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Article

Industrial Electricity Pricing and Renewable Energy: A Temporal Analysis of the Effect of Taxes

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Abstract: This study investigates the Industrial Electricity Pricing (IEP) profiles of 22 OECD countries to understand the effect of taxes to overall prices. Clustering analysis was performed on pricing data from the year 2000 to 2018 to observe how prices evolved. Ordinal logit regression analysis was performed to determine possible associations between the clustered groups and the percentage share of renewables generated (REG). Other independent variables indicating economic and market structures were also considered. Clustering results for both prices before and after tax indicated three pricing clusters, termed low, median, and high pricing clusters. IEP in Italy and Germany were found to have the highest effect owing to taxes while IEP in countries such as the US, Norway, Canada, and Denmark were least affected by taxes. Regression results show positive associations between the clustered profiles and REG. The positive association between the non-taxed component of IEP and a unit increase of REG is 1.41 times, whereas the positive association of overall IEP price (including taxes) and a unit increase of REG is 56.26 times, which is 39.9 times higher. Our results show that REG penetration as such has had a minimal effect on IEP over the time under consideration, but rather taxation on IEP coincidental with REG penetration, has contributed to IEP increases.

Keywords: Clustering analysis; Industrial electricity pricing; Renewable Energy; Ordinal regression analysis; Electricity tax

1. Introduction

Renewable energy technology innovations have created major changes in how different societies are adapting and changing given the move towards net zero emissions (Xu et al., 2023). Given that electricity availability is vital for most societies, investigating its prices and demand patterns over certain periods could reveal more insights. The demand for electricity both for household and industrial use has increased over the years due to several factors including automation, emerging technologies and increased electrification (Xenos et al., 2016) (Fischer et al., 2020). To meet the growing demand and the need to preserve the environment, (Irandoust, 2018), (Aziz and Jahan, 2023) (Wang et al., 2023) noted that countries have been exploring several green energy alternatives to add to their total energy mix. While it is not disputable that electricity demand has practically or consistently been in an upward trend over the years, electricity pricing has been debatably described as volatile, either having downward or upward trends over the year (Macedo et al., 2020, Dehghan and Amin-Naseri, 2022, Cieplinski et al., 2021). The uncertainty in the trend of electricity pricing has partly contributed to the prominence and increased research activity in the area of electricity pricing as indicated by (Kolb et al., 2020). Countries will, therefore, find it desirable to understand and accurately predict their trends in electricity pricing.

As both developed and developing countries will be keen on ensuring electricity is available and affordable to their households, the affordability of electricity for industrial usage is likely to pose more of a concern due to its corresponding development and economic implications (Lebepe and Mathaba, 2024) (Koster et al., 2024). On one hand, high industrial pricing of electricity in a country

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might mean companies that largely depend on electricity for their operations might become uncompetitive with companies in neighbouring countries with cheaper pricing just as observed by, (Moerenhout et al., 2019), (Li and Yuan, 2021). Moreover, the possibility of passing on the increased cost to customers or seeking out alternative independent electricity generation plans at some costs are likely outcomes of increased pricing. On the other hand, low electricity pricing can ensure competitiveness for industries with significant dependence on electricity and also increased consumption as discussed by (Ai et al., 2020), (González and Alonso, 2021). There have also been some arguments towards the possible negative effects of low electricity pricing (Yang and Faruqui, 2019) (Cieplinski et al., 2021). According to (Ai et al., 2020), low electricity pricing could further encourage environmental pollution by heavy industries and high-energy consumers. As noted by (International-Energy-Agency, 2020a) end-user electricity price varies among different countries due to the contribution of different taxes levied (e.g., Value-added tax, environmental tax, excise tax etc.) and also if the structure of the market is either liberal or regulated (Trebbien et al., 2023). According to (Adom et al., 2017) there is no solid consensus on the increasing or decreasing effect of renewables on electricity pricing. In addition, they noted studies that have attempted to investigate the impact of other factors such as national developmental indices, electricity demand, market reforms (e.g., deregulation) and other green energy initiatives on decreasing or increasing electricity pricing over time.

This research, while attempting to understand the adaptation of societies to renewable technology penetration, primarily studies the before-tax and after-tax components of IEP profiles. We systematically grouped 22 OECD countries over a period of nineteen years (2000-2018) for our study. Our timespan of analysis is deliberately chosen to account for a period without global electricity market shocks such as the pandemic and the conflict in Europe. We excluded the data for 2019 due to data gaps across the different data sets used in section 3.1. Our secondary interests seek to determine the association of the share of renewable energy (Wind, Solar Photovoltaics (PV) and solar Thermal) with the pricing clusters (to generically study the association on countries), while also attempting to consider the effects of economic and market structures of the countries being examined. The unique contributions in our work are highlighted as follows: (i) Application of clustering analysis to investigate the IEP of a selected panel of countries, to determine the ordinal number of clusters. (ii) The use of clustered industrial electricity prices to understand the contribution of taxes, as the share of renewables increases. (iii) The application of a regression model to fit the regression variables with the ordinal IEP clusters and to observe the relationship of the variables with pricing clusters. Therefore, this study presents a novel clustering-dependent regression to analyse temporal IEP profiles. The study also takes into consideration variables related to the economic structure of a country such as the gross domestic product per capita, and other market structures of the country such as energy imports, greenhouse gas emissions, etc.

Our study contributes to the body on knowledge by providing a temporal analysis of nearly two decades of data and identifying that renewable technologies as such do not contribute to increased prices. Our methodology using a combination of temporal clustering and regression based clustering is unique in establishing the relationship between IEP and the effect of taxes on IEP. Knowing the impact of taxes on IEP along with economic and market factors can help in the formulation of sustainable tax policies can assist decision-makers and policymakers as countries transition towards decarbonisation of their electric grids, without overburdening electricity consumers and negatively impacting economic growth.

The structure of the following sections in this paper is presented below; a review of related literature on IEP including possible factors affecting its increase or decrease and the motivation for the use of the clustering technique as part of the methodology is presented in section 2. This is followed by section 3, which provides the datasets and the analytical methods i.e., clustering and regression model used in the study. Section 4 presents the results from the grouping of the IEP profiles and the results of the regression analysis. Section 5 subsequently discusses the clustering

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results and the associations of the selected factors on the price groupings. Conclusions, recommendations, and future directions regarding the study are presented in section 6..

2. Literature Review

The IEP for the EU market was studied by (del-Río et al., 2019). Their findings suggest a 67% increase in IEP in 15 EU countries between 2003 and 2013. They however admitted a decrease in industrial electricity prices within the years 2013 and 2014 by 1% respectively and suggested a longer period of observation to conclude on the trend. (Kolb et al., 2020) studied electricity pricing in Germany by analyzing spot market demand data and supply data between 2014 and 2018. Their arguments were largely in favour of a reduction in spot-market electricity prices, though they acknowledged some earlier research indicating an increase in electricity pricing for German households between 2000 and 2019. (Macedo et al., 2020) researched wholesale electricity pricing based on the balance of demand and supply in Portugal. Similarly to (Kolb et al., 2020), their findings not only show the decreasing price of electricity but also reveal an increase in its volatility. (Cieplinski et al., 2021) examined the renewable energy policy paradox and its effect on electricity pricing in the Italian market, while (Moreno et al., 2014) and (González and Alonso, 2021) studied the association between IEP in Spain and the cost of energy from fuel. The findings of (Moreno et al., 2014) indicated a positive association between IEP and the price of petroleum products. Alternative energy sources such as renewables were recommended to combat increasing electricity prices impacted by uncertain and mostly volatile prices of petroleum products. The period of study (González and Alonso, 2021) was between 2015 and 2019. Their research efforts were aimed at finding out the causes of industrial electricity pricing disparity in Spain and the other EU member countries. Their findings revealed that the electricity prices of Spain were higher than other neighbouring EU countries. The reason suggested was due to the little or no electrical interconnection of Spain with the rest of Europe.

(Yang and Faruqui, 2019) researched electricity pricing (industrial, commercial, wholesale and retail) using the electricity deregulation experience of the United States (US) as a case study. Their findings revealed that either lower or higher electricity pricing should not be a determinant for appraising the success of market reforms introduced. (Ai et al., 2020) supported this observation using China as a case study and noting that reducing IEP possibly can promote some but not a desirable high-quality economic transformation. Their study suggests that an increase of about 1% in industrial electricity prices has a direct and indirect increase of 12.4 % and 2% in industrial green productivity respectively.

As (Yang and Faruqui, 2019) further indicated, electricity pricing is affected by many factors and the effects of the factors on pricing are often difficult to eliminate. (Kolb et al., 2020) and (del-Río et al., 2019) suggested the need for ongoing research activities in the area of determining the impact of renewables on electricity pricing. As indicated by (Adom et al., 2017) and (del-Río et al., 2019) there appears to be a lack of author agreement on the impact of renewables on electricity pricing. (Adom et al., 2017) concluded that renewable energy supply would possibly increase the uncertainty level in electricity prices. (del-Río et al., 2019) their study of IEP for 15 EU countries between 2003 and 2013 observed a positive relationship between Industrial electricity pricing and share of renewable energy and Gross domestic product per capita.

Artificial Intelligence techniques and algorithms in electricity pricing for predictions and pricing analysis have gained prominence among researchers (Oyewole and Thopil, 2023). For example, the trust algorithm for electricity forecasting models of Heistrene et al.,(2023) and the electricity price forecasting machine learning model of Iwabuchi et al.,(2022). Clustering a form of unsupervised machine learning has over the years seen increased use in electricity pricing studies. The use of clustering as noted by (Rhodes et al., 2014), (Motlagh et al., 2019) (Liu et al., 2020) and (Müller, 2021) has been very effective in pattern recognition and analyses of both static and time series data such as in electricity consumption, demand or load profiles. (Rhodes et al., 2014) stressed the importance of the use of clustering in grouping load profiles, revealing outliers or grouping the electricity

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consumers. (Liu et al., 2020) emphasized the effective use of clustering algorithms such as the k-means and its variants such as k-medoids, and fuzzy c-means when analyzing time-series data. (Ruiz et al., 2020) in their study found the k-means and k-medoids clustering algorithm to be effective in extracting information from time series raw-energy data from buildings. (Salehi and Rezaei, 2023) used the k-means clustering and point estimate methods to solve the probabilistic load flow (PLF) problem in distribution networks. As much of the use of clustering techniques has been limited to the grouping of energy data such as electricity load profiles, consumption or demand, its vast potential in recognizing patterns in datasets such as electricity pricing data is yet to be fully harnessed. Therefore, our study primarily applies clustering to study IEP data.

3. Datasets and Methods

The datasets used for this study use a panel dataset, such as in (Irandoust, 2018) (Hassan et al., 2024) targeting twenty-two (22) countries majorly selected within the OECD group of countries. The data used for our study was specifically from the period 2000 to 2018. We did not include data for the year 2019 because of data gaps across multiple datasets, and the period from 2020 onwards not taken into account due to global energy price volatility due to the pandemic and the war in Europe.

3.1. Datasets

Annual time series datasets obtained are categorized and further described below:

(1) Industrial Electricity Pricing Excluding Tax (IEPET) and Industrial Electricity Pricing Including Tax (IEPIT)

The method of computing these prices is further detailed in (GOV.UK, 2024) and (Department-for-Business-Energy&Industrial-Strategy, 2024). As indicated in (International-Energy-Agency, 2020a) and (Department-for-Business-Energy&Industrial-Strategy, 2024) the industrial electricity prices possibly depend on the market structure and different tax structures of the respective countries. The tax components being considered are those that are levied or paid for the consumption of electricity by the industrial sectors. These do not include taxes paid by industries such as power plants for the generation of electricity from various energy fuels. All price units expressed (GOV.UK, 2024) in pence/kWh were converted to the United States cents per kilowatt-hour (cents/kWh) using annual average exchange rates (OECD-Data, 2020).

(2) Total Electricity Generated per year in Terawatt hour: TEG (TWh) and Renewable Energy Generated per year in Terawatt hour: REG (TWh): We focused on the renewable sources of energy from wind, solar PV and solar thermal to make up REG (TWh) for this study. These sources of renewable energy have been shown in the literature to have some impact on the trend of electricity pricing (Kolb et al., 2020) (Macedo et al., 2020). Moreover, there has been rapid expansion and more developmental and market interest in the use of these green sources of energy in recent years. TEG (TWh) and REG (TWh) were needed to calculate the percentage of renewables in the total energy generated by the countries. The percentage (which we have termed REG) was obtained from the ratio of REG (TWh) and TEG (TWh). Data for TEG (TWh) and REG (TWh) for our study was for the years 2000 to 2018 (International-Energy-Agency, 2020b).

(3) Economic data on Gross Domestic Product per capita in local currency i.e., GDPpc (The-World-Bank-Databank, 2020).GDPpc for the twenty-two countries was captured for further association studies with the electricity pricing data. Similarly to the energy sources data, the economic data for this study was available for the years 2000 to 2018. As discussed by (Oosthuizen et al., 2021) GDPpc indicates the level of economic activity in a country.

(4) Greenhouse gas emissions by energy industries as a percentage of total emissions (EIE) (OECD-Data, 2021):The data obtained for the study was from the year 2000 to 2018. EIE captures the emissions of greenhouse gases such as Carbon dioxide(CO_2), Nitrous oxide(N_2O), Chlorofluorocarbons (CFC) etc. An increase in the EIE reflects an increase in activities of humans using fossil fuels in manufacturing, energy generation, transportation etc. For countries within the

European Union (EU), data on EIE gives a measure of the influence of energy control policies such as the Emissions Trading Scheme(ETS) which puts a cap allowance on the permitted amount of greenhouse gases to be emitted (European-Commission), therefore being a factor that can impact electricity prices by affecting the cost of energy production. For other countries outside the EU, the EIE data could indicate the extent of country-specific efforts at limiting greenhouse gases, which in turn might affect electricity prices by increasing or decreasing the cost of energy.

(5) Energy imports, net (% of energy use) (The-World-Bank-Databank, 2020):

The volatility of prices in the international markets could be linked to energy imports, consequently affecting the price of electricity produced from such energy fuels imported. As described by (Moreno et al., 2012), this also gives an indication of countries' dependence on energy imports or simply Energy dependency (ED). The data available for our study was from 2000 to 2018.

We represent the electricity pricing data excluding and including tax with boxplots for the 19 years in Figures 1 and 2 respectively. In addition, Figure 3 shows the box plot of tax data obtained from the difference between the excluding and including tax data. All the box plots reveal the dispersion and skewness for each country. In addition, it is also easy to observe the prices below the first quartile (25%), median (50%), third inter-quartile price values (25% and 75%), the possible outliers for each country, and maximum and minimum data values. A statistical summary of the data used is presented in Table A1 of the Appendix A.

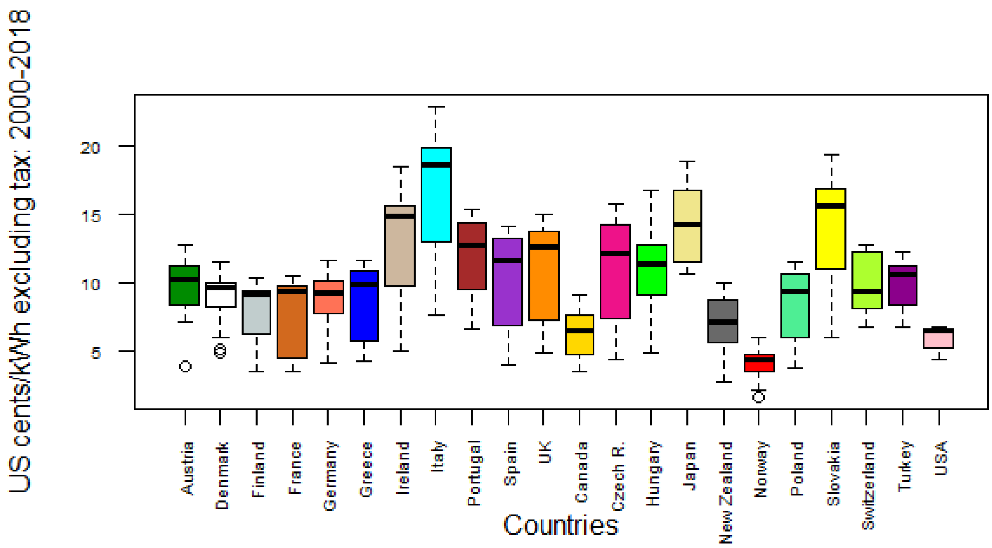

Figure 1. Boxplot of Industrial Electricity Pricing Excluding Tax (IEPET) dataset 2000-2018.

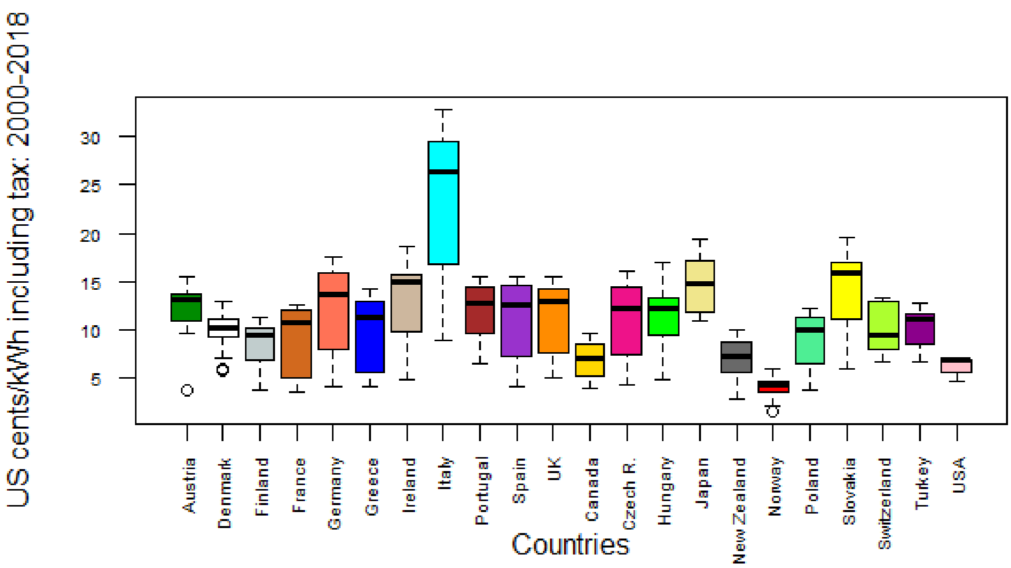

Figure 2. Boxplot of Industrial Electricity Pricing including Tax (IEPIT) dataset 2000-2018**.**

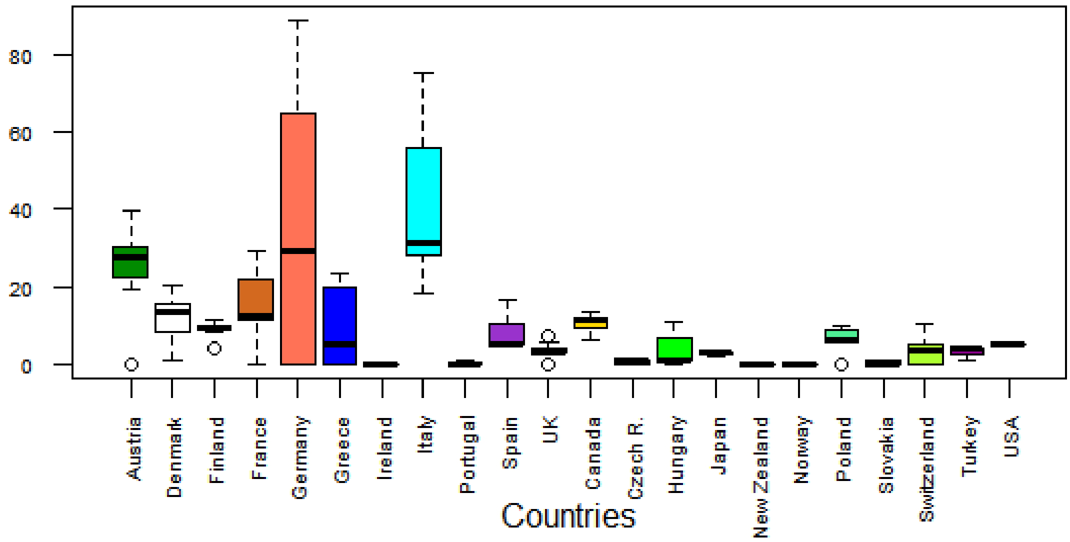

Figure 3. Boxplot of the percentage difference of IEPIT and IEPET: 2000 to 2018.

Figure 1 shows Italy with the highest variation in yearly pricing excluding tax and a wide variation in absolute prices as well. Norway showed the lowest yearly pricing with minimal variation during the 19 years considered.

Similarly, Figure 2 shows Italy retaining the highest absolute prices when taxes are included and with the widest variation. Norway showed the lowest absolute prices with taxes being included and the variation in pricing, out of the 22 countries during the 19 years.

Figure 3 shows the variation of the year-on-year % difference in pricing (IEPIT vs IEPET) representing the % tax from 2000 to 2018. Germany is shown to have the highest and widest variation of year-on-year tax change along with Italy, while the variation for countries such as the USA, Ireland, Norway, New Zealand, and Finland has been low to minimal. These variations can be observed in more detail on a time-scale plot in Figure 4.

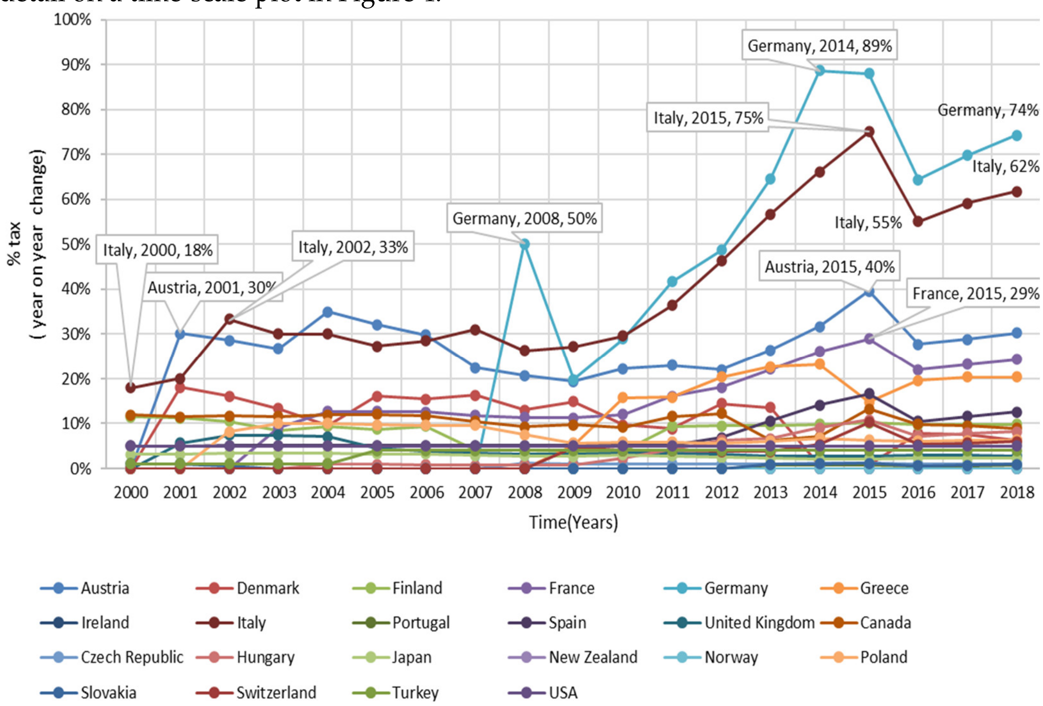

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Figure 4. Year on year change in tax (in %): 2000 to 2018**.**

Figure 4 shows that both Italy and Germany had more than 50% increase in % tax between 2000 and 2018. Italy and Austria showed the highest year on year tax increases (in %) between 2000 and 2008. Since 2008, Germany has shown the highest year on year tax increases (in %), with increases peaking in 2014 (at 89%). All the countries in the study, except for France, Austria, Italy, and Germany, showed a tax increase of below 25% year on year over the 19 years.

3.2. Method of Analysis

A flow chart of the methods employed in this study is presented in Figure 5. Our research employed clustering and regression analysis. R-statistics software program (version 4.2.0) and Microsoft Excel were used for data analysis and visualization. We specifically used the NbClust library (Charrad et al., 2015) and other time series functions in R for the clustering analysis. For the regression analysis, we used the MASS library (Venables and Ripley, 2002) and the Stargazer library (Hlavac, 2018) within the R statistics library.

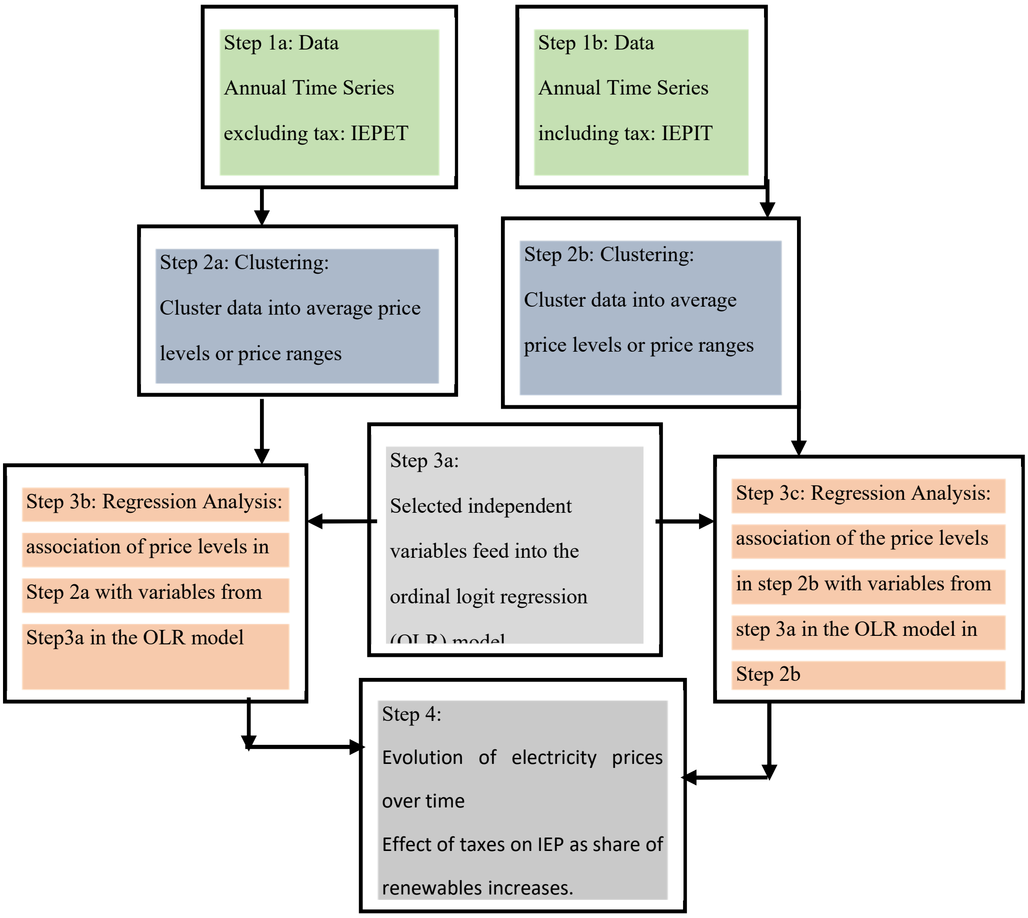

Figure 5. Summary of methods employed in the study**.**

3.2.1. Determining the Pricing Cluster Levels

We performed clustering analysis for the IEP time-series datasets (excluding and including tax). The 22 countries were categorized into price levels using the k-means clustering algorithm. The k-means technique was used due to its popularity among other clustering techniques (Xu and Wunsch, 2010),(Pereira and Frazzon, 2020), (Carreon et al., 2023) and versatility (Liao, 2005) in clustering time series static data. In addition, the k-means technique and its variants are well used in energy profiling studies such as (Rhodes et al., 2014), (Al-Wakeel and Wu, 2016), (Liu et al., 2020), (Ruiz et al., 2020),(Rajabi et al., 2020) and (Zhou, 2022). The k-means clustering puts into levels or groups a dataset by optimizing a particular similarity/dissimilarity measure or distance function iteratively (Liao, 2005) (Nguyen et al., 2021). We follow the approach of (Rhodes et al., 2014) (Pereira and Frazzon, 2020) and (Sekula, 2015) using the NbClust to determine the optimal number of clusters in the dataset before clustering is performed.

3.2.2. Ordinal Logistic Regression (OLR) Model

The regression model used in this study was dependent on the results obtained from the clustering analysis. OLR gives outputs in log odds and is also referred to as the proportional odds model (Sanguineti and Maran, 2024). This model is used when there is a need to obtain a relationship between independent variables and dependent variables when there is a form of order in the dependent variable (with three or more levels such as low, median, high in our case) (Liu and Koirala, 2012), (Brant, 1990) (Bilder and Loughin, 2014) and (UCLA:-Statistical-Consulting-Group, 2021).

$$logit\left(P(Y \leq j)\right) = \delta_{j1} X_1 + \cdots + \delta_{jn} X_n + \alpha_{j0} \qquad (1)$$

For $j = 1, 2 \cdots, J - 1$ and n = number of independent variables

J => The number of categories or levels of the ordinal dependent variable

Y=> Ordinal dependent variable (levels or categories)

X_n => n Independent variables

α_{j0} => Intercept dependent on the number of categories or levels of the ordinal dependent variable minus one ($j = 1, \cdots, J - 1$)

δ_{jn} => Coefficients dependent on the j and the number of independent variables

$(n: 1 \cdots n)$

$P(Y \leq j)$ => Probability (cumulative) of the dependent variable Y less than or equal to a specific ordinal category or level $j = 1, \cdots, J - 1$.

$$logit\left(P(Y \leq j)\right) = \log\left[\frac{P(Y \leq j)}{P(Y > j)}\right] \qquad (2)$$

Equation referred (2) is referred to as the logit or the log odds equation

As discussed by (Mauracher et al., 2019) POA emphasizes the parallelism between the dependent variable (Y) categories or levels. (Kasza and Wolfe, 2014) described POA as attempting to fit a series of logistic regression models to different categories (cluster groupings in our case) where the coefficients of independent variables do not change for each of the logistic regressions though the intercepts could differ

The POA provides a limitation to the OLR model for which studies such as (Fullerton and Xu, 2012) provided suggestions to overcome this limitation through relaxation of the assumption.

However, the approach we used in dealing with this limitation, especially if any of the variables failed the test, was to remove the independent variable from the OLR model and re-compute the OLR. Brant's test (Schlegel, 2020) was conducted to validate the fit of the OLR model used. According to the Brant test, the parallel or proportional regression assumption determines the fit of the model for all the variables through the omnibus (all the variables together) and for each variable through their respective results. The assumption holds for the omnibus and individually when the probability (p) of the omnibus is greater than 0.05 level of significance (i.e., $p \geq 0.05$) and does not hold if $p<0.05$. In addition, Brant's test also shows the validity of the assumption for each variable included in the model. Figure 6 provides a flowchart of the regression analysis procedure followed in this study to conduct the regression after results are obtained from the clustering.

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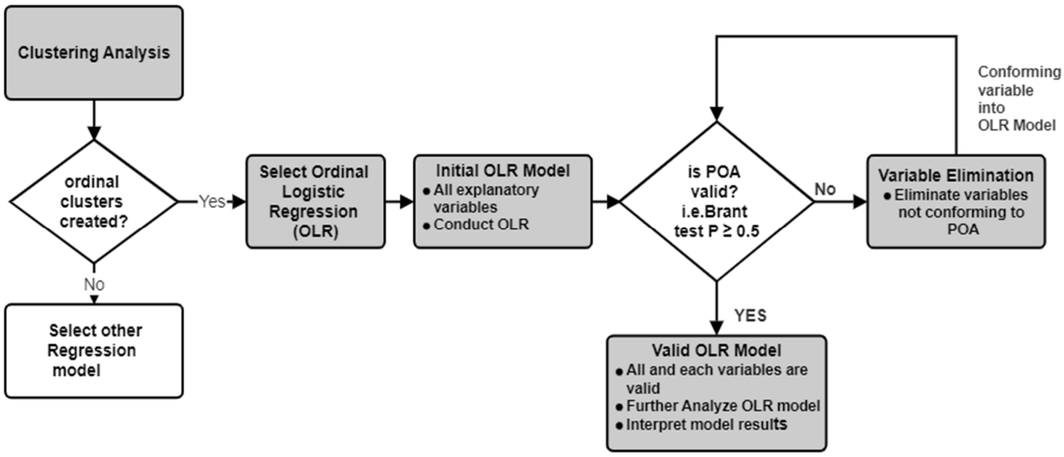

Figure 6. Regression analysis procedure in this study.

4. Results

4.1. Results of Cluster Analysis

4.1.1. Industrial Electricity Pricing Excluding Tax

The optimal number of clusters obtained was three (3). The price ranges (centre bounds) and countries in each price range (cluster sizes) are shown in Table 1. Cluster 1a (price grouping between 3.954 and 8.622 cents/kWh) includes prominent EU member countries (such as Denmark, France, and Germany), North American countries (such as Canada and, the US) and includes New Zealand. Cluster 2a (price grouping between 5.373 and 12.253 cents/kWh) consists of a greater number of EU countries except for Switzerland and the UK. Similarly, to cluster 2a, cluster 3a (price grouping between 7.898 to 16.666 cents/kWh) consists of a smaller number of EU countries and Japan

Table 1. IEPET showing price categories or ranges (Excluding tax).

Cluster 1a (low-range) Price range (cents/kWh): 3.954 - 8.622	**Cluster 2a (Median-range) Price range (cents/kWh): 5.373- 12.253**	**Cluster3a (high-range) Price range (cents/kWh): 7.898- 16.666**
Denmark	Austria	Ireland
Finland	Portugal	Italy
France	Spain	Japan
Greece	UK	Slovakia
Germany	Czech Republic	
Canada	Hungary	
New Zealand	Switzerland	
Norway	Turkey	
Poland		
USA		

In Figure 7, we present the combined time series plot for all the 22 countries including the three clusters identified. Figures B1 to B3 (in the Appendix A) show the time-series plot of the clusters and the cluster averages obtained. For all countries, we observed upward and downward trends of prices with a few countries falling below 5 cents/kWh and a few above the 15 cents per kWh through the

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years considered. In between this trend are periods of a sharp drop in electricity prices around 2010 and 2015. The price plots of each cluster in Figures A1 to A3 (in the Appendix A) also illustrate this clearly. The time-series cluster plot indicates an upward movement of prices between 2000 and 2010. However, this upward trend declined and plateaued between 2010 and 2015.

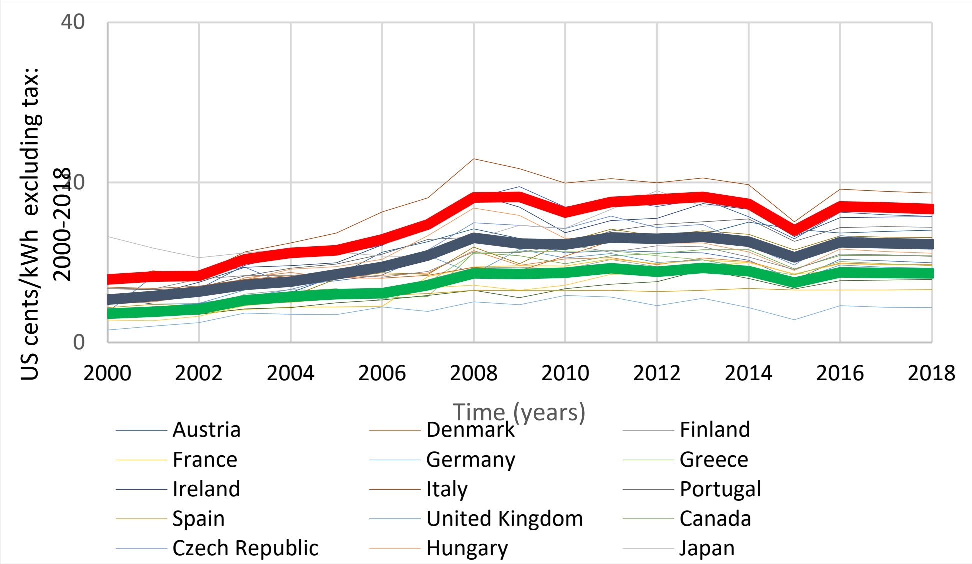

Figure 7. Plot of countries and clusters obtained for IEPET.

4.1.2. Industrial Electricity Pricing Including Tax

The optimal number of clusters obtained in this category of industrial pricing data was three (3). Although the optimal number of clusters for the including and excluding tax were the same, the compactness of the clusters obtained for each category of pricing varied. The average within-cluster sum of squares obtained for the excluding tax and including tax were 401.64 and 551.73 respectively. This clustering metric shows that the excluding tax clusters were tighter compared to the including tax clusters and that the inclusion of taxes created more variation in prices as shown in the boxplot in Figure 3 above. The clustering result showing the grouping of countries is presented in Table 2. We also present similar results showing the time-series clustering of the countries in Figure 8

Table 2. IEPIT clusters of countries with price categories or ranges (including tax).

Cluster 1b (low-range) Price range (cents/kWh): 4.331 – 9.877	**Cluster 2b (Median-range) Price range (cents/kWh): 5.808- 14.606**	**Cluster 3b (high-range) Price range (cents/kWh): 8.893- 30.200**
Denmark	Austria	
Finland	Germany	Italy
France	Ireland	
Greece	Portugal	
Canada	Spain	
New Zealand	UK	
Norway	Czech Republic	
Poland	Hungary	
Switzerland	Japan	
Turkey	Slovakia	
USA		

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In Figure 8, we present the combined time series plot of the 22 countries including the three clusters obtained. Figures A4 to A6 (in the Appendix A) show the time-series plot for the cluster and the cluster averages obtained.

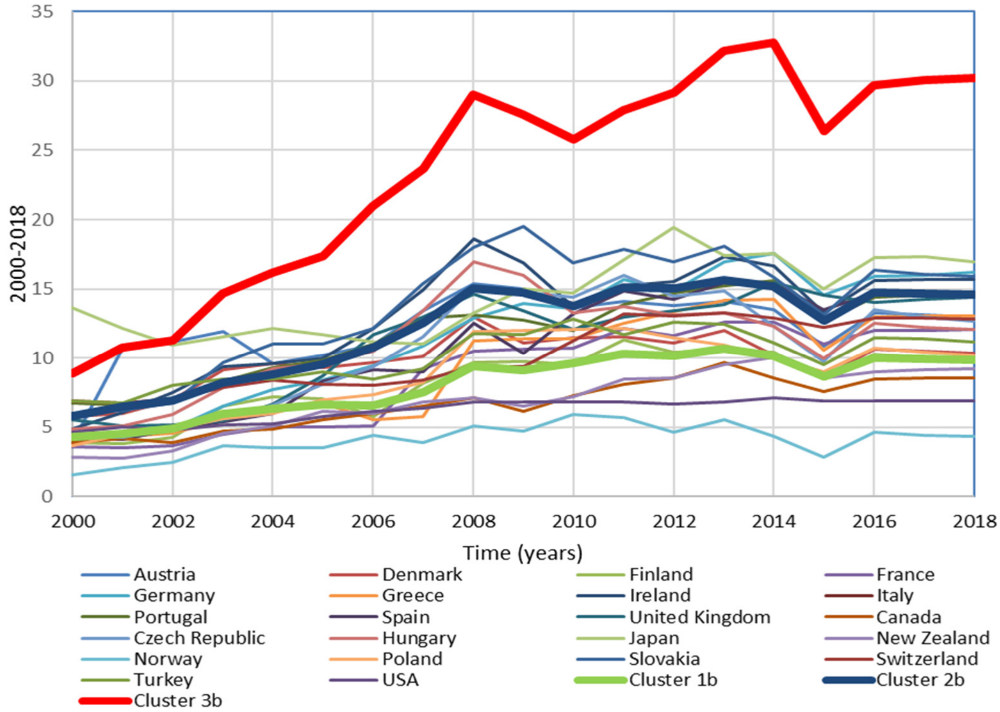

Figure 8. Plot of countries and clusters obtained for IEPIT.

For all the countries in the period of study, comparable upward and downward trends similar to that of the excluding tax (section 4.1.1) were observed. While a plateau-like pricing trend between 2010 and 2015 was observed in the prices excluding tax plots of Figure 7 (also see Appendix plots A1 to A3), an increasing pricing trend was observed in the prices including tax plots of Figure 8 (also see Appendix plots A4 to A63). The majority of countries showed price movements between 5 cents/kWh and 20 cents/kWh in the 19 years of study.

4.2. Results of Regression Analysis

4.2.1. Regression Results Excluding Tax

The OLR results for IEPET are presented in this section. The first model (Model 1a) includes all the independent variables. Model 1a coefficients are presented in Table 3, and simply represented (without the mathematical formulation) in terms of the independent variables considered below:

Table 3. IEPET regression models and Brant tests towards satisfying POA.

Independent variables	Model 1a Logit coefficient	Model 1a Brant test	Model 1b Logit coefficient	Model 1b Brant test	Model 1c Logit coefficient	Model 1c Brant test
REG	1.2369	0.82	-0.1406	0.98	0.3434	0.7
GDPpc	0.0061	0.11	0.0005	0.11	0.0007	0.2
EIE	-0.0577	0.02	-	-	-	-
ED	0.0286	0.06	0.0326	0.02	-	-

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Model (All variables)*	n/a	0.03	n/a	0.06	n/a	0.4

* Brant's test for this suggests whether the model representing all variables violates or supports the proportionality assumption. Brant tests Values < 0.05 violate POA and values >= 0.05 support POA, - Variable not included in the model due to previous violations of the Proportional Odds Assumption (POA), , n/a: no coefficient values are returned.

Model 1a: Cluster (IEPET) ~ (REG)+(GDPpc)+(EIE)+(ED)

The variable EIE in Model 1a failed the POA assumption, and as discussed in section 3.2.2 this was removed from the regression analysis to obtain Model 1b. The description of Model 1b is given as:

Model 1b: Cluster (IEPET) ~ (REG)+(GDPpc)+(ED). The variable ED also failed the POA assumption and was removed from the regression analysis to obtain Model 1c.

Model 1c satisfied the POA in the omnibus (section 3.2.2) and for the individual variables (REG and GDPpc) and is simply represented as,

Model 1c: Cluster (IEPET) ~ (REG)+(GDPpc).

The regression results showing the coefficient of the regression and validity of the POA (Brant test) for models 1a, 1b and 1c are presented in Table 3.

Model 1a shows a positive association in REG, and ED with IEPET. A negative association is obtained in EIE. However, the association values will not be further discussed given the failed POA of the model. Model 1b conformed to the POA assumption, although only the ED variable did not individually conform to the assumption. In Model 1c, the overall model confirmed the POA and the individual variables consisted of the REG and GDPpc. The logit coefficient and other significance tests for Model 1c (satisfying the POA) are presented in Table 4.

Table 4. Regression results for Model 1c satisfying the POA.

Independent Variable	Logit coefficient (log odds)	Odds ratio	Std error	t-value	p-value	95% confidence interval for logit coefficient (2.5%, 97.5%)
REG	0.3434	1.410***	0.0059	394.44	0	(0.3318,0.35502)
GDPpc	0.0007	1.001***	0.0001	5.21	0	(0.0004,0.0009)

For the variable REG in Tables 3 and 4, the logit coefficient is interpreted as a 0.34 increase being expected at the cluster level, given a 1 % increase in renewables, assuming all the other variables are kept constant. A better interpretation is that of the exponentiated value of the logit coefficient (odds ratio) in Table 4. Keeping all other variables constant when the renewable mix variable (REG) increases by 1%, it is 1.410 times more likely for the IEPET of countries to move from a lower pricing category to a higher pricing category. The association of GDPpc showed a similar positive effect as REG although this was of a lesser magnitude with 0.1% odds of moving to a higher pricing category. The variables REG and GDPpc are significant as shown by the P-value ($p<0.01$) and confidence interval (assuming normality).

4.2.2. Regression Results Including Tax

The first model considered under the including tax category (Model 2a) consists of all the independent variables. Based on the regression experimentation discussed in section 3.2.2, other models were obtained. The description of Model 2a is given below:

 doi:10.20944/preprints202502.1490.v1

Model 2a: Cluster (IEPIT) ~ (REG)+(GDPpc)+(EIE)+(ED).

The ED variable was removed from Model 2a to give Model 2b due to Model 2a's violation of the POA. Model 2b is obtained given the description below:

Model 2b: Cluster (IEPIT) ~ (REG)+(GDPpc)+(EIE)

The regression results for Models 2a and 2b are presented in Table 5 below:

Table 5. IEPIT regression model results with variables satisfying the POA.

Independent variables	Model 2a Logit coefficient	Model 2a Brant test	Model 2b Logit coefficient	Model 2b Brant test
REG	4.8069	0.27	4.03	0.37
GDPpc	0.0003	0.06	0.0005	0.07
EIE	-0.0087	0.54	-0.0081	0.93
ED	0.0327	0	-	-
Model (All variables)*	n/a	0	n/a	0.25

*Brant's test for this suggests whether the model representing all variables violates or supports the proportionality assumption. Brant tests Values < 0.05 violates POA and values >= 0.05 support POA - Variable not included in the model due to previous violations of the POA or incomplete data, , n/a: no coefficient values are returned.

Similar to section 4.2.1, Model 2a represents the model when all the variables are included in the regression. In Model 2a, a positive association was obtained for REG, GDPpc and ED, while a negative association was obtained for EIE. Due to the failed POA, our discussions of Model 2a will be limited. The OLR validity for the including tax terminates with Model 2b. The model including its associated variables satisfied the POA. Additionally, Model 2b showed a positive association with the ordinal dependent variable (for REG and GDPpc), while a negative association was observed for EIE. The regression results and other significance tests for Model 2b which confirms the POA are presented in Table 6 below.

Table 6. Regression results for Model 2b.

Independen t Variable	Logit coefficient (log -odds)	Odds ratio	Std error	t-value	p-valu e	95% confidence interval for logit coefficient (2.5%, 97.5%)
REG	4.03	56.26***	0.0061	652.10	0.00	(4.0179,4.0421)
GDPpc	0.0005	1.001***	0.0001	4.8471	0.00	(0.0003,0.0007)
EIE	-0.0081	0.992	0.009	-0.9071	0.36	(-0.0258, 0.0094)

Significant at *p<0.1; **p<0.05; ***p<0.01 and also with the confidence interval. A narrow confidence interval as shown by the upper and lower limit suggests precision at the estimate of the log-odds.

The interpretation of the regression analysis of the IEPIT is also similar to that of section 4.2.1 except that the effect of the tax components included can be inferred. Given a 1 % increase in REG,

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assuming all the other variables are kept constant, a 4.03 increase is expected in the cluster level. Also using the exponentiated value, as REG increases by 1%, it is 56.26 times more likely for the IEPIT of the countries under study to move from a lower pricing category to a higher pricing category keeping all other variables constant.

The association of GDPpc in the category of including tax showed a similar positive effect as that of REG although this was of a lesser magnitude and marginal when compared. The marginal effect is further confirmed by the odds ratio value of (1.001). The significance of the variables REG and GDPpc in the model is also shown by the p-value ($p<0.01$) and the confidence interval (assuming normality). The EIE variables showed a marginal negative logit coefficient relationship. This could be interpreted as given a 1% increase in EIE it is marginally likely for IEPIT of the countries to move from a higher pricing category to a lower one. However, the EIE is not shown to be significant at either ($p<0.1$, $p<0.05$ or $p<0.01$). The EIE variable not being significant limits our discussion on EIE for the final Model 2b. Comparing both the regression results for IEPET and IEPIT, it is observable that both % REG and GDPpc maintained their conformity to the POA through the iteration. Looking at the final models representing before-tax pricing (Model1c) and after-tax pricing (Model2b), as REG increases the effect of the tax is amplified.

The effect of GDPpc on pricing was found to be minimal. The logit coefficient for GDPpc was approximately equal (1.001) in both cases. The EIE showed a negative association with IEPIT and conformity to the POA in the final after-tax model 2b.

For IEPET, a negative association was also observed but not in the final pre-tax model 1c. The EIE log-odds coefficient for the penultimate Model 1b (IEPET) and final Model 2b (IEPIT) suggests that as the percentage of greenhouse gas emissions increases, the tax component effect is reduced.

5. Discussion

5.1. Discussion on Cluster Analysis

In this section, we discuss the clustering results obtained, including the importance of countries falling into the different clusters.

5.1.1. Industrial Pricing Excluding Tax

As seen in Table 1, countries that were grouped in the low-price range such as Denmark, Germany, Canada, US suggest a mix of reasons that contribute to lower pricing. These reasons could range from such countries having been able to promote favourable energy policies such as market liberalization and being able to develop technologies that to a large extent optimize the production and supply of electricity cheaply from their respective local resource endowment or imported fuel. This was also noted by (Hassan et al., 2024). The middle-price range suggests that countries that fall in this category such as Spain, the UK, and Turkey to an appreciable extent have been able to optimize the production of electricity from available local resources and endowment. However, due to reasons ranging from being net energy importers, the type of fuel utilized in generating electricity (for example production from gas produces less energy and of a higher cost than coal) to more stringent policies on renewables, and the impact of external factors have culminated in more increase in price compared to the low-range countries. Countries falling in the higher-price range such as Italy, Japan, and Ireland tend to depend more on energy imports compared to the median range group. In addition, the high cost of electricity production, transmission and distribution have also affected electricity prices. For example, Italy has been noted to be affected by the peninsula’s geographical shape of the country thus resulting in different market prices of electricity(Ghiani et al., 2020), while in Ireland electricity is largely generated from price-sensitive natural gas (Gore et al., 2023).

In summary, yearly inflation rate specific to each country, the amount of local energy-source endowment (e.g., weather patterns, natural fuel and mineral resources) possessed by different countries, such as cheap fossil fuels in the US, cheap coal in Australia, inexpensive hydroelectricity

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in Scandinavia and Canada, cheap nuclear energy resource in France, high wind power generation in Denmark, high solar power generation in Germany and the cost of exploitation of these resources to a considerable measure, also contributes to the pricing category a country will fall into in comparison with other countries. Within geographically large countries such as the US, Canada and Australia significant internal variations in pricing can occur due to variation of the type of local resource endowment. However, the effect of internal resource endowment is not within the scope of this study.

5.1.2. Industrial Pricing Including Tax

Our clustering results classifying Italy as having very high IEP including tax might be consistent with the observation noted by (International-Energy-Agency, 2020a) and (Finnish-Energy-Industries, 2010). The period of study (Finnish-Energy-Industries, 2010) is not recent but is being covered within our period of study from 2000 to 2018. They concluded that Italy, Germany, and the Netherlands have one of the highest electricity consumption taxes for energy-intensive industries, providing little or no relief. These results appear consistent with recent findings by (Peña and Rodríguez, 2019) (International-Energy-Agency, 2020a) and (IEEE-Spectrum, 2020), specifically indicating high electricity pricing in Germany. (International-Energy-Agency, 2020a) specifically indicated that countries such as Germany and Italy impose higher taxes that other countries do not impose on their industrial consumers such as the excise tax. These findings of high electricity prices due to high taxes specifically in EU countries are supported by(Karimu and Bali Swain, 2023). Our studies align with this by indicating a move in Germany from a lower pricing category to a median category when taxes were included. In addition, (Finnish-Energy-Industries, 2010) stated that companies in countries such as the US, Switzerland, Portugal and Great Britain are not subjected to power consumption tax which might partly explain why the US and Switzerland still retain low prices after tax.

(Peña and Rodríguez, 2019) their study of household electricity pricing showed that some EU countries such as Italy, Germany, Austria, and Spain had increasing pricing with all taxes included. Tax change in countries with high prices such as Germany, Italy, Spain, and Austria have increased with a wide disparity, while tax change in countries with low prices such as the US, Norway, and Finland has been minimal with a low disparity. A further explanation of the low pricing as revealed by (International-Energy-Agency, 2020a) for Norway and other Scandinavian countries is connected to the abundance of renewable sites guaranteeing low production costs, while the US is reported to have benefited from low fuel costs.

In summary, when taxes are included, countries falling in the median range (compared to the low range) partly suggest a higher electricity consumption tax levied by the governments of such countries. In addition, the median-range end-user electricity price is also connected to the high import of energy fuels, unfavourable government policies and external factors such as volatility in global prices of energy fuels. As discussed by (Halbrügge et al., 2021), (Min, 2022), (Aguirre et al., 2023) the impact of the COVID-19 pandemic and more recently the Russian-Ukraine conflict has been an external factor affecting the global production and supply of energy. High energy prices have been noted to increase the price of consumer electricity (Khudaykulova et al., 2022). Countries in the high price range (such as Italy) compared to the countries falling in the median range suggest a much higher tax component levied. This is also connected to the dependence on fossil fuel imports and the value-added tax and excise tax levied on consumers

The box plot of our dataset in Figure 3 confirms large variability in IEPIT. The time series plot of Figure 4 shows the extent of annual tax increases for some countries such as Germany and Italy in comparison to countries such as the US, New Zealand, Canada, and Finland which had very low variability in taxes. Figures 3 and 4 though could indicate the extent of tax change per country but are insufficient to reveal possible related reasons for countries having similar electricity prices as noted earlier. Also, Figure 4 may not show the contribution of the taxes as the share of renewables increases.

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5.2. Discussion on Regression Analysis

5.2.1. Regression Analysis Excluding Tax (Model 1c)

Based on our results in section 4.2.1, as the share of renewables (Wind, Solar PV, and Solar thermal) increases, it is more likely for the IEP (IEPET) of the countries under study to move from lower pricing to higher pricing.Our result for GDPpc is consistent with the findings of (del-Río et al., 2019) and (Oosthuizen et al., 2021) who showed a positive association of GDPpc with retail electricity pricing based on the EU panel data reviewed. As (del-Río et al., 2019) noted, GDPpc reveals information about the structure and development of an economy. Moreover, (Oosthuizen et al., 2021) described GDPpc information as an indicator of demand metrics for electricity.

5.2.2. Regression Analysis Including Tax (Model 2b)

With the addition of taxes to IEPET and as the share of renewables increases, our association results indicate a higher chance of the countries moving to a higher category of pricing. As earlier indicated, tax components have varied across countries. For example, taxes have been higher in certain countries such as Italy, and Germany, while countries such as the US, France, Canada, and Denmark have levied low taxes in comparison. Our results for pricing including taxes are partly consistent with the discussion of a move of countries such as Germany into a higher degree of electricity pricing due to an increase in electricity tax and high output of renewables (IEEE-Spectrum, 2020).

With the introduction of taxes, GDPpc showed a similar positive association with electricity pricing data in both final models (1c and 2b). The comparative values indicate that for the period of study and based on our panel data, the effect of the introduction of taxes was not very important to bring about a higher magnitude of a positive association of GDPpc with IEP.

EIE continued to show a negative association compared to REG and GDPpc when taxes were included. However, the association was of lesser magnitude compared to the excluding tax (Model 1a) value of EIE. The non-significance of EIE (Model 2b) even at $P<0.1$ limits our discussion on the association in this section as non-significant variables might affect the precision of the model. Looking at our regression results for IEPET and IEPIT in the 19 years, we observed that as the share of renewables increased the contribution of taxes has had a much higher impact than what price increases due to inflation would have contributed to as seen in the price before tax. Regression results showed 38 times greater positive association with the introduction of taxes as the share of renewables increased. Therefore, our argument based on the regression, clustering and literature review is not on whether factors such as the introduction of renewables will lead to industrial electricity price increases or not but that the contribution of taxes has been significant in the period of study. Furthermore, our findings, while in line with the literature (del-Río et al., 2019) and (Oosthuizen et al., 2021) about renewable technologies being attributed to price increases, also highlight that taxes are the primary reason for price increases. These reiterate the paper's main contribution including the clustering analysis.

6. Conclusion

Using clustering techniques IEP of end-users consisting of both prices excluding tax termed as IEPET and pricing after tax (IEPIT) can be studied to understand the evolution of prices as societies adapt to increases in renewable technologies. Furthermore, OLR analysis could associate explanatory factors with price movements within the cluster groupings obtained. The clustering results indicated three (3) different IEP groups, excluding and including tax. Each group had a low-price range, median-price range, and high-price range. Countries with high dependence on energy imports and unfavourable production environment or inadequate local energy sources are more likely to be in the medium to the higher range of electricity pricing groups both before and after-tax components are included.

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The IEPET and IEPIT data showed an increasing trend from 2000 to 2018, though certain periods of price decrease were observed within the years. The periods of the electricity price study (either quarterly or annually) enunciate the increasing or decreasing IEP. Taxes, inflation, and external factors might have contributed to the price increases over the 19 years in the study, but the contribution of taxes has been more significant.

The findings of this research are useful – firstly – in identifying key factors contributing to increasing or decreasing IEP. Regression results show that taxes have an amplifying effect on IEP, as a function of the share of renewable energy varies. This implies that with adequate monitoring and evaluation of tax regulations, countries can manage the pricing increases after tax. Secondly, individual countries can understand the types of national energy policies, technological developments, or tax interventions in the industrial sectors that have been beneficial in keeping prices low or high. For example, the policies of green energy alternatives introduced by the US and Germany have had different effects on electricity pricing (IEEE-Spectrum, 2020). While taxes (and prices to some extent) have soared in Germany and Italy, prices have remained stable in the US. Countries within the same region, such as the EU with interconnections in energy markets, can also institute better policies to ensure that their pricing is not far below or far above the average pricing in the region. Thirdly, developing economies that have been fossil fuel dependent and with a growing industrial base, will find studies about IEP useful when transitioning their electricity technology portfolio. Based on this study, additional factors that could cause countries to fall in the median and high-range IEPET and IEPIT include the high cost of energy production. This can result in high living standards for people in such countries, as industries often transfer high production costs of goods and services to final consumers. Countries with low-range pricing can take advantage of their cheaper electricity pricing to further grow their industrial base and export electricity to other countries.

Based on the regression results, it may be argued that a reduction in renewables (thereby increasing fossil fuels) will be a justifiable pathway to a reduction in industrial electricity pricing. However, the environmental cost (particularly external costs) associated with non-renewable electricity generation, outweighs the increases in pricing due to taxes (Oosthuizen et. al, 2022). Therefore, it would be counterintuitive to focus on reducing renewable electricity generation to avoid increasing prices in the short run. Rather, the focus should be on reducing the environmental cost on non-renewable electricity generation in the long run.

Similar investigations in non-OECD regions such as Africa, Latin America, and parts of Asia may reveal other interesting conclusions. Obtaining good-quality historical data sets for these regions is a challenge (Zhai et al., 2023). Furthermore, studies on electricity price variation internally within large countries (such as the USA and Canada) rather than using annual single pricing could reveal additional insights. A comparative analysis of household and industrial electricity pricing patterns could further offer more insights into the discussion of electricity pricing for better policy formulation and industry use.

The grouping of countries into clusters presents an average overall effect of the independent factors on the IEP data. The association between pricing and renewable energy considered in this study could be enhanced if additional renewable sources such as hydroelectric energy and bioenergy are integrated. Developing countries face additional social and economic development pressures, as compared to OECD countries. In such cases, multi-criteria analysis can be used to consider explanatory factors such as regulatory systems and other possible qualitative factors that can have an impact on industrial electricity prices. Lastly, using other econometric/regression models and validity tests that can investigate some of the variables that did not conform to the POA of the OLR analysis, could provide new directions.

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Conflicts of Interest: The authors declare no conflicts of interest

Appendix A

Table A1. Descriptive statistics for the Data input.

Data type	Number of observations	Minimum value	Maximum Value	Mean	Standard deviation
IEPET(US cents)	418	1.580139	22.94675	9.700091	4.063308
IEPIT (US cents)	418	1.580139	32.76514	10.64532	5.050645
REG	418	0.000000	0.51	0.051	0.077
GDPpc	418	7774.482	4262321	386160.4	966938.0
EIE	418	6.06	48.81	27.95	11.04
ED	418	-843.481879	93.981260	11.192270	149.064917

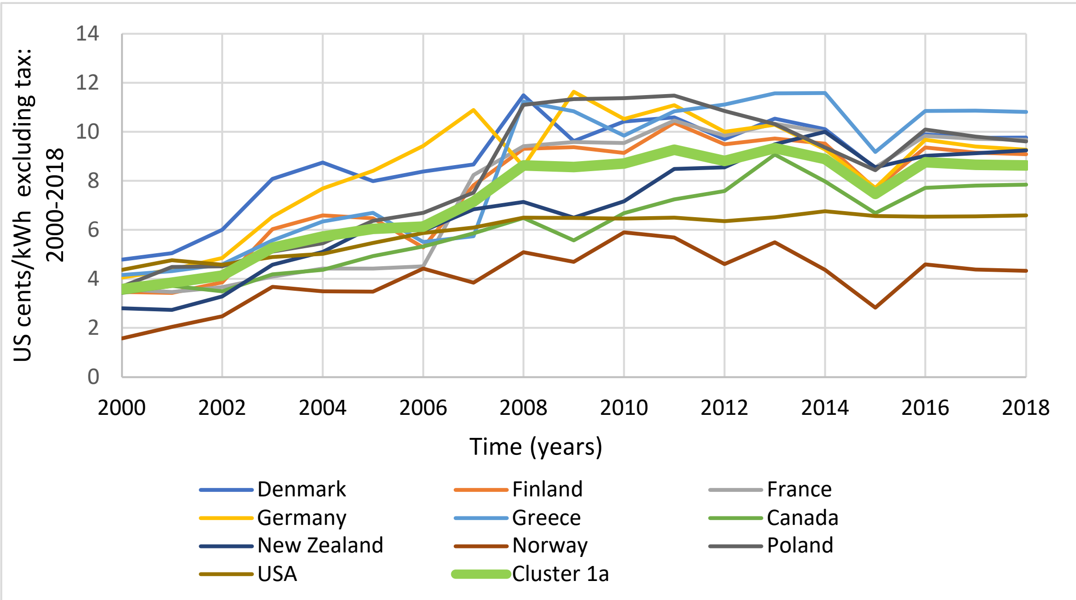

Figure A1. Plot of countries within the low-range pricing cluster (Excluding tax).

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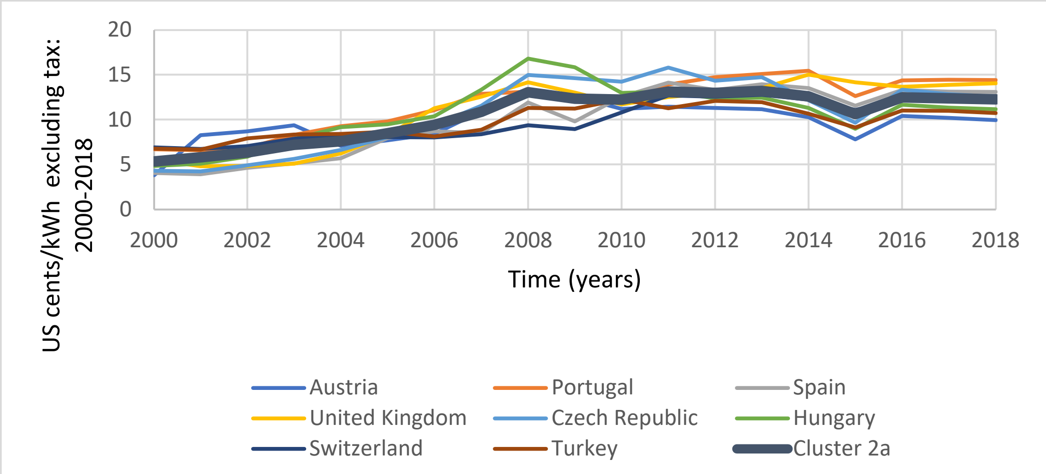

Figure A2. Plot of countries within the median-range pricing cluster (Excluding tax).

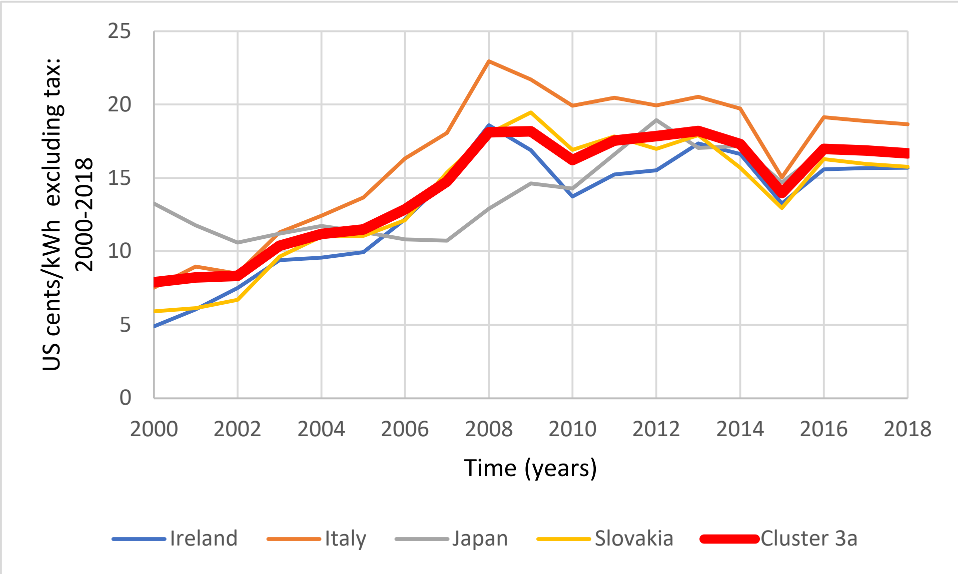

Figure A3. Plot of countries within the high-range pricing cluster (Excluding tax).

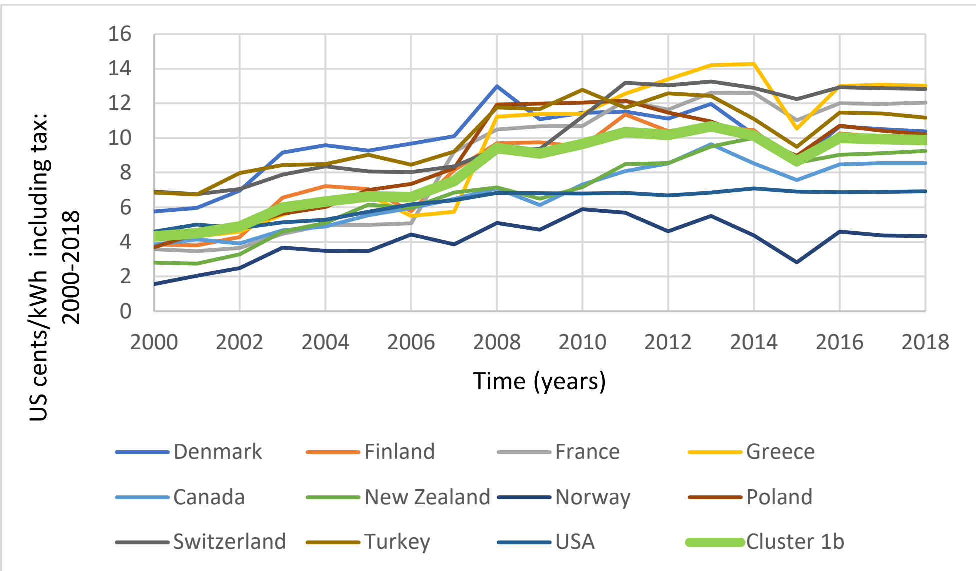

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Figure A4. Plot of countries within the low-range pricing cluster (Including tax).

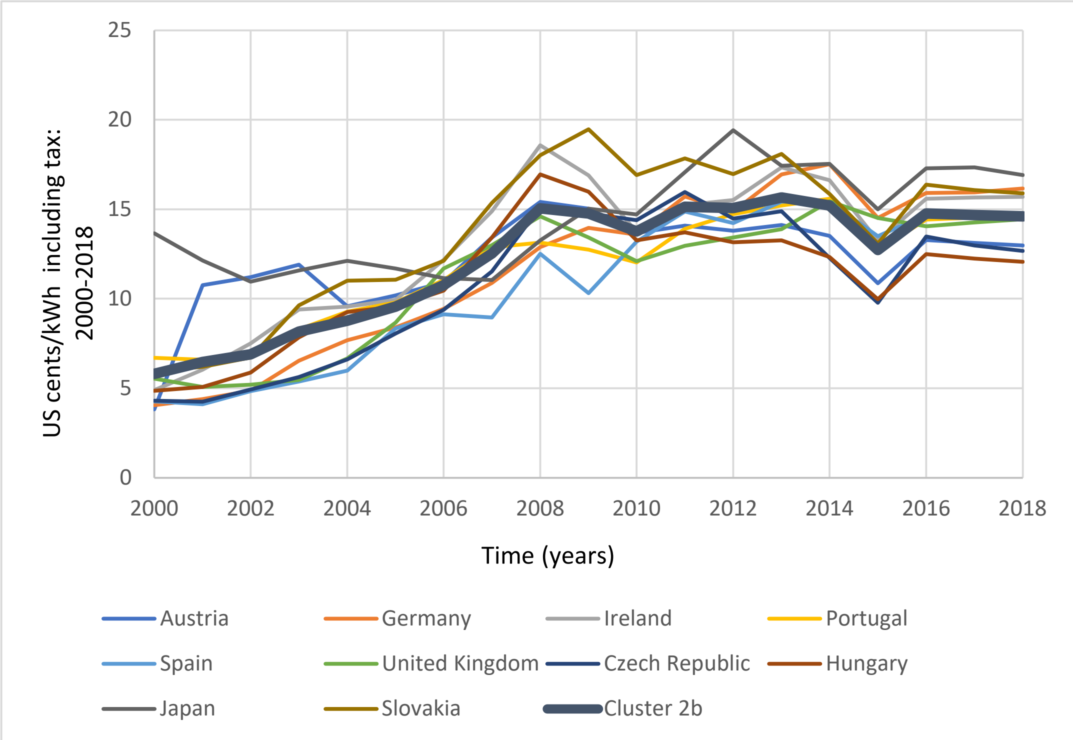

Figure A5. Plot of countries within the median-range pricing cluster (Including tax).

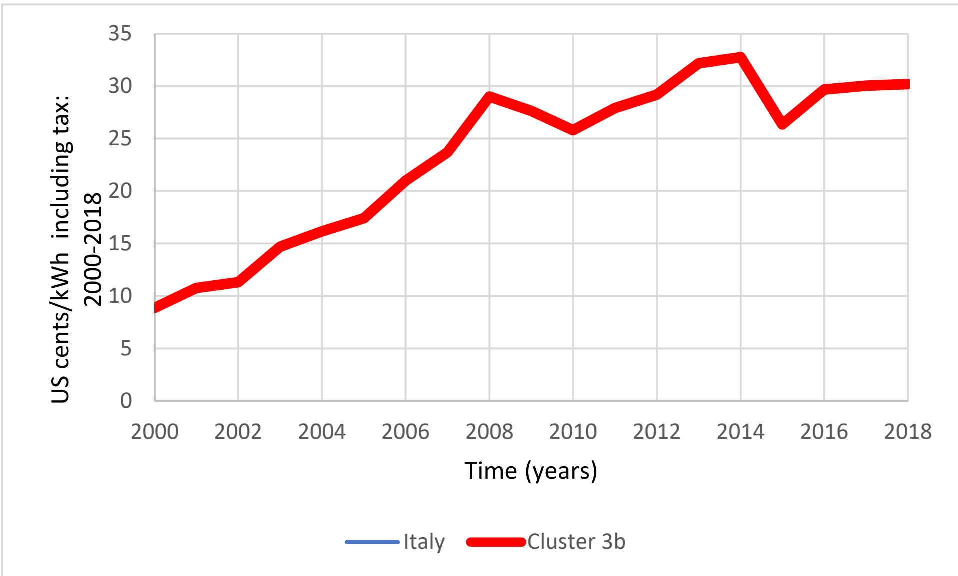

Figure A6. Plot of the countries within the high-range pricing cluster (Including tax).

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