International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(5), 227-234.

Electricity (Dis)Integration? An Analysis of Price Convergence and its Determinants in European Electricity Markets

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Received: 11 April 2025 **Accepted:** 14 July 2025 **DOI:** https://doi.org/10.32479/ijeep.20269

ABSTRACT

In light of the energy crisis, stricter climate policies, and disruptions from the COVID-19 pandemic and the war in Ukraine, understanding the convergence of electricity prices is essential, as it reflects market integration. This study assesses price convergence in 23 European electricity markets from January 2015 to December 2024 using monthly wholesale day-ahead prices. We employ a novel approach based on the Payne test (Payne et al., 2022), which allows for two structural breaks and accounts for cross-sectional dependence. To further explore the determinants of convergence, we apply clustering methods and logistic regression to assess the influence of cross-border interconnections, national electricity mix structures, and regional characteristics on electricity price dynamics. The findings indicate a persistently low integration of electricity market. Importantly, convergence is not strongly linked to physical interconnections between countries. Instead, differences in the structures of the national electricity mix emerge as more influential. Regional dynamics also play a role, with Northern and Central Western Europe showing greater convergence tendencies. These findings highlight structural obstacles to full market harmonisation and suggest that future policy should focus not only on infrastructure, but also on aligning electricity generation strategies and fostering regional cooperation to support a more integrated electricity market.

Keywords: Electricity Markets, Stochastic Convergence, Market Integration, Electricity Mix, European Regions
JEL Classifications: Q41, Q48, C33

1. INTRODUCTION

Global changes in electricity markets, along with challenges related to price integration and supply security, have never been as critical as they are today. The shocks triggered by the energy crisis - intensified after 2021 - highlight both the strengths and weaknesses of the integrated electricity market. On the one hand, market integration facilitates electricity flows; for example, the implementation of the Interim Coupling (ICP) mechanism links day-ahead electricity markets across several countries. On the other hand, this integration exposes infrastructural and regulatory shortcomings, leading to an uneven distribution of costs and varying national responses to price shocks.

In theory, the integration of the electricity market should provide greater price stability, transmission efficiency, and a more optimal use of energy resources. However, in practice, the European energy system experiences unprecedented instability due to global geopolitical tensions, evolving climate policies, and the growing share of renewable energy sources (Hille, 2023; Jin et al., 2023).

The issue of price convergence in electricity markets is extensively explored in the literature. Researchers employ range of methods - including cointegration analysis (de Menezes & Houllier, 2016; Gugler et al., 2018), MGARCH models (Houllier et al., 2013), causality tests (Bunn & Gianfreda, 2010), and copula models (Du & Lai, 2017) - to capture the degree of price convergence. However, the results of these studies remain inconclusive: some point to advancing market integration, while others suggest that local conditions still dominate over market mechanisms. Moreover, previous analyses focus on specific timeframes or groups of countries, often overlooking dynamic structural changes and pairwise relationships between individual countries.

This study aims to address these gaps by applying a relatively novel methodological approach, the Payne test (Payne et al., 2022), to a dataset covering the years 2015 to 2024. We examine stochastic convergence, which allows us to assess whether price shocks are transitory or lead to permanent market integration. Importantly, our analysis goes beyond general price convergence in Europe by exploring country-level relationships, thereby enabling the identification of groups of countries with similar price dynamics. We also examine the impact of cross-border interconnections and regional divisions within Europe on price convergence. In addition, we investigate whether price convergence is more likely among countries with similar electricity mix structures or whether these characteristics play no significant role.

The analysis proceeds in two stages: first, we apply the Payne et al. test (2022) to identify stochastic convergence between country pairs. In the second stage, we investigate the determinants of convergence by considering the level of cross-border interconnections, grouping countries based on similarities in their electricity mix, and analysing European regions. To further explore these potential drivers of convergence, we employ a logistic regression model to examine the impact of all factors considered on the convergence of electricity prices.

The objective of this paper is to assess the degree of price convergence in European electricity markets between 2015 and 2024, and to determine whether this convergence is influenced by cross-border interconnections, national electricity mix structures, and European regions. The findings of this study may not only improve the understanding of pricing mechanisms in electricity markets, but also provide valuable insights for policymakers seeking to strengthen the stability of the European electricity sector.

The article is structured as follows. Section 2 provides a literature review. Section 3 describes the methodology, including the Payne test, clustering methods, and logistic regression. Section 4 discusses the data. Section 5 presents the empirical results. Finally, Section 6 concludes the paper.

2. LITERATURE REVIEW

In recent years, the European electricity market has undergone significant transformations, shifting from nationally centralised systems towards an integrated market. Competition and liberalisation are introduced in both the electricity generation and retail segments (Saez et al., 2019). The expansion of cross-border interconnections increases transmission capacity between countries, playing a pivotal role in the integration of European electricity markets (Newbery et al., 2016). As a result, research interest in electricity price convergence grows considerably.

The literature on the integration and convergence of European electricity markets is extensive and comprises a wide range of empirical analyses. Interestingly, depending on the adopted methodology, data selection, and time horizon, researchers obtain mixed results.

De Menezes and Houllier (2016) investigate the integration of the electricity market in nine European countries by analysing the convergence of wholesale electricity prices using fractional cointegration analysis. Their findings indicate that the persistence of price convergence depends on interconnection levels and geographic proximity. Gugler et al. (2018) employ cointegration analysis and error correction models to examine price cohesion in Europe, finding an increase in market integration during 2010–2012, followed by a decrease from 2012–2015. This decline points to the need for further investment in cross-border transmission capacity. Similarly, Bunn and Gianfreda (2010) apply causality and cointegration tests to assess integration trends in the German, French, Dutch, Spanish, and British electricity markets between July 2001 and July 2005. They show that integration is driven more by interconnection capacity than by geographic proximity. Comparable conclusions are drawn by de Menezes and Houllier (2013), who apply MGARCH models with constant and time-varying correlations to daily electricity prices. A similar approach is taken by Du and Lai (2017), who use copula models to examine price integration and find strong interdependence between the French, German, Austrian, and Swiss markets.

Other studies explore the cointegration of electricity prices using the beta, sigma and club convergence frameworks. Telatar and Yasar (2020) show that for 12 EU countries between 2003 and 2017, neither beta nor sigma convergence occurs, suggesting that electricity prices remain largely influenced by country-specific factors. Similar conclusions are presented by Cassetta et al. (2022a; 2022b), who find no evidence of convergence in electricity and natural gas prices across the EU-28 from 2008 to 2018, despite efforts toward market integration and regulatory harmonisation. Their analysis identifies slow beta convergence but no sigma or club convergence, either within or between identified country clusters. Bhattacharya et al. (2023) also apply the club convergence approach, demonstrating that the share of renewable energy sources may influence a country's membership in different electricity price convergence clubs in Europe.

More recent studies on the convergence of electricity prices introduce novel methodological frameworks. One example is Karatepe (2024) who use RALS-LM tests with two structural breaks to evaluate the stochastic convergence of wholesale prices in 19 European countries from 2013 to 2021. Her results suggest that relative wholesale electricity prices are stationary, implying that price shocks are only transitory in nature.

The literature review highlights that interdependencies among electricity markets have increased steadily in recent decades. However, existing studies on price convergence typically do not account for both structural shifts and cross-country correlation simultaneously, an analytical gap that this study aims to address.

3. METHODOLOGY

3.1. The Payne Test for Stochastic Convergence

Based on the LM test proposed by Schmidt and Phillips (1992), an extended version is developed by Payne et al. (2022). Earlier, the test was refined by Lee and Strazicich (2003) to account for two structural breaks. This development is particularly relevant in time-series analysis of electricity prices, where rare events – so-called 'black swans' – can cause permanent changes in the price level.

Compared to the original test by Schmidt and Phillips, the version by Lee and Strazicich (2003) more frequently leads to rejection of the null hypothesis, increasing the risk of false positives. This tendency becomes even more pronounced when additional structural breaks are included. Payne et al. (2022) address this issue by incorporating cross-correlation into the test procedure.

In their study, Payne et al. compare their approach with those of Schmidt and Phillips (1992) and Lee and Strazicich (2003) in the context of testing for stationarity in CO☐ emissions across selected countries. They show that the classical LM test leads to the fewest rejections of the null hypothesis. Allowing for structural breaks increases the number of rejections significantly, especially when breaks in the trend are considered – nearly five times more often than breaks in the level. While the Payne et al. test still tends to reject the null more often than the original LM test, the inclusion of cross-correlation reduces rejections compared to the Lee and Strazicich version.

3.2. Clustering Methods

To identify groups based on the category of electricity mix for 23 selected European countries, three clustering methods are applied: hierarchical clustering (Ward, 1963), k-means clustering (MacQueen, 1967), and partitioning around medoids - PAM (Kaufman and Rousseeuw, 1990). The use of different clustering techniques aims to incorporate them into an original approach based on majority voting, which supports the final expert decision. A country is assigned to the group in which it appears in at least two of the three methods.

3.3. Logistic Regression

One of the most commonly used models for situations in which the dependent variable assumes binary (discrete) values, such as 0 or 1, is logistic regression (Maddala et al., 1992). In such a model the variable y_t was assumed to take value 1 with a given probability p_t (Pr (y_t = 1) = p_t. The relationship between the dependent variable and its explanatory variables is expressed by the following equation:

$$p_t = \mathrm{F}(X_t\, \beta) \tag{1}$$

where $F(\cdot)$ denotes a known function linking p_t with X_t and β. In the case of logistic model, this function takes the following familiar form:

$$F\left(X_t \beta\right) = \frac{1}{1+e^{-X_t \beta}} \tag{2}$$

where:

X_t represents the matrix of explanatory variables,
β denotes the vector of model parameters.

The parameters are estimated using the maximum likelihood method.

4. DATA

Our analysis consists of two stages. In the first stage, we apply the test proposed by Payne et al. (2022) to examine the presence of stochastic convergence of electricity prices among country pairs. In the second stage, we investigate the variables that may determine this convergence.

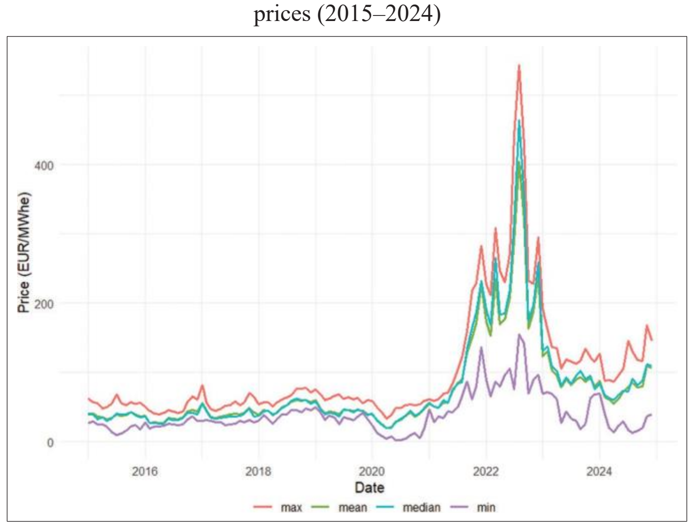
4.1. Description of Electricity Prices Data

The study uses data sourced from Ember[1], which reports monthly wholesale day-ahead electricity prices. The dataset covers 23 European countries, grouped into the following regional markets: CWE: Austria (AT), Germany (DE), Belgium (BE), the Netherlands (NL), France (FR), Switzerland (CH), CEE: the Czech Republic (CZ), Slovakia (SK), Hungary (HU), Romania (RO), Poland (PL), Slovenia (SI), SEE: Greece (EL), NORD: Denmark (DK), Estonia (EE), Finland (FI), Latvia (LV), Lithuania (LT), Sweden (SE), Norway (NO), IBERIA: Portugal (PT), Spain (ES), APENNINE: Italy (IT). The period analysed spans from January 2015 to December 2024.

As part of the first stage of analysis and before applying the Payne et al. test (2022), we examine the trends and volatility of electricity prices. Figure 1 presents four monthly statistical indicators that describe electricity prices: Mean, median, minimum, and maximum. The data indicate a relatively stable price level between 2015 and 2021, with moderate fluctuations. From 2021 onwards, a sharp increase in electricity prices is observed, peaking in August 2022. After 2023, prices stabilised at levels higher than those seen

1 Source: ember-energy.org/data/european-wholesale-electricity-price-data/ (accessed on 6 January 2025)

Figure 1: Summary statistics of monthly average wholesale electricity prices (2015–2024)



Source: Authors

before the energy crisis, although they continue to exhibit greater volatility compared to the precrisis period. In particular, during the peak period, the difference between maximum and minimum prices increased significantly, which may indicate a growing difference in electricity prices between countries during the crisis.

4.2. Description of the Determinants of Stochastic Convergence

In the second stage of the analysis, we consider three factors that can determine the convergence of electricity prices. The first is the cross-border interconnection (INTER) between countries. The second is the structure of the electricity mix. The third is the geographical division of Europe into regions.

Interconnectors[2] are links that constitute infrastructure enabling the physical transmission of electricity between national transmission systems. Their presence promotes the integration of electricity markets and supports the process of price convergence. In practice, they may take the form of submarine cables, underground cables, or overhead lines. In our analysis, INTER is defined as a binary indicator that takes the value of 1 if there is a technical possibility for electricity to flow between a given pair of countries and 0 otherwise. On average, such a possibility exists for approximately 29% of the analysed country pairs.

In the next step, to assess the impact of the composition of the electricity mix on price convergence, we classify countries into three groups based on the similarity of their electricity mix. This classification is based on three variables: the share of electricity generated from renewable energy sources (RES), the share of electricity generated from nuclear energy sources (Nuclear), and the share of electricity generated from coal and natural gas (Fuel). Data for all shares are sourced from the EMBER database[3], with a monthly frequency.

Figure 2 illustrates the structure of the electricity mix in the countries analysed, distinguishing between three main sources: renewable energy sources (RES), nuclear energy (Nuclear), and fossil fuels (Fuel). The chart reveals significant heterogeneity between countries. Austria, Denmark, Lithuania, and Norway exhibit a dominant share of RES, while countries such as France and Slovakia rely on nuclear energy. In contrast, the electricity mix in Poland, Estonia and the Netherlands is still largely based on fossil fuels. Furthermore, Table 1 presents descriptive statistics for the shares of the three energy sources in the electricity mix. The average share of RES in countries is 44.67%, with values ranging from 13.27% to 98.25%, indicating substantial variation in the deployment of renewables. The share of nuclear energy is distributed much more broadly, with a mean of 19.69% and a median of only 8.95%, suggesting that nuclear power is concentrated in a limited number of countries. The share of fossil fuels averages 35.64%, yet ranges widely-from near 0% to over 83%.

To account for the regional dimension of electricity price convergence, we divide Europe into five geographical regions (CWE, CEE, SEE, NORD, IBERIA) based on the Study on Energy Prices and Costs Report (European Commission, 2024) as described in Table 2. Each regional variable is a binary indicator that takes the value of 1 if a given country pair belongs to the same region and 0 otherwise. The low mean values across all regions (ranging from 0.00 to 0.08) reflect the fact that most of the country pairs in the sample span different regions. The highest proportion of observations within-region is found for the NORD region (0.08), followed by CWE and CEE (both 0.06).

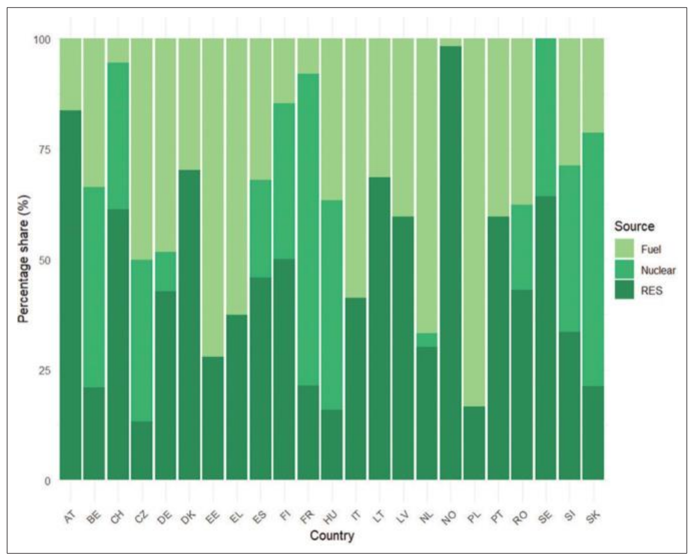
5. EMPIRICAL RESULTS

5.1. Stochastic Convergence Analysis

5.1.1. Data transformation

In the first stage of the analysis, which aims to examine the presence of stochastic convergence between country pairs, the data is transformed. Based on the monthly electricity price,

Figure 2: Share of energy sources in the electricity mix by country



Source: Authors

Table 1: Descriptive statistics of electricity mix structure

Variable	Mean	Median	Maximum	Minimum	Std.deviation
RES	44.67	42.70	98.25	13.27	23.06
Nuclear	19.69	8.95	70.59	0.00	22.38
Fuel	35.64	33.70	83.30	0.02	22.84

Source: Authors

Table 2: Regional classification of European countries used in the analysis

Region code	Region name	Countries
CWE	Central Western European Region	AT, DE, BE, NL, FR, CH
CEE	Central Eastern European Region	CZ, SK, HU, RO, PL, SI
SEE	South-East European Region	EL
NORD	Northern European Region	DK, EE, FI, LV, LT, SE, NO
IBERIA	Iberian Peninsula	PT, ES
APENNINE	Apennine Peninsula	IT

Source: European Commission, 2024

2 Source: iea.org
3 Source: https://ember-energy.org/data/, accessed on 6 January 2025

time series of the logarithm of price ratios are constructed for all possible combinations of country pairs, as described by the following formula:

$$y_t = \log\left(\frac{P_{i,t}}{P_{j,t}}\right), \tag{3}$$

where:
- $P_{i,t}$ monthly price of 1 euro/MWhe in country "i",
- $P_{j,t}$ monthly price of 1 euro/MWhe in country "j".

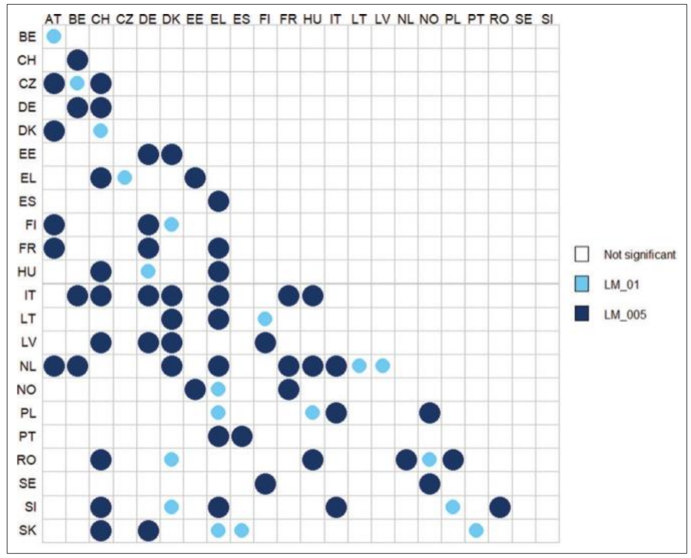
This approach, based on the analysis of logarithmic price differences between countries to assess convergence, was previously applied, among others, by Karatepe (2024) in the context of integration of the electricity market. As a result of this procedure (3), 253 unique time series are obtained and subsequently subjected to stationarity analysis. If a given series exhibits characteristics of stationarity, it can be assumed that a price convergence process occurs between the corresponding pairs of countries. This would indicate that the price difference between these countries remains relatively stable during the analysis period.

5.1.2. Payne test results

To verify the hypothesis about the existence of electricity price convergence among 23 selected European countries, the Payne test is used. The methodology involved creating two variables, LM_005 and LM_01, to assess the price convergence between countries. LM_005 is assigned a value of 1 if the null hypothesis is rejected at a 5% significance level in the Payne test, indicating stochastic convergence, and 0 if convergence is not observed. LM_01 follows a similar construction, but the critical significance level is set at 10%. On average, electricity price convergence is observed in 22% of country pairs at the 5% significance level and 30% at the 10% significance level.

Figure 3 illustrates the extent of electricity price convergence between individual countries. The dark blue cells indicate country pairs where convergence is confirmed at the 5% level, while the light blue cells represent additional cases where convergence is observed at the 10% level. The visualisation highlights that convergence is relatively limited: only 56 of the 253 country pairs show convergence at the 5% threshold, and 75 pairs at the 10% level. This confirms that price alignment remains partial across the European electricity market.

Figure 3: Pairwise electricity price convergence in Europe based on Payne test results



Source: Authors' computation (2025)

5.2. Analysis of Determinants of Electricity Price Convergence

5.2.1. Electricity mix

Among the various factors that may influence the convergence of electricity prices, the structure of the electricity mix plays an important role. To investigate this, a cluster analysis is performed based on the share of specific energy sources in the electricity mix of each country. Table 3 shows the results of the clustering for 23 European countries.

Table 3: Clustering results based on the structure of the electricity mix

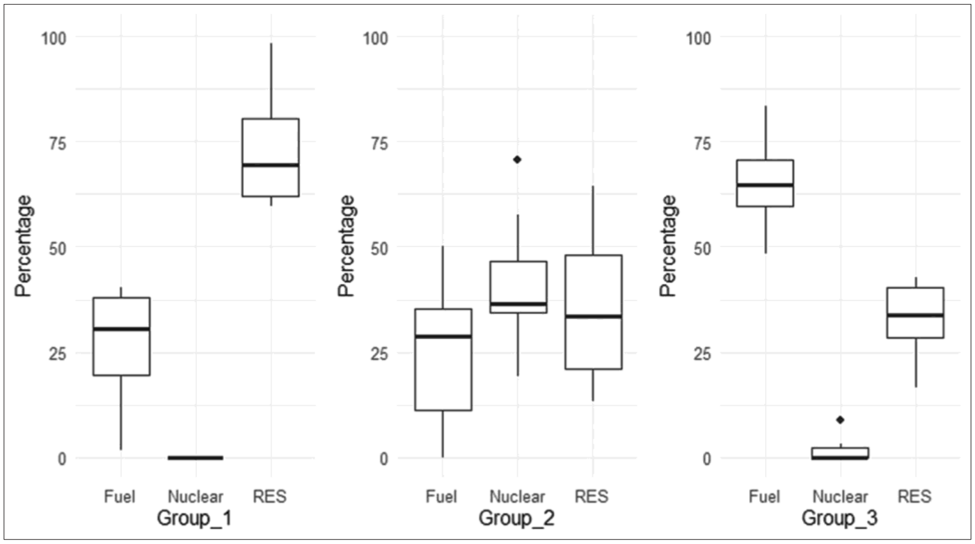
Method	Group_1	Group_2	Group_3
K-means	AT, CH, DK, ES, FI, LT, LV, NO, PT, RO, SE	BE, CZ, FR, HU, SI, SK	DE, EE, EL, IT, NL, PL
Hierarchical	AT, DK, LT, LV, NO, PT	BE, CH, CZ, ES, FI, FR, HU, RO, SE, SI, SK	DE, EE, EL, IT, NL, PL
PAM	AT, DK, LT, LV, NO, PT	BE, CH, CZ, ES, FI, FR, HU, RO, SE, SI, SK	DE, EE, EL, IT, NL, PL
Final groups	AT, DK, LT, LV, NO, PT	BE, CH, CZ, ES, FI, FR, HU, RO, SE, SI, SK	DE, EE, EL, IT, NL, PL

Source: Authors' computation (2025)

The countries selected for the analysis are grouped into three clusters: Group_1 (dominated by renewable sources), Group_2 (dominated by nuclear sources), and Group_3 (dominated by mainly fuel). The number of countries in each group varies depending on the clustering method applied. As observed, the results obtained using hierarchical and PAM methods are identical. When the k-means method is applied, Group_3 remains consistent with the other approaches, whereas countries such as Switzerland, Spain, Finland, Romania and Sweden are classified into the group based on renewable sources. Ultimately, the expert selection of groups for further analysis corresponds to those identified using hierarchical and PAM methods.

Figure 4 shows boxplots presenting descriptive statistics for the three variables – RES, Nuclear, and Fuel. It can be observed that both Group_2 and Group_3 are characterised by a share of renewable energy sources in the electricity mix of approximately 30%. Similarly, Group_1 and Group_2 exhibit a fossil fuel share of around 30-40%. It is important to note that the variable Fuel includes natural gas, which is present in the electricity mix of nearly all the countries considered.

Figure 4: Boxplots for the variables RES, nuclear and fuel



Source: Authors

Using the previously identified groups, binary variables are constructed for country pairs to present the following combination:

- MM – Both countries belong to Group_2 (55 observations),
- RR – Both countries belong to Group_1 (15 observations),
- FF - Both countries belong to Group_3 (15 observations),
- RM – One country belongs to Group_1 and the other to Group_2 (66 observations),
- RF - One country belongs to Group_1 and the other to Group_3 (36 observations),
- FM - One country belongs to Group_3 and the other to Group_2 (66 observations).

The most frequent configurations are the mixed pairings RM and FM, each with a mean of 0.26, indicating that these combinations are the most common in the dataset. The MM group, while also relatively frequent with a mean of 0.22, is slightly less dominant. In contrast, the RR and FF configurations are much less common, each with a mean of 0.06.

5.2.2. European regions

Another variable analysed in terms of its impact on the outcome of the Payne test is the regional classification of countries. Based on the classification described in chapter 4.2, we analyse three combinations:

- CWE – Both countries belong to the Central Western European region (15 observations),
- CEE – Both countries belong to the Central Eastern European region (15 observations),
- NORD – Both countries belong to the Northern European region (21 observations).

Due to the small sample sizes, the SEE, Iberian and Apennine regions are excluded from the analysis.

5.3. Results of the Logistic Regression Analysis

To examine whether all variables analysed jointly affect the outcome of the Payne test at both the 5% and 10% significance level, logistic regression models are used. Table 4 presents the results of these models.

Table 4: Logistic regression results

Variable	Model LM_005	Odds ratio LM_005	Model LM_01	Odds ratio LM_01
Intercept	−1.82***	0.16	−1.61***	0.19
INTER	0.12	1.13	−0.52	0.59
CWE	1.52**	4.57	1.70***	5.49
CEE	0.09	1.09	0.77	2.16
NORD	1.11*	3.03	1.28**	3.62
RR	−0.12	0.88	−0.31	0.73
FF	1.57*	4.82	1.75***	5.73
RM	−0.48	0.62	0.25	1.29
RF	0.44	1.55	0.76	2.14
FM	0.76	2.13	0.95*	2.59

*, **, and *** indicate significance at levels of 10%, 5%, and 1%, respectively

In both models, the variable INTER does not demonstrate a statistically significant effect on the likelihood of price convergence, indicating that the mere presence of a cross-border interconnection does not determine price convergence between countries. This may suggest that the technical availability of energy transmission infrastructure does not directly translate into price convergence processes without the support of additional factors.

Geographical location proves to be a significantly more important factor. Country pairs belonging to the Central Western Europe (CWE) region are more than four times as likely to experience price convergence in the LM_005 model and more than five times as likely in the LM_01 model. A similar trend is observed for pairs of countries in the Northern European region, where countries have approximately three times higher chances of convergence in both the LM_005 and LM_01 models. In the case of Central Eastern Europe (CEE), the effect is not statistically significant, which may suggest that this region continues to exhibit greater price divergence and lower market integration.

The structure of the electricity mix also plays a significant role. Country pairs in which both countries relied on fossil fuels (FF) have a more than four times greater likelihood of convergence in the LM_005 model and more than five times greater in the LM_01 model. A moderate, yet significant effect is also observed for pairs where one country belongs to the nuclear group and the other to the fossil fuel group (FM), although this effect is only present in the LM_01 model. Other combinations (RES-Nuclear and RES-Fossil) do not show statistically significant relationships. On the contrary, country pairs based exclusively on renewable energy sources (RR) do not differ significantly in terms of price convergence compared to other pairs and do not exhibit a discernible impact on convergence. This may be attributed to the greater variability and instability of RES production, which complicates the synchronisation of market prices.

6. CONCLUSION

This study analyses electricity prices among 23 European countries during the period 2015-2024. By applying the Payne et al. test (2022) for stochastic convergence, combined with cluster analysis and logistic regression models, it delivers new insights into the integration of the electricity market in Europe. The analysis explicitly considers factors that may influence price convergence, including the presence of cross-border interconnections, regional characteristics, and differences in national electricity mix structures.

Key findings can be summarised as follows. First, the Payne test reveals that price convergence is identified in only about 30% of the country pairs analysed. This finding underscores that full market integration is far from being achieved, despite years of liberalisation and harmonisation efforts at the EU level. Second, the convergence of electricity prices does not appear to depend on the presence or absence of cross-border interconnections between countries. Logistic regression analysis confirms that physical infrastructure between countries is not enough to make electricity prices similar. This result may be surprising, given that the development of transmission infrastructure is one of the cornerstones of the European Union’s electricity market integration policy. It suggests that the existence of cross-border interconnections does not guarantee effective market integration. Third, the price convergence appears to be influenced much more strongly by regional factors and the composition of the electricity mix. Countries in the Northern and Central Western European regions are more likely to experience convergence, whereas the Central Eastern European region does not consistently exhibit such tendencies. Additionally, convergence tends to occur between countries dominated by fossil fuels or between countries where one has a diversified mix and the other relies on renewable sources or fossil fuels. These findings imply that regional factors and the structure of the electricity mix play a more significant role in shaping price convergence than interconnection alone.

Our study has significant policy implications. First, strengthening interconnections alone is unlikely to deliver full price convergence. Second, more attention should be paid to the role of electricity mix generation, especially the influence of fossil fuel dependence and renewable diversification on price dynamics. Electricity strategies should consider how different generation technologies interact across borders and influence marginal pricing. As the EU progresses with its decarbonisation goals, it is essential to recognise that countries with very different electricity sources, such as fossil fuels, renewables, or nuclear, may not respond similarly to common-market rules. Third, regional differences should not be ignored. It may be more effective to improve cooperation and coordination within specific regions - such as North or Central West Europe - rather than applying the same rules to the entire EU. Stronger cooperation within these regional clusters could offer more realistic and effective paths toward market integration. Such efforts may facilitate a more coherent and resilient electricity market landscape across Europe in the future.

Ultimately, the results indicate that the integration of the electricity market in Europe is a far more complex process than a matter of transmission infrastructure alone. The fact that the existence of cross-border interconnections does not significantly affect price convergence points to the limited effectiveness of policies focused solely on infrastructure investment. Regional factors and the structure of the electricity mix play a crucial role. Therefore, EU policies should go beyond merely supporting the construction of interconnections - further regulatory harmonisation and support for structural changes in national electricity systems are also essential.

7. ACKNOWLEDGMENTS

This research was funded by the National Science Centre (NCN), Poland, grant No 2023/51/B/HS4/01182.

REFERENCES

Bhattacharya, M., Inekwe, J.N., Liddle, B. (2023), The role of renewable energy sources in residential electricity prices: A club convergence analysis across selected European countries. Applied Economics, 55(44), 5157-5171.

Bunn, D.W., Gianfreda, A. (2010), Integration and shock transmissions across European electricity forward markets. Energy Economics, 32(2), 278-291.

Cassetta, E., Nava, C.R., Zoia, M.G. (2022a), A three-step procedure to investigate the convergence of electricity and natural gas prices in the European Union. Energy Economics, 105, 105697.

Cassetta, E., Nava, C.R., Zoia, M.G. (2022b), EU electricity market integration and cross-country convergence in residential and industrial end-user prices. Energy Policy, 165, 112934.

de Menezes, L.M., Houllier, M.A. (2016), Reassessing the integration of European electricity markets: A fractional cointegration analysis. Energy Economics, 53, 132-150.

Du, J., Lai, K.K. (2017), Modeling dependence between European electricity markets with constant and time-varying copulas. Procedia Computer Science, 122, 94-101.

European Commission. (2024), Study on Energy Prices and Costs Evaluating Impacts on Households and Industry: 2024 Edition. Available from: https://op.europa.eu/en/publication-detail/-/publication/78756c15-F263-11ef-981b-01aa75ed71a1

Gugler, K., Haxhimusa, A., Liebensteiner, M. (2018), Integration of European electricity markets: Evidence from spot prices. Energy Journal, 39, 41-66.

Hille, E. (2023), Europe’s energy crisis: Are geopolitical risks in source countries of fossil fuels accelerating the transition to renewable energy? Energy Economics, 127, 107061.

Houllier, M.A., de Menezes, L.M. (2013), A Fractional Cointegration Analysis of European Electricity Spot Prices. In: Conference: European Energy Market (EEM), 2012 9th International Conference.

Jin, Y., Zhao, H., Bu, L., Zhang, D. (2023), Geopolitical risk, climate risk and energy markets: A dynamic spillover analysis. International Review of Financial Analysis, 87, 102597.

Karatepe, S. (2024), Convergence of wholesale electricity prices across european markets: Are we there yet? Toplum Ekonomi ve Yönetim Dergisi, 5(1), 1-14.

Kaufman, L., Rousseeuw, P.J. (1990), Partitioning Around Medoids (Program PAM). New York: John Wiley. p68-125.

Lee, J., Strazicich, M.C. (2003), Minimum lagrange multiplier unit root test with two structural breaks. Review of Economics and Statistics, 85(4), 1082-1089.

MacQueen, J. (1967), Some methods for classification and analysis of multivariate observations. In: Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability. United States: University of California Press. p1.

Maddala, G.S., Lahiri, K. (1992), Introduction to Econometrics. Vol. 2. New York: Macmillan.

Newbery, D., Strbac, G., Viehoff, I. (2016), The benefits of integrating European electricity markets. Energy Policy, 94, 253-263.

Payne, J.E., Lee, J., Islam, M.T., Nazlioglu, S. (2022), Stochastic convergence of per capita greenhouse gas emissions: New unit root tests with breaks and a factor structure. Energy Economics, 113, 106201.

Saez, Y., Mochon, A., Corona, L., Isasi, P. (2019), Integration in the European electricity market: A machine learning-based convergence analysis for the Central Western Europe region. Energy Policy, 132, 549-566.

Schmidt, P., Phillips, P.C.B. (1992), Lm test for a unit root in the presence of deterministic trends. Oxford Bulletin of Economics and Statistics, 54(3), 257-287.

Telatar, M.E., Yaşar, N. (2020), The convergence of electricity prices for European union countries. In: Regulations in the Energy Industry: Financial, Economic and Legal Implications. Berlin: Springer.

Ward, J.H. (1963), Hierarchical grouping to optimize an objective function. Journal of the American Statistical Association, 58(301), 236.