticity in the present investigation can be compared to previous research on European countries. Our analysis found that the average of the predicted revenue elasticities was 0.57. This is the same as [48] value of 0.62 but less (H. S [49]) range of 0.88–0.93 and [44] value of 0.9. Our research suggests that the earnings elasticity in Spain is a touch higher, at 0.64 than what [50] discovered. This study's overall cost elasticity of −0.49 is lower than the −0.54 found by Ref. [51] but higher than the long-run cost elasticity of −0.31 to −0.20 found by Ref. [52]). Comparatively, the cost elasticity of our prediction is more significant [53]estimate of 0.20. This analysis estimates higher price elasticity for Spain than [54], who found an elasticity of −0.20. Variations in predicted elasticities can be attributable to several factors, as highlighted by meta-analysis studies [55], including the specifications of the consumption model and the estimation method, the type of data (i.e., time series information vs. section or survey data), the type of consumer, the country, the sample period, and the type of link where the work has been published. All 12 countries have somewhat cost-inelastic demand for household power, meaning that any strategy focused on energy efficiency utilizing just price increases would have little effect on decreasing electricity usage and would result in a substantial loss in the welfare of consumers. Consequently, European lawmakers should keep moving toward enhancing the energy effectiveness of devices and buildings and raising users' awareness of and exposure to sustainable behaviors if they are to achieve the long-term objectives of decarburization.

6. Conclusion and policy recommendations

This paper aims to add to the existing research on evaluating price and revenue elasticities for household energy demand by utilizing an original econometric methodology based on the automatic choice of model, saturating methods, and Auto-metrics. Using an automated process, we could choose all the important variables influencing electricity consumption, identify aberrations and breaks, and arrive at consistent estimation of elasticities.

Applying a yearly time series from 1994 to 2022, the requirement for domestic electricity in Romania, Belgium, Finland, Germany, Latvia, Ireland, Estonia, Spain, Greece, Luxembourg, Sweden, and Bulgaria was approximated. In the end, a well-defined error correction method was chosen for each country. When urge and procedure dummies were added to the requirements to find outliers and breaks that happened at unknown times, a co-integrating relationship was found between electricity use, revenue, electricity cost, and the weather parameters HDD and CDD. Electricity was shown to be an average commodity (with an expected long-run revenue elasticity lower than 1). It was inelastic for all 12 countries, revealing commonalities across the major European countries through household demand's long-run cost and income flexibility. Revenue elasticities varied from an estimated 0.94 in Romania to a flat 0 in Germany, while price elasticities ranged from a negative 0.90 in Ireland to a positive 0.09 in Luxembourg. The predicted elasticities varied from country to country, which the study attributes to variances in GDP per individual and energy consumption. The inelastic nature of residential power demand to changes in electricity prices has significant implications for selecting the best policy instrument to encourage energy saving in Europe. Any policy that relies entirely on higher prices (such as electricity taxes) may significantly decrease consumer satisfaction while slightly reducing consumption. Therefore, policymakers in the EU should keep pushing for different energy efficiency programmers to cut down on energy consumption.

6.1. Policy recommendations

The policy suggestions have been implemented based on the findings of the analysis mentioned above. The first step that must be taken is for the government and policymakers in the European Union to start a comprehensive energy efficiency program for homes. These programs could include measures like tax credits and incentives for putting energy-saving equipment in private residences. In addition, lawmakers in the EU need to start public awareness programs to teach households about the benefits of using energy-efficient devices and behaviors. Further, the federal government of the European Union may encourage electrical companies to implement time-of-use pricing plans, which would reduce retail electricity rates. Customers are encouraged to move energy-intensive activities to cheaper "off-peak" times of the day when power costs are reduced using such models.

Second, the federal government of the EU should focus more on net metering and feed-in tariffs, which allow homeowners to sell clean energy surpluses to the grid at favorable rates. By taking this course of action, a financial incentive would be established for the production of renewable power. In addition, by encouraging activities to reduce carbon emissions, such as the development of solar power projects, many homes can share the benefits of a single green energy system. In addition, the EU government should offer tax breaks and other financial benefits to households that purchase green energy-related equipment. Such incentives may reduce the initial expenditure for green energy systems and speed up their widespread adoption. Finally, lawmakers and the EU government should develop broad, long-term energy plans that highlight the gradual move to renewable, green energy sources and set specific goals for the implementation of sustainable energy.

6.2. Future directions

Therefore, European legislators should continue making efforts to improve the energy efficiency of devices and structures and increase users' awareness of and involvement in sustainable behaviors if decarburization is to serve its long-term goals. The growth of the financial sector, the fluctuation of economic policy, and the internationalization of economies are all issues that could have an impact on both fossil fuels and renewable energy and should be taken into account in future research. It is also important to note that the EU serves as the primary case study in this investigation. The scope of future studies could be broadened to include many countries, offering a broader overview of the global energy dynamics. In addition, researchers can enrich the literature by using cutting-edge econometric methods like rolling window causality and spectral tools to understand energy consumption patterns and causation interrelationships better.

The paper's primary findings highlight possible new directions for further study. The empirical investigation may be expanded to include all of Europe to learn more about the existence and scope of regional patterns in residential energy use. In addition, this method can be used to estimate power consumption in factories. The study's results also create a detailed cost-benefit analysis to assess different policy options for achieving the EU's ongoing decarburization target. These alterations are shelved for additional study.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Wen huang: Investigation, Formal analysis, Data curation, Conceptualization. **heng li:** Writing – review & editing, Writing – original draft, Visualization. **Zhein Li:** Writing – review & editing.

Declaration of competing interest

It is submitted that, the above mentioned manuscript is originally written in all aspects and submitted for the possible publication in Journal of Heliyon. This manuscript tries to fill the gap of literature for the Heliyon. We declared that there is no conflict of interest among the all authors and they are unanimously agreed to submit this in journal of Heliyon.

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