

Article

Determinants of Energy Prices in the European Union for the Period 2017–2025—An Econometric Analysis

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Abstract

Currently, a major challenge for European economies is the volatility of electricity prices, which affects costs borne by households and firms, as well as inflation, economic competitiveness, and energy security. Although the literature has analysed various determinants of electricity prices, there is still limited evidence on the comparative short- and long-term effects of fiscal factors, the natural gas market, and the transition to renewable energy within the Member States of the European Union. This paper analyses the relationship between household electricity prices and a set of economic, climate, and fiscal determinants in EU countries over the period 2017–2025, using panel data econometric methods. The methodology includes pooled OLS models, fixed and random effects estimators, unit root tests, cross-sectional dependence (Pesaran CD) tests, cointegration analysis, and a Panel ARDL-PMG framework, complemented by robustness checks using FMOLS and DOLS-type estimators. The results indicate the existence of a stable long-run equilibrium relationship between the analysed variables, as well as significant cross-sectional dependence among countries, reflecting common shocks and interconnected dynamics in EU energy markets. Fixed effects models are used as the baseline specification, while PMG-ARDL and other dynamic estimators are employed for robustness analysis. The results are consistent across different econometric specifications. The conclusions highlight the dominant role of Household Gas Prices as the main determinant of electricity prices, while energy productivity shows a positive association with electricity price levels. Climate variables exhibit weak and unstable effects, and environmental taxes do not show statistically significant impacts within the sample period. Overall, the findings underline the importance of energy market dynamics, structural factors, and the ongoing energy transition in shaping electricity price developments in the European Union.



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1. Introduction

Increased competition in the electricity market, market liberalization, and the need to ensure affordable tariffs for end users have motivated the European Union and national

governments to promote investments in cleaner, safer, and more sustainable energy sources, while gradually reducing direct market intervention in the long term.

In this context, electricity price dynamics can be considered a key indicator of the performance of market reforms, reflecting the degree of competition and convergence towards efficient pricing levels that benefit end users, as electricity remains an essential commodity [1] for both industrial activity and households.

The focus on household electricity prices, rather than industrial prices, is justified by several factors: greater data availability and comparability at Eurostat level, higher transparency of household tariff structures, and differences in vulnerability and regulatory treatment between households and firms.

In addition, household electricity prices exhibit more homogeneous behavioural patterns compared to firms, whose energy procurement strategies are more heterogeneous due to direct access to producers, long-term contracts, tax exemptions, and VAT-related adjustments.

Following the armed conflict in Ukraine, which started in 2022, the European Union has faced increased pressure to reduce its dependence on fossil fuel imports. Beyond supply risks, one of the most significant challenges has been the high volatility of electricity prices, which complicates adjustment processes for end users over short time horizons.

Moreover, electricity markets differ substantially from other commodity markets due to the limited storability of electricity and the real-time balancing requirement between supply and demand. As a result, prices are highly sensitive to short-term shocks and exhibit strong volatility. These characteristics have led both national governments and EU institutions to strengthen energy security policies, promote renewable energy integration, support market liberalization, and enhance resilience against external shocks and climate-related risks [2–5].

Despite these efforts, important research gaps remain. Existing studies often fail to fully capture cross-country interdependencies within the European electricity market, while forecasting models typically rely on isolated country-level analyses that do not account for structural linkages between Member States.

Furthermore, regional disparities and cross-border transmission effects remain insufficiently explored. This highlights the need for empirical frameworks capable of capturing both heterogeneity and cross-sectional dependence in EU energy markets.

At the same time, the transition towards renewable energy sources introduces additional complexity into price formation mechanisms. Renewable generation is inherently more variable and weather-dependent compared to conventional fossil fuel-based generation, which may increase short-term price volatility and amplify system-level uncertainty [6].

In this context, the paper investigates the determinants of household electricity prices across EU27 countries over the period 2017–2025.

The empirical strategy combines pooled OLS, fixed and random effects models, panel unit root tests, cointegration analysis, and a Panel ARDL-PMG framework, complemented by robustness checks using alternative estimators and Driscoll–Kraay standard errors. The fixed effects model is used as the baseline specification, while PMG-ARDL is employed as the main dynamic framework.

The originality of the study lies in the joint analysis of macroeconomic, climate, and policy-related determinants, including heating and cooling degree days, energy productivity, energy market structure indicators, natural gas prices, environmental taxes, electricity imports, and renewable energy penetration.

The study tests two main hypotheses: (H1) structural energy market variables significantly influence household electricity prices, and (H2) natural gas prices represent a key determinant of electricity price dynamics in the EU.

The structure of the paper is as follows: Section 1 introduces the topic and motivation; Section 2 reviews the literature; Section 3 presents data and methodology; Section 4 discusses empirical results; and Section 5 concludes.

2. Literature Review

World literature clearly captures the importance of electricity prices as shaping factors of the energy sector, consumers, producers and distributors, as well as national, regional and global economies.

From price peaks, negative price developments, short and long-term developments in electricity prices, energy demand and supply, fuel prices, CO₂ price, energy mix, competitiveness, liberalization, deregulation, renewable energy, weather conditions to climate change [7–16], all of these are included as explanatory variables in studies that demonstrate that prices influence not only the forward and real-time evolution of the energy market by providing good predictions for future developments, but that they also have a multiplier effect and a broader impact on the economy.

The literature shows that prices are influenced by both traditional market factors, such as supply and demand, and by liberalization processes, dependence on energy resources and the transition to renewable sources.

Together, these perspectives provide a broad and complex framework of theoretical approaches for analysing the determinants of electricity prices in the European Union.

Thus, the Table 1 summarizes the main theories used to explain the evolution of electricity prices.

Table 1. A selection of specialized literature on the determinants of energy prices in Europe.

Economic Theory	Explanation for Analyzing Electricity Prices	Prevailing Methodologies	Representative Studies
The theory of supply and demand	Price formation and volatility through the interaction between demand, supply and marginal costs of production	Econometrics, equilibrium models, time series (ARIMA, GARCH, NARDL), Machine Learning	[6,8,13,14,17,18]
Market liberalization theory	The effect of competition, reforms and market integration on price levels and stability	Institutional, comparative analyses, competition models and strategic behaviour	[7,12,19–23]
Resource dependency theory	The influence of fossil fuels, security of supply and energy mix on energy prices	Cointegration, multifuel models, institutional analyses and fuel-switching	[3,9,11,24]
Energy transition theory	The impact of renewable energy, decarbonization and climate policies on electricity prices	Panel analyses, merit order effect, RES integration models, legislative and climate analyses	[1,15,25–28]

Source: authors' systematization based on the investigated specialized literature.

Also, studying the dependence between electricity prices, renewable energy sources and demand, based on a multivariate model for Germany, Durante et al., (2022) [27] find a strong association between electricity prices, demand, and renewable energy sources, providing directions for additional measures that would provide incentives for green energy generation.

In the same direction, Moutinho et al., 2015 [29] analyzed four groups of European countries (eastern, western, southern and northern), emphasizing the conclusion that sustained steps are being taken to reduce CO₂ emissions at the European level, through

an energy mix that mainly aims at switching to cleaner fuels and reducing fossil fuels in energy production.

In this regard, Trujillo-Baute et al., 2018 [28], studying whether the increase in support costs for renewable electricity was the main determining factor in the increase in retail energy prices, found that the impact of renewable energy promotion costs on these prices is small but positive.

Therefore, the literature often captures similar but also contradictory and complementary opinions, emphasizing that various strategies and reforms, including the more aggressive introduction of renewable sources or extremely competitive generation markets, must be approached with caution, as energy market reforms sometimes end in failures [20], not always managing to provide stable and low prices for end consumers.

Starting from the specialized literature, the determinants of the electricity price treated in this paper can be mainly included in the energy transition theory (three indicators used justifying the inclusion in this category quite well: Renewable energy use, Environmental taxes, Energy productivity) and subsequently in the demand and supply theory, the resource dependence theory and the market liberalization theory, there being a relatively balanced mix between the factors that justify the possible inclusion in these three latter categories.

Our study is primarily grounded in energy transition theory. Within this framework, studies such as Cludius et al. (2014) [30] demonstrate how the structure of the energy system and the integration of renewable energy sources affect electricity prices through the merit-order effect. More recent contributions [31,32] further show that the integration of renewable energy sources, the diversification of the energy mix, the reduction in dependence on energy imports, and the mitigation of vulnerability to energy shocks have direct implications for the tariffs paid by household consumers. These studies also suggest that the cost effects associated with renewable energy expansion are largely transitional rather than permanent.

From a supply-and-demand perspective, the literature [33–38] focuses on electricity price formation and forecasting, emphasizing the fundamental role of the interaction between consumption and production. The findings indicate that system flexibility, supply shocks, demand fluctuations, and market-balancing mechanisms significantly affect electricity prices. Furthermore, Zachmann et al. (2023) [38] show that, during the European energy crisis, rising natural gas prices were the main channel through which volatility was transmitted to electricity markets. This finding underscores the importance of strengthening energy infrastructure, interconnections, and long-term contractual arrangements to reduce the impact of market fluctuations on household consumers. Consequently, by examining the evolution of natural gas prices as a determinant of residential electricity prices, our study can also be situated within the supply-and-demand framework.

In addition, our analysis incorporates elements of resource dependence theory, albeit without providing strong empirical evidence in its support. In this regard, it aligns with recent studies showing that energy dependence can hinder economic development, whereas import diversification and greater availability of energy resources contribute to enhanced energy security and more sustainable economic growth [39,40].

Finally, although market concentration does not emerge as a significant explanatory factor in our model, the inclusion of this variable allows our study to engage with the literature on electricity market liberalization. Research in this area [41–44] suggests that increased competition and market opening can improve efficiency and contribute to lower prices. At the same time, these processes create new challenges related to price formation mechanisms, consumer protection, and the design of the institutional and regulatory framework governing electricity markets.

In this context, our study attempts to fill the knowledge gap by combining heating and cooling days, environmental taxes, energy productivity, gas prices, renewable energy and electricity imports into a single explanatory framework for the functioning of energy prices in the EU. Our study also falls within the limited application of ARDL models in studies of electricity pricing in the EU, and by analyzing in comparison with other models, we try to highlight the possibility of improving this method for the study of electricity prices in the European Union.

3. Methodology

The analysis examines the relationship between a set of macroeconomic and structural indicators considered relevant determinants of household electricity prices in the European Union. The empirical analysis covers the period 2017–2025 and uses a balanced panel dataset consisting of EU Member States. The relatively short time dimension of the panel ($T = 9$) represents an important limitation of the study, which is reflected in both the interpretation of results and the econometric strategy. Accordingly, the analysis focuses on short-run within-country variations, with fixed effects estimations serving as the primary empirical framework to control for unobserved country-specific heterogeneity.

Missing values are treated using linear interpolation, while extrapolation is applied only in limited cases. Approximately 8% of observations are generated through imputation. A sensitivity analysis excluding imputed observations confirms that the results remain stable, indicating that findings are not driven by data construction procedures. Original series containing negative values are adjusted using a constant prior to logarithmic transformation. All variables are expressed in natural logarithms to allow elasticity interpretation and reduce heteroscedasticity.

The dependent variable is defined exclusively as household electricity prices (EPHC), and all interpretations are restricted to price formation mechanisms. The empirical strategy follows a parsimonious specification framework in order to avoid overfitting and model proliferation, with fixed effects as the baseline estimator. Pooled OLS is used as a benchmark, while random effects are reported for comparison due to potential correlation between unobserved heterogeneity and explanatory variables in energy price models.

To address heteroskedasticity and cross-sectional dependence, robustness checks are performed using robust least squares and Driscoll–Kraay standard errors. In the presence of cross-sectional dependence, fixed effects and PMG estimators remain consistent but may produce inefficient standard errors; Driscoll–Kraay corrections therefore ensure valid inference by adjusting standard errors without altering coefficient estimates.

Potential endogeneity between household electricity prices and key explanatory variables is acknowledged, as energy prices, policy variables, and market conditions may be jointly determined within the energy system. Although no instrumental variable approach is implemented due to data limitations, the inclusion of fixed effects, lagged dynamics, and alternative estimators helps mitigate, though not eliminate, endogeneity concerns. The results should therefore be interpreted as conditional associations rather than causal effects.

The Panel ARDL (PMG) model is used strictly as a supplementary dynamic specification to capture short-run adjustments and error-correction dynamics. Given the short time dimension, it is not used for primary long-run inference, which remains outside the scope of this study.

Unit root and cointegration tests are interpreted as indicative only due to the short panel dimension. They are not used to support formal long-run structural modelling. Consequently, all dynamic specifications are treated as robustness checks rather than as instruments for causal or equilibrium inference.

The variables used in the analysis are presented in Table 2.

Table 2. Presentation of the used indicators.

Name of the Variable	Abbreviation	Unit of Measure and Detailed Description	Source of Data
Electricity price components for household consumers—annual data (from 2007 onwards)	EPHC	Annual, Consumption of kWh—all bands Energy and supply, no taxes, Euro	Eurostat, [nrg_pc_204_c_custom_21797113]
Energy productivity	EP	Annual, Euro per kilogram of oil equivalent (KGOE)	Eurostat, [sdg_07_30]
Energy Market Indicator	EMI	Annual, Electricity, Largest company—electricity generation, Percentage	Eurostat, [nrg_ind_market_custom_20072775]
Heating degree days by country—annual data	HDD	Annual, Number, Heating degree days	Eurostat, [nrg_chddr2_a_custom_21797891]
Cooling degree days by country—annual data	CDD	Annual, Number, Cooling degree days	Eurostat, [nrg_chddr2_a_custom_21797891]
Gas prices components for household consumers—annual data	GPHC	Consumption of GJ—all bands, Energy and supply, Euro, Kilowatt-hour, no taxes	Eurostat, [nrg_pc_202_c_custom_21798067]
Environmental taxes by economic activity (NACE Rev. 2)	ENVTAX	Annual, Energy taxes, Million euro, Households	Eurostat, [env_ac_taxind2_custom_21797203]
Imports of electricity and derived heat by partner country	IMPE	Annual, Electricity, Gigawatt-hour	Eurostat, [nrg_ti_eh_custom_21798269]
Use of renewables for electricity	URE	Annual, Renewables and biofuels, Gross electricity production—Renewable Energy Directive, Gigawatt-hour	Eurostat, [nrg_ti_eh_custom_21798269]

These notations are also used when taking logarithms, so the acronym of the indicators reflects the natural logarithm of the values of the variables mentioned above. Source: <https://ec.europa.eu/eurostat> (19 May 2026) [45]; authors' conceptions.

The final dataset consists of 243 observations. Although the time dimension is limited, the panel structure ensures sufficient cross-sectional variation for estimation.

Econometric strategy and model specification

The empirical strategy is designed to identify the short-run relationship between household electricity prices and their main determinants while accounting for unobserved heterogeneity across EU Member States. The empirical strategy deliberately limits the number of alternative estimators to avoid overfitting and model proliferation.

Given the relatively short time dimension of the panel ($T = 9$), the analysis prioritizes static panel estimators, which are more appropriate in settings with limited time variation. Dynamic and long-run estimators are used only as robustness checks rather than as core specifications.

The baseline econometric model is specified as:

$$EPHC_{it} = \alpha + \beta X_{it} + \mu_i + \varepsilon_{it}$$

where μ_i captures country-specific fixed effects, and X_{it} represents the vector of explanatory variables.

The main estimation strategy is based on the fixed effects (FE) model, which controls for unobserved time-invariant heterogeneity across countries. The analysis follows a clear hierarchical structure, with fixed effects as the baseline specification and all other estimators used strictly for robustness validation. Given the short time dimension of the panel ($T = 9$), unit root and cointegration test results are interpreted with caution. These tests are used only to provide indicative information regarding the time-series properties of the variables and are not used to support formal long-run structural modelling. Accordingly, no long-run structural interpretation is derived from these tests.

4. Results and Discussion

To analyze the relationship between the dependent and independent variables, descriptive statistics are reported in Table 3.

Table 3. Description of the selected variables' statistics.

	Mean	Median	Maximum	Minimum	Std_Dev	Sum	Skewness	Kurtosis	Jarque Bera	Probability
EPHC	0.0923	0.0760	0.3133	0.0263	0.0502	22.4403	1.4214	2.1998	130.8329	0.0000
EP	2.1311	2.1053	3.3403	1.1878	0.4125	517.8807	0.4725	0.4548	11.1390	0.0038
EMI	3.6749	3.6951	4.6151	2.3174	0.5623	893.0203	−0.1432	−1.0847	12.7453	0.0017
HDD	7.7770	7.8968	8.6371	5.7275	0.5480	1889.8169	−1.5419	2.7206	171.2344	0.0000
CDD	3.6378	3.7646	6.8647	0.0000	1.9654	883.9987	−0.3847	−0.8728	13.7096	0.0011
GPHC	0.0437	0.0344	0.1232	0.0109	0.0238	10.6209	1.1934	1.0307	68.4387	0.0000
ENV TAX	7.1622	7.2752	10.5122	2.9308	1.6868	1740.4207	−0.1158	−0.0672	0.5897	0.7446
IMPE	8.9039	9.4058	11.3695	0.0000	2.06414	2163.6693	−3.2911	11.5322	1785.2429	0.0000
URE	9.5838	9.7557	12.5640	5.1534	1.6697	2328.8779	−0.4863	0.1583	9.8333	0.0073

Source: authors' calculations, analysis performed using Eviews9 and Python 3.14.

The results indicate substantial variability across EU Member States, reflecting heterogeneity in both energy prices and structural energy indicators. Most variables present distributions close to normality, although some skewness is observed in variables such as electricity imports (IMPE) and heating degree days (HDD).

Cross-sectional dependence and stationarity

The Residual Cross-Section Dependence Tests report the results of the Breusch–Pagan LM test ($LM = 1206.044$, $p < 0.001$) and the Pesaran scaled LM test ($LM = 31.253$, $p < 0.001$), both of which reject the null hypothesis of cross-sectional independence (Table 4). In contrast, the Pesaran CD test does not provide strong evidence of statistically significant cross-sectional dependence, suggesting weaker or more limited cross-sectional correlation across units.

Table 4. Residual Cross-Section Dependence Tests.

Test	Statistic	d.f. (Degrees of Freedom)	p-Value
Breusch–Pagan LM	1206.0440	351	<0.0001
Pesaran Scaled LM	31.2525	—	<0.0001
Pesaran CD	1.2679	—	0.2048

The panel dataset comprises 27 cross-sectional units observed over 9 periods, resulting in 243 observations. Cross-sectional means were removed during the computation to mitigate cross-sectional dependence. Source: authors' calculations, analysis performed using Eviews9 and Python.

Regarding stationarity properties, the Im–Pesaran–Shin (IPS) test suggests non-stationarity in levels for most variables, whereas the second-generation CIPS test indicates a mixed order of integration, highlighting heterogeneity across panel members.

These results support the use of panel estimation techniques that are robust to both cross-sectional dependence and heterogeneous integration properties.

While the Breusch–Pagan LM and scaled LM tests suggest cross-sectional dependence, the Pesaran CD test fails to reject the null hypothesis of cross-sectional independence. The results indicate the presence of some common shocks at the panel level, but their intensity seems to vary across the cross-sectional units.

This result justifies the use of second-generation panel unit root tests and estimation techniques robust to cross-sectional dependence.

Multicollinearity analysis (VIF)

To assess potential multicollinearity among the explanatory variables, Variance Inflation Factors (VIFs) were computed for all independent variables included in the base-line model. The final dataset used for estimation contains 243 observations and 11 variables. The multicollinearity analysis was conducted exclusively on the eight explanatory variables included in the model (EP, EMI, HDD, CDD, GPHC, ENVTAX, IMPE, and URE). The dependent variable (EPHC), the country identifier (country), and the time variable (year) were not included in the VIF calculation, as they do not belong to the set of explanatory regressors.

Since the regression specification includes an intercept term, centered VIF values are used as the primary diagnostic measure.

The Variance Inflation Factor (VIF) results are presented in Table 5.

Table 5. Variance Inflation Factors (Centred VIF).

Variable	Centred VIF
URE	8.69
ENVTAX	7.61
HDD	3.92
CDD	3.25
EP	1.96
IMPE	1.92
EMI	1.47
GPHC	1.30

Source: authors' calculations, analysis performed using Eviews9 and Python 3.14.

The results indicate that multicollinearity does not represent a severe concern in the estimated model. The highest centred VIF values are observed for Renewable Energy Use (URE) and Environmental Taxes (ENVTAX), with values of 8.69 and 7.61, respectively. Although these values suggest a moderate degree of correlation with the remaining explanatory variables, they remain below the conventional critical threshold of 10 commonly used in econometric analyses. The remaining regressors exhibit relatively low centred VIF values. These results indicate limited shared variance among the explanatory variables and suggest that each regressor contributes distinct information to the model.

Unit root testing-Levin-Lin-Chu, CIPS

To further assess the stability and normality of the data set, additional tests were performed, one of which was the Augmented Dickey–Fuller (ADF) test for unit root (see Table 6).

In Table 6, the results of the unit root panel tests (LLC and IPS) show that all variables have different levels of stationary interpretation; some become stationary after the first difference, thus being integrated of order I(1). LLC Test (Levin, Lin & Chu) has probability values below 0.05 for almost all variables at the level (except URE). If we were to strictly follow LLC, we would conclude that the variables are stationary at the level, i.e., it would

be I(0). IPS Test (Im, Pesaran & Shin) has probability values well above 0.05 for absolutely all variables at the level. This indicates that none of the variables are stationary at the level. But the IPS test is considered more robust and flexible than LLC; thus, the best option is I(1) for all variables. This might suggest the need to use cointegration methods or dynamic models in the analysis. In Table 7, the result for second-generation tests such as CIPS shows a mix between variables integrated at the level and at the first difference, which suggests CIPS confirms I(1) properties of the variables and the need once again to approach cointegration tests.

Table 6. Used variables unit root Augmented Dickey–Fuller test.

Variable	LLC (Level)		IPS (Level)		LLC (1st Diff.)		IPS (1st Diff.)		Order of Integration
	Statistic	Prob **	Statistic	Prob **	Statistic	Prob **	Statistic	Prob **	
EPHC	−3.9842	0.0000 ***	1.3613	0.9133	−9.1083	0.0000 ***	−1.8149	0.0348 **	I(1)
EP	−8.41177	0.0000 ***	0.3465	0.6355	−9.9393	0.0000 ***	−2.6569	0.0039 ***	I(1)
EMI	−14.8998	0.0000 ***	−0.8059	0.2102	−16.8985	0.0000 ***	−4.3558	0.0000 ***	I(1)
HDD	−11.9150	0.0000 ***	−0.2943	0.3843	−7.6335	0.0000 ***	−2.4509	0.0071 ***	I(1)
CDD	−6.9193	0.0000 ***	0.0147	0.5059	−8.6707	0.0000 ***	−4.1174	0.0000 ***	I(1)
GPHC	−14.7072	0.0000 ***	−1.0251	0.1527	−14.6113	0.0000 ***	−4.0990	0.0000 ***	I(1)
ENV TAX	−3.2872	0.0005 ***	0.9878	0.8384	−5.5358	0.0000 ***	−2.4395	0.0074 **	I(1)
IMPE	−12.5383	0.0000 ***	−0.5734	0.2832	−14.3557	0.0000 ***	−4.2029	0.0000 ***	I(1)
URE	−0.7832	0.2167	0.9562	0.8305	−5.2260	0.0000 ***	-	-	I(1)

Panel unit root test, Series: D(EPHC), D(EP), D(EMI), D(HDD), D(CDD), D(GPHC), D(ENV TAX), D(IMPE), D(URE), Sample:2017–2025, Exogenous variables: Individual effects, User-specified lags: 1, Newey–West automatic bandwidth selection and Bartlett kernel, Balanced observations for each test. LLC is Levin, Lin & Chu t , IPS is Im, Pesaran and Shin W -stat. Source: authors' calculations, analysis performed using Eviews9 and Python 3.14. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 7. Second-generation unit root tests to control CIPS.

Variable	CIPS	Order of Integration
EPHC	−2.8852	I(0) 1%
EP	−1.1986	I(1)
EMI	−2.9775	I(0) 1%
HDD	−2.3977	I(0) 5%
CDD	−2.5137	I(0) 5%
GPHC	−2.7303	I(0) 1%
ENV TAX	−3.2667	I(0) 1%
IMPE	−2.5898	I(0) 5%
URE	−3.1642	I(0) 1%

Source: authors' calculations, analysis performed using Python.

Table 8 presents the correlation matrix between the independent and dependent variables, the dependent variables being EP, EMI, HDD, CDD, GPHC, ENV TAX, IMPE, URE. All correlation values (except CDD and HDD correlation) are below or close to 0.70, indicating a low risk of multicollinearity.

It is worth noting that Energy productivity (EP) shows a positive correlation with price developments, suggesting that price developments, especially in the direction of their increase, can lead companies and households to invest in renewable energy and in energy efficiency measures, improving the overall factors of production. One explanation for a similar evolution between energy productivity and energy prices is the rebound effect, i.e., reinvestment occurs in related, additional activities, which cancel out the reduction in gross energy consumption. Also, the transition to green energies, the skillful use of

cheap resources and the modernization of networks involve high capital costs that are often reflected in the price paid by household consumers. At the same time, increasing energy productivity in certain areas launches a competition to obtain the best market conditions, putting pressure on market competitors, often leading to price increases, and price increases can in the short term reduce productivity due to the increased financial pressure on companies and the population, but in the medium and long term they launch a new challenge for increasing energy productivity. Another interesting factor worth analysing is heating degree days (HDD); it evolves slightly in the opposite direction to the evolution of prices for household consumers (EPHC), so despite relatively milder winters in recent years at EU level, against the backdrop of successive regional shocks, the effect on prices was rather adverse.

Table 8. Used variables correlation matrix.

	<i>EPHC</i>	<i>EP</i>	<i>EMI</i>	<i>HDD</i>	<i>CDD</i>	<i>GPHC</i>	<i>ENV TAX</i>	<i>IMPE</i>	<i>URE</i>
EPHC	1								
EP	0.4619	1							
EMI	−0.0157	−0.3015	1						
HDD	−0.2832	−0.0036	−0.3878	1					
CDD	0.0543	−0.3055	0.3147	−0.7233	1				
GPHC	0.6950	0.3173	−0.1893	−0.0300	−0.1407	1			
ENV TAX	0.1009	0.4139	−0.3563	0.2534	−0.0973	0.0779	1		
IMPE	−0.1626	0.0456	−0.3883	0.5366	−0.2710	−0.0546	0.4858	1	
URE	0.0807	0.3502	−0.4361	0.3659	−0.1532	0.1738	0.9154	0.5658	1

Source: authors' calculations, analysis performed using Eviews9 and Python.

At the same time, there is an inverse correlation between imports and energy prices; electricity imports can evolve in the opposite direction to prices due to contractual rigidities, infrastructure gaps and dependence on coupled external markets. Thus, when in interconnected countries in a region, there is a massive surplus of cheap energy; it automatically enters the importing country, leading to a reduction in domestic electricity prices. Also, when imports decrease, due to contractual rigidity, domestic energy prices can still remain high.

Based on the correlation matrix and the previous information, we construct a panel regression equation, testing also the fixed and random effects, and before analysing the results, we first present the potential, intuitive direction of evolution of the independent variables in relation to the dependent variable, namely Electricity prices for household consumers (EPHC) (see Table 9).

The equations are represented by the form:

$$Y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \varepsilon \quad (1)$$

where Y = the dependent variable, Electricity prices for household consumers (second semester data)—EPHC, α = Constant; β_{1-8} = x_1 – x_8 coefficients variables slopes; x_1 – x_8 = independent variables, the regression coefficients of the panel data for electricity price: Energy productivity (EP); Energy Market Indicator (EMI); Heating degree days (HDD); Cooling degree days (CDD); Gas prices for household consumers (second semester data) (GPHC); Environmental taxes by economic activity (ENV TAX); Imports of electricity and derived heat by partner country (IMPE); Use of electricity renewables (URE); ε = error term.

Table 9. Intuitively expected sign of the regression coefficients of the independent variables of the linear regression model.

Independent Variable	Expected Effect	Reason
Energy productivity (EP)	$\beta_1 < 0$	Higher efficiency of energy use usually reduces cost pressure
Energy Market Indicator (EMI)	$\beta_2 > 0$	A high value indicates that electricity production is concentrated in the hands of a single company, therefore higher electricity prices for household consumers.
Heating degree days by country (HDD)	$\beta_3 > 0$	Heating demand might be increased by cold weather
Cooling degree days (CDD)	$\beta_4 > 0$	High temperatures increase the use of air conditioners and the demand for electricity, which can lead to higher prices.
Gas prices for household consumers (GPHC)	$\beta_5 > 0$	Very important driver of marginal cost
Environmental taxes by economic activity (ENV TAX)	$\beta_6 > 0$	Environmental taxes increase production costs and are partially transferred to consumers through higher tariffs.
Imports of electricity (IMPE)	$\beta_7 < 0$ (fmc), $\beta_7 > 0$ (ufmc)	In particular, the influence on energy prices is negative if the international situation is bad, increasing the price of energy. When there is high demand or there are periods of low domestic energy production, imports raise the price of electricity.
Use of renewables for electricity (URE)	$\beta_8 > 0$ (short run), $\beta_8 < 0$ (long run)	In the short term, under the influence of state subsidies for renewable products and services, the electricity price may increase, but in the long term, the use of renewable energy can substantially reduce the price of electricity.

Abbreviations: unfavourable market condition (ufmc), favourable market condition (fmc). Source: authors' conception.

Cointegration testing—Pedroni, Kao and Westerlund

In order to continue the analysis, we perform a series of cointegration tests (see Table 10).

Table 10. Pedroni, Kao, Westerlund cointegration test results.

Test	Statistics	Value	Prob/Decision
Pedroni	Panel PP	−3.947	0.000 ***
Pedroni	Group PP	−7.706	0.000 ***
Kao	ADF	−5.823	0.000 ***
Westerlund	t-stat	−3.034	Cointegration ***

Note: *** $p < 0.01$. All tests reject H_0 (absence of cointegration). Source: authors' calculations, analysis performed using Eviews9 and Python.

The results of the Pedroni test indicate the presence of a cointegration relationship between the variables. The Panel PP (−3.947, $p < 0.01$) and Group PP (−7.706, $p < 0.01$) statistics reject the null hypothesis of absence of cointegration, confirming the existence of a long-run equilibrium between the dependent variable and the independent variables.

The Kao test confirms the existence of a cointegration relationship between the analysed variables. The ADF statistic (-5.823 , $p < 0.01$) rejects the null hypothesis of absence of cointegration, validating the presence of a long-term equilibrium between energy consumption in the residential sector (EPHC), energy price (EP), climate indicators (HDD, CDD), gas price (GPHC), environmental taxes (ENVTAX), energy imports (IMPE) and the share of renewable energy (URE).

The Westerlund test indicates the presence of a long-run equilibrium relationship among the variables, as the null hypothesis of no cointegration is rejected ($t\text{-stat} = -3.03$). This confirms that the variables move together in the long run.

The results of the cointegration tests used unanimously reject the null hypothesis of no cointegration at the 1% significance level.

These results provide robust evidence for the existence of a long-run equilibrium relationship between the price of electricity in the residential sector and the explanatory variables considered. Therefore, the use of cointegration series estimation techniques (FMOLS, DOLS or PMG) is justified in the subsequent analysis.

Robustness analysis—robust least squares method, FMOLS or DOLS

If we start from pooled OLS, it can be observed (see Table 11) that for EPHP, R-squared, and respectively adjusted R-squared are considerable, explaining 63.59% and 62.35% of the evolution of the dependent variable, respectively.

Table 11. Electricity prices regression equation results for OLS pools and Robust Least Squares in relation to its determinants.

OLS Pools				Robust Least Squares				
Variables	Coefficient	Std. Error	p-Value	Variables	Coefficient	Std. Error	z-Statistic	p-Value
Constant	0.0075	0.0678	0.9118					
EP	0.0392 ***	0.0067	<0.001	EP	0.0252 ***	0.0041	6.0908	0.0000
EMI	0.0090 **	0.0043	0.0365	EMI	0.0055 *	0.0028	1.9261	0.0541
HDD	−0.0106	0.0072	0.1383	HDD	−0.0050 **	0.0024	−2.1399	0.0324
CDD	0.0031 *	0.0018	0.0928	CDD	0.0017 **	0.0009	1.9638	0.0496
GPHC	1.3750 ***	0.0947	<0.001	GPHC	1.8344 ***	0.0707	25.9625	0.0000
ENVTAX	0.0059 *	0.0032	0.0703	ENVTAX	0.0023	0.0024	0.9415	0.3464
IMPE	0.0008	0.0013	0.5596	IMPE	−0.0008	0.0010	−0.8354	0.4017
URE	−0.0072 **	0.0035	0.0402	URE	−0.0035	0.0026	−1.3235	0.1857
Model Statistics	Value			Model Statistics	Value			
Obs.	243	Durbin-Watson	0.5459	Obs.	243	Deviance		0.1339
Countries	27	Log likelihood	505.4505	R-squared	0.4632	Scale (MAD)		0.0209
Period	2017–2025	Hannan-Quinn criterion	−4.0339	Adjusted R-squared	0.4472	Rn-squared statistic		5178.338
R ²	0.6359	Mean dependent var	0.092347	Robust R-squared (Rw-squared)	0.8089	Prob. (Rn-squared statistic)		0.0000
Adjusted R ²	0.6235	Akaike info criterion (AIC)	−4.0860	Akaike Information Criterion (AIC)	320.6210			
F-statistic	51.0937 ***	Schwarz criterion	−3.9566	Schwarz Criterion (BIC)	351.7926			

For OLS pools, Dependent variable: **EPHC**. Balanced panel dataset comprising 27 EU countries observed over the period 2017–2025 (243 observations). Statistical significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust Least Squares estimation is based on M-estimation with bisquare weighting function (tuning = 4.685) and median-centered MAD scale estimator. Robust standard errors were computed using the Huber Type I covariance matrix. Source: authors' calculations, analysis performed using Eviews9 and Python.

Based on previous tests and suggestions for further work, Robust Least Squares seems a better fit.

The estimated equation for the general model of OLS pools is:

$$\text{EPHC} = \beta_0 + \beta_1 \times \text{EP} + \beta_2 \times \text{EMI} + \beta_3 \times \text{HDD} + \beta_4 \times \text{CDD} + \beta_5 \times \text{GPHC} + \beta_6 \times \text{ENV TAX} + \beta_7 \times \text{IMPE} + \beta_8 \times \text{URE}$$

The results are presented in Table 11.

The results indicate Robust Least Squares estimation for the EPHC; EP has a positive and highly significant effect on EPHC ($\beta = 0.0252$, $p < 0.01$). Similarly, GPHC exhibits the strongest positive association with EPHC ($\beta = 1.8344$, $p < 0.01$). Climate-related variables show mixed effects: HDD negatively affects EPHC ($\beta = -0.0050$, $p < 0.05$), whereas CDD exerts a positive influence ($\beta = 0.0017$, $p < 0.05$). EMI is only marginally significant at the 10% level ($\beta = 0.0055$, $p < 0.10$). In contrast, ENV TAX, IMPE, and URE do not display statistically significant effects. The model explains approximately 46.3% of the variation in EPHC ($R^2 = 0.463$), while the robust goodness-of-fit measure ($Rw^2 = 0.809$) suggests a strong fit after accounting for potential outliers and deviations from classical regression assumptions.

The estimation results reveal a high degree of consistency between the Fixed Effects and Random Effects specifications (see Table 12). Energy Productivity (EP) and Household Gas Prices (GPHC) are positively and significantly associated with household energy prices, indicating that affordability constraints and gas market developments constitute the main drivers of residential energy costs. While the Energy Market Indicator (EMI) appears significant under the Fixed Effects estimator, this relationship disappears in the Random Effects model, suggesting that its influence is largely captured by country-specific heterogeneity. The Hausman test strongly supports the Random Effects specification (p -value = 0.9999), indicating that unobserved country-specific effects are not correlated with the explanatory variables and confirming the suitability of the RE model for subsequent interpretation and policy discussion.

Regarding the random effects model, a one-unit increase in the energy productivity indicator (EP) is associated with an increase of approximately 0.046 units in the energy price for household consumers, while a one-unit increase in the gas price for households (GPHC) leads to an increase of approximately 1.35 units in the energy price, confirming the dominant role of gas costs in the formation of residential energy prices.

The Panel ARDL (PMG) results (see Table 13) indicate strong persistence in electricity prices, as shown by the positive and statistically significant coefficient of the lagged dependent variable ($\text{EPHC}_{t-1} = 0.5522$, $p < 0.01$). Gas prices (GPHC) emerge as the most robust determinant across specifications, exhibiting a positive contemporaneous effect ($\beta = 1.2903$, $p < 0.01$) and a significant negative lagged effect ($\beta = -0.6563$, $p < 0.01$), suggesting a short-term adjustment process following shocks in gas prices. The remaining explanatory variables are not statistically significant at conventional levels, indicating limited direct short-run effects within the PMG framework. The model explains approximately 78% of within-country variation in electricity prices, while the poolability test rejects full homogeneity across countries ($p = 0.030$), supporting a heterogeneous panel specification.

For the energy productivity (EP), the ARDL model indicates a positive coefficient, although individual significance varies across specifications. The Error Correction Model (ECM) (see Table 14) shows a positive, marginally significant effect ($p \approx 0.08$), supported by Driscoll–Kraay standard errors (≈ 0.07 , significant). This positive relationship suggests that higher energy productivity may be associated with upward pressure on electricity prices in the short term. This may reflect structural adjustments in energy systems, including investment dynamics and efficiency-related cost transmission rather than direct consumption effects.

Table 12. PanelOLS estimation summary for fixed and random effect results for household energy prices (EPHC).

Variables	Fixed Effects (FE)	Random Effects (RE)	Statistic	FE	RE
Constant	−0.1103 (−0.4672)	0.0866 (0.8126)	Obs.	243	243
			Countries	27	27
EP	0.1148 *** −35.433	0.0463 *** −36.583	Time periods	9	9
			R ² (Overall)	−0.4653	0.5947
EMI	−0.0403 *** (−2.7580)	−0.0033 (−0.3860)	R ² (Within)	0.7094	0.6859
			R ² (Between)	−23.572	0.4477
HDD	0.0300 −13.434	−0.0160 (−1.4946)	F-statistic	63.461 ***	59.741 ***
			Prob (F-statistic)	0.0000	0.0000
CDD	−0.0012 (−0.5017)	0.0012 (0.5600)	Hausman Specification Test		
			Test Statistic	p-value	Preferred Model
GPHC	1.2080 *** −124.320	1.3504 *** −154.530	0.0674	0.9999	Random Effects
ENV TAX	−0.0097 (−0.7420)	−0.0028 (−0.5446)			
IMPE	−0.0033 (−1.4602)	−0.0010 (−0.5148)			
URE	−0.0080 (−0.7391)	0.0010 (0.1771)			

Notes: The dependent variable is household energy prices (EPHC). t-statistics are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. FE denotes Fixed Effects and RE denotes Random Effects estimators. The Hausman test fails to reject the null hypothesis, indicating that the Random Effects specification is consistent and efficient. Source: authors' calculations, analysis performed using Python.

Table 13. ARDL-PMG model effect results.

Variable	Coefficient	Statistic	Value
Constant	−0.2183 (−0.9271)	Number of countries	27
EPHC _{t−1}	0.5522 *** (55.446)	Number of observations	216
EP	0.0699 (15.430)	Time periods	8
EP _{t−1}	−0.0419 (−0.5447)	R ² (Within)	0.7813
EMI	−0.0039 (−0.2739)	R ² (Overall)	0.2661
EMI _{t−1}	0.0115 (0.8062)	R ² (Between)	−0.4677
HDD	0.0119 (0.6726)	F-statistic	36.143 ***
HDD _{t−1}	−0.0143 (−0.9579)	Robust F-statistic	471.34 ***
CDD	−0.0015 (−0.8740)	Poolability Test (F)	1.6617 **

Table 13. *Cont.*

Variable	Coefficient	Statistic	Value
CDDt−1	−0.0006 (−0.3047)	Poolability Test <i>p</i> -value	0.0300
GPHC	1.2903 *** (60.632)		
GPHCt−1	−0.6563 *** (−30.947)		
ENV TAX	−0.0018 (−0.1435)		
ENV TAXt−1	0.0173 (14.525)		
IMPE	−0.0015 (−13.192)		
IMPEt−1	0.0018 (10.747)		
URE	0.0315 (15.923)		
UREt−1	−0.0257 (−15.221)		

Notes: The dependent variable is household energy prices (EPHC). *t*-statistics are reported in parentheses. Cluster-robust standard errors are reported. Lagged variables are denoted by *t* − 1. Significance levels: *** *p* < 0.01, ** *p* < 0.05, * *p* < 0.10. Source: authors' calculations, analysis performed using Python 3.14.

Table 14. Error Correction Model (ECM) and Driscoll–Kraay results.

Variable	ECM Coef.	Driscoll–Kraay	Significance	Economic Interpretation
EP	0.077	0.070 ***	+ / weak	Positive effect on electricity price levels
EMI	−0.006	−0.004	n.s.	Insignificant direct effect
HDD	0.016	0.012	n.s.	Slight positive effect from colder temperatures
CDD	0.0005	−0.0015 *	weak	Mixed / unstable cooling effect
GPHC	1.242 *	1.290 *	***	Dominant positive effect, main determinant
ENV TAX	−0.006	−0.002	n.s.	No significant influence
IMPE	−0.0012	−0.0015 **	**	Positive delayed impact from imports
URE	0.020	0.032	n.s.	Mixed effects, net neutral
ECT	−0.478 *	−1.000 *	***	Strong error correction, stable convergence

Source: authors' calculations, analysis performed using Python 3.14. *** *p* < 0.01, ** *p* < 0.05, * *p* < 0.10.

The coefficient is negative for Energy Market Indicator EMI but statistically insignificant across ARDL, ECM, and Driscoll–Kraay methods, indicating no robust direct effect on electricity prices. This may reflect indirect impacts in the long term or collinearity with other energy variables.

HDD has a positive but statistically weak effect in the ARDL-PMG model, implying that colder temperatures slightly increase electricity prices through higher heating demand. However, this effect is unstable due to energy efficiency improvements and regional climatic variations.

Effects of CDD are mixed: insignificant in ECM, and marginally significant negative in Driscoll–Kraay. This suggests electricity prices related to cooling demand might have

a substitutive or offsetting effect compared to heating, likely influenced by appliance efficiency and energy consumption structure.

GPHC emerges as the strongest driver of energy consumption, with highly significant positive coefficients across ARDL (≈ 1.29), ECM (≈ 1.24), and Driscoll–Kraay (≈ 1.29). The negative significant lag effect signals a dynamic adjustment process. This reflects the scale effect of infrastructure and economic expansion driving electricity price levels.

The Environmental Tax (ENV TAX) has no significant effect in any model variant, likely due to the limited magnitude of taxes during the study period or delayed structural impacts.

Energy imports (IMPE) show a positive and delayed significant effect on consumption based on ECM and Driscoll–Kraay results, suggesting higher availability through imports increases electricity prices through higher import dependence, demonstrating external energy dependency.

The renewable energy (URE) results are consistently insignificant. This indicating neutral net effects on electricity prices, consistent with offsetting effects of renewable penetration and system adjustments.

The ECM’s Error Correction Term (ECT) coefficient (-0.478 , $p < 0.01$) confirms a stable long-term equilibrium relationship, with approximately 48% of disequilibrium corrected each period.

The results presented in Table 15 suggest that the main findings remain broadly stable across alternative estimation methods. In particular, Energy Productivity (EP) and Household Gas Prices (GPHC) exhibit positive coefficients in most specifications, indicating a robust association with household electricity prices.

Table 15. Robustness analysis across alternative econometric specifications.

Variables	Pooled OLS	Robust Least Squares (M-Estimation)	Fixed Effects (FE)	Fixed Effects (Robust SE)	Dynamic Panel Model (DOLS/ARDL-PMG)	Panel ARDL (PMG)
Const	0.0075 (0.1109)	-	-0.1103 (-0.4672)	-0.1103 (-0.4380)	-0.1881 (-0.7996)	-0.2183 (-0.9271)
EPHC_L1	-	-	-	-	0.2903 (-57.945)	0.5522 (-55.446)
EP	0.0392 (-5.8238)	0.0252 (-6.0908)	0.1148 (-3.5433)	0.1148 (-3.7689)	0.0479 (-1.3380)	0.0699 (-1.5430)
EP_L1	-	-	-	-	-	-0.0419 (-0.5447)
EMI	0.0090 (-2.1031)	0.0055 (-1.9261)	-0.0403 (-2.7580)	-0.0403 (-2.7017)	-0.0147 (-0.9446)	-0.0039 (-0.2739)
EMI_L1	-	-	-	-	-	0.0115 (0.8062)
HDD	-0.0106 (-1.4872)	-0.0050 (-2.1399)	0.0300 (-1.3434)	0.0300 (-1.1892)	0.0324 (-1.4625)	0.0119 (0.6726)
HDD_L1	-	-	-	-	-	-0.0143 (-0.9579)
CDD	0.0031 (-1.6876)	0.0017 (-1.9638)	-0.0012 (-0.5017)	-0.0012 (-0.7011)	0.0006 (0.2625)	-0.0015 (-0.8740)

Table 15. Cont.

Variables	Pooled OLS	Robust Least Squares (M-Estimation)	Fixed Effects (FE)	Fixed Effects (Robust SE)	Dynamic Panel Model (DOLS/ARDL-PMG)	Panel ARDL (PMG)
CDD_L1	-	-	-	-	-	−0.0006 (−0.3047)
GPHC	1.3750 (−1.4522)	1.8344 (−2.59625)	1.2080 (−1.2432)	1.2080 (−7.7932)	1.1437 (−1.1752)	1.2903 (−6.0632)
GPHC_L1	-	-	-	-	-	−0.6563 (−3.0947)
ENV TAX	0.0059 (−1.8181)	0.0023 (0.9415)	−0.0097 (−0.7420)	−0.0097 (−0.7878)	−0.0013 (−0.0976)	−0.0018 (−0.1435)
ENV TAX_L1	-	-	-	-	-	0.0173 (−14.525)
IMPE	0.0008 (0.5842)	−0.0008 (−0.8385)	−0.0033 (−1.4602)	−0.0033 (−2.2488)	−0.0010 (−0.4436)	−0.0015 (−1.3192)
IMPE_L1	-	-	-	-	-	0.0018 (−10.747)
URE	−0.0072 (−2.0636)	−0.0035 (−1.3235)	−0.0080 (−0.7391)	−0.0080 (−0.8764)	−0.0082 (−0.7072)	0.0315 (−1.5923)
URE_L1	-	-	-	-	-	−0.0257 (−1.5221)
Model Statistics						
Obs.	243	243	243	243	216	216
R-squared	0.6359	0.4632	0.7094	0.7094	0.7466	0.7813
R-squared (Within)	0.6614	-	0.7094	0.7094	0.7466	0.7813
F-statistic	51.094	-	63.461	63.461	58.931	36.143
Cov. Estimator	Unadjusted	Huber Type I	Unadjusted	Robust	Unadjusted	Clustered
Panel Effects (Effects)	-	-	Entity	Entity	Entity	Entity

Notes: Dependent variable: EPHC; t-statistics are reported in parentheses. FE denotes Fixed Effects; PMG denotes Panel ARDL estimator. Only the dynamic specification (PMG) includes lagged dependent variables. Robust standard errors are reported where indicated. HDD = Heating Degree Days; CDD = Cooling Degree Days; GPHC = Gas Price for Household Consumers; ENV TAX = Environmental Taxes; IMPE = Energy Imports; URE = renewable electricity generation share (%); EMI = Energy Market Indicator (market concentration/largest company share). Source: authors' calculations, analysis performed using Python.

The magnitude and statistical significance of some variables vary across models, reflecting differences in estimation techniques and underlying assumptions. For example, the Energy Market Indicator (EMI) is statistically significant only in the Fixed Effects specifications, suggesting that its impact may be influenced by country-specific characteristics.

The Robust Least Squares estimation confirms the stability of the main results after accounting for potential outliers and deviations from classical regression assumptions.

Similarly, the Fixed Effects estimates remain broadly consistent when robust covariance estimators are applied.

The dynamic specifications provide additional evidence regarding the persistence of electricity prices over time. However, given the relatively short time dimension of the panel, these results should be interpreted as supplementary robustness evidence rather than as the primary basis for inference.

Overall, the robustness analysis supports the conclusion that Energy Productivity and Household Gas Prices represent the most consistently associated determinants of household electricity prices across the alternative model specifications considered.

Based on the above findings, the formulated hypotheses are empirically tested and the results provide support for them. The results are in line with the literature review findings highlighting the robust role of determinants of price energy. Several recent studies have documented the existence of persistence and temporal dependence in electricity prices, suggesting that current price levels are strongly affected by their historical values [46–49]. In line with these findings, the results of the ARDL-PMG model estimated in the present study reveal a statistically significant effect of the lagged energy price variable on current energy prices. This result provides empirical support for the existence of price persistence and confirms that historical price patterns remain an important determinant of contemporary energy price dynamics.

Recent literature also highlights that the price of natural gas is one of the most important determinants of electricity prices for household consumers. Zakeri et al. (2023) [50] show that natural gas frequently sets the marginal price of electricity in European markets, facilitating the transmission of price shocks to the electricity market. Similar results are reported by da Silva and Cerqueira (2017) [42] and Hill (2023) [51] which confirms the existence of a strong pass-through mechanism of gas prices to retail electricity prices. The results of our study align with these conclusions, highlighting that the price of natural gas significantly explains the evolution of electricity prices for household consumers.

5. Conclusions

Thus, the study analyses the main determinants of household electricity prices using Eurostat panel data. The econometric analysis conducted for the period 2017–2025 highlights significant relationships between electricity prices (EPHC) and the economic, climatic, and fiscal factors included in the model.

The results of the pooled OLS model indicate the existence of significant statistical relationships between the explanatory variables and electricity prices, but these results are complemented and refined by fixed-effects models, which suggest the presence of significant heterogeneity across countries.

Although the Hausman test does not reject the null hypothesis, the fixed effects estimator is adopted as the baseline specification due to theoretical considerations regarding potential correlation between unobserved country-specific effects and key explanatory variables. Random effects estimates are reported only as robustness comparisons. However, given the mixed integration order of the variables, the evidence of cointegration, and the dynamic nature of electricity price adjustment, the PMG-ARDL framework constitutes the primary econometric specification for inference, while random effects, fixed effects, DOLS, ECM, and Driscoll–Kraay estimators are used as complementary robustness checks. The fixed effects model is reported as a complementary specification and diagnostic benchmark, while additional estimators are employed to assess robustness and stability under alternative econometric assumptions. The consistency observed across specifications, particularly in terms of sign, magnitude, and statistical significance of key variables, strengthens con-

fidence in the empirical findings and suggests that results are not driven by a specific estimator choice.

Unit root tests indicate mixed integration properties, with variables being either stationary or integrated of order one, justifying the use of an ARDL framework.

The Pesaran CD test indicates the presence of cross-sectional dependence between countries, suggesting the existence of common shocks and interconnected dynamics within EU energy markets. This justifies the use of estimation techniques robust to cross-sectional dependence, such as Driscoll–Kraay standard errors.

Cointegration tests suggest the existence of a long-run statistical relationship between the analysed variables, supporting the use of ARDL-PMG models as a complementary dynamic specification. However, given the short time dimension of the panel, these results are interpreted strictly as statistical associations rather than structural long-run equilibrium relationships.

Robustness tests (FMOLS proxy, DOLS proxy, and robust fixed effects models) confirm the stability of the estimated coefficients and the consistency of the econometric relationships.

Natural gas prices exert the strongest positive influence on household electricity prices, highlighting the continued exposure of the EU electricity market to fossil fuel price shocks, while renewable energy deployment contributes to moderating price pressures over time. The study confirms findings from previous literature. Both fixed effects and random effects specifications consistently identify Household Gas Prices (GPHC) as the most influential determinant of electricity prices, while the estimated effects of other variables exhibit some sensitivity across specifications. Electricity prices exhibit persistence over time, indicating that past price levels remain an important determinant of current prices.

The positive effect of energy productivity across all estimators suggests that improvements in energy efficiency are associated with upward pressure on electricity prices in the short run. This may reflect structural adjustments in energy systems, including investment dynamics and cost transmission mechanisms rather than direct consumption effects.

Household Gas Prices (GPHC) emerge as the principal explanatory driver, highlighting the strong interdependence between residential energy markets and electricity price formation. The robustness of results across alternative estimation techniques strengthens confidence in the empirical findings. The significant autoregressive component identified by the PMG-ARDL model suggests that electricity price shocks tend to persist over time, reinforcing the importance of policies aimed at improving energy affordability and market stability.

This study identifies the main determinants of household electricity prices across European Union countries, highlighting the dominant role of structural and economic variables, with GPHC as the primary driver. Electricity prices show a moderate short-run response to changes in explanatory variables. Climatic factors such as HDD and CDD exhibit weak and inconsistent effects, suggesting partial adaptation through energy efficiency and system adjustments. Environmental taxes and the energy market indicator do not exhibit statistically significant effects on electricity prices within the study period, highlighting the limited short-run transmission of these factors.

The error correction results support adjustment dynamics toward a statistical long-run relationship with relatively fast convergence.

The main contributions of this study include extending the analysis to 2025, including the post-energy crisis period, providing EU-27 level evidence on electricity price determinants, jointly analysing environmental taxes and gas prices, and identifying key short- and medium-run drivers.

Potential limitations include the use of annual data that may mask short-term volatility, cross-country heterogeneity, limited data availability, and potential omitted variable bias.

Despite efforts to address endogeneity concerns, it is acknowledged that retail gas and electricity prices are jointly influenced by common wholesale fuel market conditions. In addition, potential simultaneity arising from policy interventions during the 2021–2023 energy crises cannot be fully ruled out.

Future research could extend this framework by incorporating carbon pricing mechanisms, addressing energy storage constraints, and applying nonlinear models such as Markov switching approaches.

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Abbreviations

The following abbreviations are used in this manuscript:

AIC	Akaike info criterion
ARDL	Autoregressive Distributed Lag
CO ₂	Carbon dioxide
DW	Durbin–Watson statistic
EU	European Union
ECT	Error Correction Term
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
LM	Lagrange multiplier
EPHC	Electricity prices for household consumers—bi-annual data (from 2007 onwards)
EP	Energy productivity
HDD/CDD	Heating/Cooling degree days by country—annual data
GPHC	Gas prices for household consumers—bi-annual data (from 2007 onwards)
ENV TAX	Environmental taxes by economic activity
IMPE	Imports of electricity and derived heat by partner country
URE	Use of renewables for electricity
OLS	Ordinary least squares (OLS)
REM	Random Effects Model

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