Empirical Analysis of Inter-Zonal Congestion in the Italian Electricity Market Using Multinomial Logistic Regression

energies

MDPI

Article

Empirical Analysis of Inter-Zonal Congestion in the Italian Electricity Market Using Multinomial Logistic Regression

Mahmood Hosseini Imani

Department of Energy, Politecnico di Torino, 10129 Torino, Italy; mahmood.hosseiniimani@polito.it

Abstract: The increasing integration of renewable energy sources (RESs) into the Italian electricity market has heightened inter-zonal congestion challenges as power flows vary across importing and exporting zones. Utilizing a Multinomial Logistic Regression model as an empirical approach, this study investigates the key factors driving inter-zonal congestion between zonal pairs from 2021 to 2023, focusing on how local and neighboring zones' RES generation (wind, solar, and hydropower) and demand dynamics impact congestion probabilities. The findings reveal that increased local RES generation generally reduces the likelihood of congestion for importing regions but increases it for exporting zones. Specifically, higher wind and solar production in importing zones like CNOR and CSUD alleviates congestion by reducing the need for imports, while in exporting zones, such as NORD and CALA, increased RES generation can exacerbate congestion due to higher export volumes. Hydropower production shows similar trends, with local production mitigating congestion in importing zones but increasing it in exporting zones. In addition to the effects of local generation and demand within each zonal pair, the generation and demand from neighboring zones also have a notable and statistically significant impact. Although their marginal effects tend to be smaller, the contributions from neighboring zones are essential for comprehending the overall congestion dynamics. These insights underscore the need for strategic RES placement to enhance market efficiency and minimize congestion risks across the Italian zonal electricity market.

Keywords: inter-zonal congestion; Italian electricity market; RESs integration; zonal price; multinomial regression model

Citation: Hosseini Imani, M. Empirical Analysis of Inter-Zonal Congestion in the Italian Electricity Market Using Multinomial Logistic Regression. *Energies* **2024**, *17*, 5901. https://doi.org/10.3390/en17235901

Academic Editor: Yuji Yamada

Received: 17 October 2024
Revised: 13 November 2024
Accepted: 23 November 2024
Published: 25 November 2024

1. Introduction

The rapid advancement of Renewable Energy Sources (RESs), particularly wind, solar, and hydropower generation, has revolutionized the energy sector, presenting significant opportunities and challenges. These developments are reshaping the economic and technological landscape of power grids globally.

Economically, integrating additional RESs into the grid necessitates a thorough evaluation of revenues and costs. This includes understanding the impact on spot prices and the broader market dynamics. Moreover, the variability of RESs introduces complexities in maintaining a balanced electricity transmission system as the balance between supply and demand becomes more intricate. On the other hand, the introduction of substantial renewable energy capacities and production has implications for network functionality and congestion management. Certain regions rich in natural resources are ideal for renewable energy projects. However, the infrastructure in these areas may not support the efficient transfer of this energy to consumption centers, potentially leading to increased congestion and stress on the grid. Conversely, in regions where RESs can supplement local demand, it can ease congestion and stabilize the network.

The geographic disparity between energy production and consumption sites further complicates the situation. When these locations are far apart, transporting renewable energy becomes more challenging, increasing the risk of congestion. However, if renewable energy production is strategically aligned with consumption needs, it can have a stabilizing effect on the grid.

Interconnecting zonal grids and enhancing transmission capacities are crucial for effectively integrating RESs. In the zonal electricity market with interzonal transmission lines with different bidding zones (exporting and importing zones), the impact of RES generation on congestion is a critical area of study.

Recent studies have extensively examined the effects of RES integration into the electricity market across various countries, employing data analytics and sophisticated econometric models. These studies utilize historical data on electricity prices, demand, and RES production to provide valuable insights into the economic and operational impacts of RESs [1–9].

An empirical analysis focusing on a market in the United States, MISO, over an eight-year period (2008–2016) identified a substantial influence of wind generation on reducing wholesale electricity prices, with a decrease ranging from $0.14 to $0.34 per MWh for each additional 100 MWh of wind generation. Notably, the marginal impact of wind on prices has diminished over time due to shifts in supply and demand dynamics and market structure adaptations to better accommodate variable generation [3]. This study underscores the strong influence of wind on price reduction; however, it is limited in its focus on pricing without exploring the impact on inter-zonal congestion or grid reliability. Furthermore, while the diminishing marginal impact of wind over time is noted, it lacks an analysis of how shifts in congestion might accompany changes in market structure.

Building on this, a study examining the Spanish electricity market from 2015 to 2020 found that electricity flows and RES production significantly influence day-ahead prices. Employing a combination of SARMAX and GARCH models, the study revealed a Merit Order Effect (MOE) where wind and solar PV power reduce prices at most times of the day. Interestingly, while wind power significantly increases price volatility, electricity inflows help stabilize prices and reduce volatility, indicating the complex interplay between renewable generation and market stability [10]. While the findings add valuable insights into price volatility, the study does not address the effects on inter-zonal congestion under transmission constraints.

Similarly, in Western Denmark, where wind energy accounts for more than 50% of the yearly production, an analysis of market data from 2009 to 2021 revealed that although extreme price fluctuations are slightly rising, the value factor of wind energy remains stable. This stability is linked to the region's adaptable infrastructure, which includes power plants, interconnectors, and the electrification of district heating. This infrastructure effectively handles the high levels of wind energy [11]. However, it lacks an analysis of how such infrastructure impacts congestion. The results from Western Denmark are consistent with those from China, where a review of the wind Feed-in Tariff (FIT) policy from 2005 to 2016 indicated notable regional variations in wind power development factors, supporting a segmented FIT policy designed for regional grids rather than a national policy [12]. While the findings emphasize policy effectiveness in managing regional RES growth, they do not address RES impacts on congestion or inter-zonal stability.

Extending this exploration to less mature electricity markets in Greece, Hungary, and Romania, a study confirmed the MOE, showing that increased RES generation leads to reduced electricity prices. The econometric models revealed that the MOE varies by country, with Hungary experiencing a more pronounced effect due to its smaller power system. Interestingly, in Romania, solar generation was positively correlated with electricity prices during high-load periods, highlighting the unique market dynamics in different regions [13]. Although it highlights regional market dynamics, it overlooks the congestion-related effects of RES.

The introduction of the NordLink interconnector between Norway and Germany further exemplifies the impact of RES on electricity markets. Quantile regression analysis indicated that NordLink reduced German electricity prices while increasing prices in Norway's NO2 region, demonstrating price convergence. Additionally, NordLink decreased price volatility in Germany but exacerbated it in NO2, particularly affecting peak prices [14]. This study provides an essential perspective on price dynamics across borders; however, it does not address congestion effects related to interconnectors. Besides this study, a recent study applied data-driven and AI approaches to address congestion challenges in sustainable energy systems, where transmission loads rise due to remote RES installations [15]. This study used Gradient Boosted Trees with SHAP values to develop an explainable model for analyzing congestion in Germany's transmission grid, identifying key congestion drivers and mitigators. The study found northern wind power to be a primary congestion driver, with cross-border trade, especially with Denmark, as a significant contributor. Conversely, alpine run-of-river generation helps mitigate congestion, highlighting the potential benefits of market design changes, such as bidding zone splits, to alleviate grid stress.

As RESs increase volatility in modern power systems, the risk of transmission congestion grows, challenging traditional power flow-based methods in capturing diverse operational scenarios. A recent study utilized a data-driven, machine learning-based model for real-time congestion risk assessment, leveraging historical and current operational data in France to provide early warnings for transmission congestion. By using Max-Relevance and Min-Redundancy (mRMR) for feature selection, this model improves computational efficiency while achieving over 93.3% accuracy in predicting congestion risk under various operational conditions [16].

Addressing the challenges of rising RES integration, Ref. [17] introduced a data-driven framework validated on the IEEE 118-bus and China Central Region power systems for intrahour congestion forecasting and proactive relief using a histogram-based gradient tree boosting (HGTB) model. By training on historical congestion data, the model predicts real-time congestion severity and probability, enabling operators to anticipate and mitigate congestion. This approach also includes a proactive relief strategy that coordinates control schemes across different time scales, effectively utilizing adjustable resources.

Moreover, modeling cross-border electricity price differences in the Nordic market using GARCH-based models revealed strong regime dependence and volatility clustering, with the Markov-switching GARCH model providing the best predictive performance. Accurate forecasts of cross-border price differences are crucial for managing risks in financial transmission rights markets [18].

In the Nord Pool market, variations in the energy supply mix significantly impact electricity prices across different Nordic countries. In ref. [19], the research conducted within the Nord Pool market is particularly insightful, as it explores how different energy sources and cross-border interactions influence electricity prices. This study has two primary objectives. The first is to estimate how changes in generation supply within Nordic countries affect neighboring countries' day-ahead prices. The second objective is to analyze the impact of cross-border energy trade and wind energy production on the price variations between Western Denmark and its Nordic neighbors. To meet these objectives, the study employs three distinct linear regression models to examine the price trends in selected regions (SP, DK1, and FI) within the Nord Pool market. By incorporating seasonal indicators and yearly binary variables, the models control for temporal fixed effects. The analysis reveals that changes in energy supply, particularly nuclear production, significantly impact electricity prices across different Nordic countries. For instance, decreases in nuclear production levels were found to affect average annual prices more substantially than increases. Furthermore, planned cross-border energy exchanges significantly influence price disparities, with varying impacts across trading partners. The most significant price differences are observed between western Denmark and southern Norway, while smaller differences are noted within intra-national trading partners.

An analysis of the Italian electricity market between 2015 and 2019 using a multivariate regression model validated the Merit Order Effect (MOE). This study demonstrated that wind and solar energy generation results in lower prices across various zones. The degree of this price reduction differs across zones, indicating that some regions are better equipped to incorporate RESs due to factors such as cross-zonal exchanges and storage capabilities. These results underscore the need for customized policy measures to improve RES integration into electricity markets [20].

As the European electricity market becomes more interconnected, managing intra-zonal congestion under national regulations presents challenges for coupled cross-zonal markets. Recent research introduces a decision-tree-based classification to categorize the various congestion management methods used by European TSOs, highlighting a trade-off between efficiency and implementation complexity. This classification reveals that, in severe congestion scenarios, precise locational signals are essential to align market clearing with network constraints, while less severe congestion can be managed with simpler methods based on congestion predictability and resource availability [21].

There are limited studies investigating the influence of RESs production on inter-zonal congestion in Italy. Ref. [22] presents a comprehensive study that examines the effect of intermittent RESs on inter-zonal congestion between different zone pairs using a multinomial logit model for the year 2015. The findings of the model indicate that an increase in the production from the local RESs reduces the likelihood of entry congestion but increases the probability of exit congestion with reference to situations with no congestion. A similar pattern is observed with increased hydroelectric production. Conversely, an increase in local demand typically raises the chances of entry congestion (caused by higher imports) and lowers the likelihood of exit congestion.

In recent literature, advanced machine learning models such as Support Vector Machines (SVM), Gaussian Process Regression (GPR), K-Means, and Neural Networks (e.g., LSTM for time-series data) have been widely used in electricity market analysis, particularly for forecasting market behavior [23–26]. These models offer high predictive accuracy by capturing complex, non-linear relationships among variables. However, they often act as "black-box" models, where the interpretability of individual variable impacts—essential for policy insights in market studies—is limited.

Our study offers several contributions to existing literature. We implemented Multinomial Logistic Regression (MLR) to assess the electricity market, particularly in the context of congestion analysis. The MLR model, in contrast to advanced machine learning models, provides clear interpretability of variable influence on zonal price differences, enabling a detailed understanding of how specific factors, such as wind, solar, and hydropower generation, affect congestion probabilities across zones. While MLR may not match the raw predictive accuracy of more sophisticated models, its interpretability is crucial for electricity market analysis, especially in the context of managing inter-zonal congestion and renewable energy integration. Additionally, we broaden the analysis by examining the updated configuration of the Italian electricity market, which now consists of seven geographical zones instead of the previous six. This allows us to assess the validity of empirical models following this structural change. Moreover, as a contribution of this study, we analyze the cross-zonal influence of RESs on neighboring zones by investigating how changes in RES production and consumption in one zone affect inter-zonal congestion in adjacent zones. Through this analysis, we examine how changes in renewable energy generation in one zone impact congestion patterns in neighboring zones. By extending the analysis beyond individual zones to consider interdependencies, we provide a more comprehensive view of how RES installations influence regional congestion dynamics across the Italian market.

The rest of the paper is organized as follows: Section 2 provides an overview of the Italian electricity market, including the inter-zonal pricing mechanism. It also presents a statistical summary of zonal price differences, demand, and intermittent RESs generation across various zones within the market. Section 3 expresses the multinomial logistic regression model and utilizes econometric models to show the relationship between independent and dependent variables. Section 4 provides empirical results and goes into depth interpreting the outcomes of the models. Lastly, Section 5 concludes the paper.

2. Italian Electricity Market

The Italian wholesale electricity market (IPEX (Italian Power Exchange)) was launched in April 2004 and transformed into an exchange in January 2005 following the liberalization of demand-side bidding [27]. The electricity market is divided into the Spot Electricity Market (MPE) and the Forward Electricity Market (MTE). The MPE includes the Day-Ahead Market (MGP), Intra-Day Market (MI), Daily Products Market (MPEG), and Ancillary Services Market (MSD).

The Italian electricity market is divided into geographical and virtual zones, structured primarily to enhance system security and manage regional transmission constraints. These zonal divisions impose limits on the physical electricity exchanges between zones, helping to prevent grid congestion and maintain stability within Italy's interconnected network. The geographical zones, defined by Terna S.p.A. (the Italian TSO) and approved by the Italian Regulatory Authority for Energy, Networks, and Environment (ARERA), include the North (NORD), Center North (CNOR), Center South (CSUD), South (SUD), Calabria (CALA), Sicily (SICI), and Sardinia (SARD). These zones are established based on grid topology, demand distribution, and the location of primary power generation sources.

In addition to these geographical zones, Italy has virtual zones representing interconnection points with neighboring countries. These virtual foreign zones facilitate cross-border trade, allowing Italy to engage in electricity imports and exports with its neighboring markets, which include France, Switzerland, Austria, and Slovenia, among others. Virtual zones help manage the flow of electricity across national borders and integrate Italy's market with the broader European electricity market.

Each zone has distinct limitations on transit flows designed to prevent congestion within zones and regulate inter-zonal transmission. As a result, the market can experience different zonal prices within the same hour, reflecting localized supply-demand balances and transmission constraints. When demand or generation patterns create bottlenecks between zones, zonal prices diverge, signaling congestion and prompting adjustments in dispatch mechanisms. This structure ensures that while the national grid remains unified, localized price signals can reflect the actual costs and constraints of delivering electricity across Italy's diverse regions, thereby enhancing efficiency in managing inter-zonal flows.

Figure 1 displays the locations of the seven geographical zones within the IPEX [28].

Figure 1. Map of the Italian geographic zone [28].

The Italian power transmission network is designed to efficiently interconnect its diverse geographical zones, ensuring reliable electricity flow across the country. The pair CNOR-CSUD represents a crucial central corridor, facilitating power flow between the populous and industrially active Center North and Center South regions. CNOR-NORD highlights the transmission pathways supporting the northern region as a highly industrialized and energy-consuming zone from the central and southern regions. The CSUD-SUD connection underscores the importance of delivering power to the southern regions, enhancing stability and supply to less industrialized but significant areas. CNOR-SARD and CSUD-SARD emphasize the vital submarine cable connections that link the mainland to the island of Sardinia, ensuring its integration into the national grid. Similarly, the SICI-CALA pair illustrates the interdependencies between Sicily and Calabria with strategic transmission lines. Lastly, the SUD-CALA connection reinforces the network's capability to supply power to the southernmost mainland zones, demonstrating the system's robustness and adaptability in addressing regional energy needs. Each of these pairs exemplifies the comprehensive and resilient nature of Italy's power transmission infrastructure, which is essential for maintaining a stable and efficient national grid.

2.1. Price Formation Mechanism

The Italian electricity price mechanism in the Day-Ahead Market (MGP) utilizes an iterative process to establish market-clearing prices [28]. Participants submit their supply offers and demand bids from the ninth day before delivery (starting at 8 a.m.) until the day before delivery (closing at 12 p.m.), indicating quantities and prices based on auction negotiation rules. Initially, the MGP algorithm operates at a national level, sorting all valid supply offers by ascending prices on a combined supply curve and all valid demand bids by descending prices on a combined demand curve. If interzonal transmission flows are within limits, the market-clearing price is determined by the intersection of these curves. However, if any interzonal transmission line constraints are violated, the market is divided into sub-markets (exporting and importing zones), each with its own merit order and demand curve. The algorithm then repeats the process within each sub-market until all network constraints are respected. After establishing the zonal prices, an average price, known as the National Single Price (PUN), is calculated. This PUN is weighted by total consumption, net pumped-storage units' consumption, and foreign zone consumption to meet the demands [28]. This iterative approach ensures that prices are determined efficiently while adhering to network constraints.

Figure 2 illustrates the price formation mechanism in the MGP.

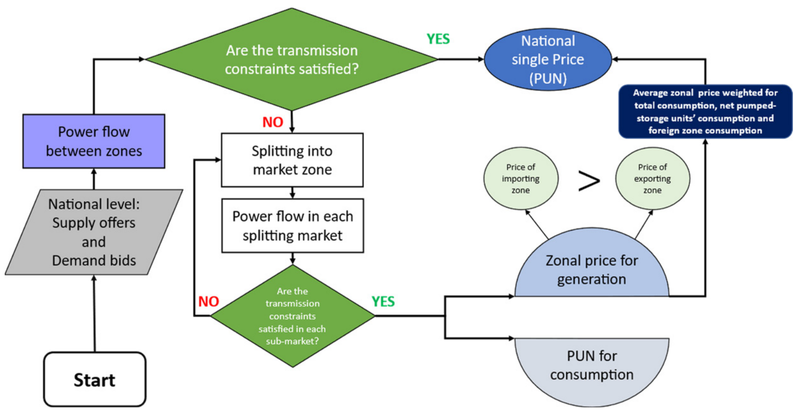

Figure 2. Diagram of the price formation mechanism in MGP.

In this context, a positive price difference occurs when the electricity price in the first zone of a pair is higher than in the second zone, indicating that the first zone is importing electricity from the second zone. Conversely, a negative price difference happens when the electricity price in the first zone is lower than in the second zone, signifying that the second zone imports electricity from the first zone.

2.2. Descriptive Statistics

This section provides a statistical summary of zonal prices, zonal demand, and zonal RES generation in the Italian electricity market for the period from 2021 to 2023, offering a comprehensive overview. The focus on this recent period (from 2021 to 2023) is especially relevant due to significant market and regulatory changes in the Italian electricity market structure, which came into effect on 1 January 2021. Notably, the redefinition of zonal boundaries included the introduction of Calabria as a new geographical zone, increasing the number of zones from six to seven. This restructuring reflects updated considerations in transmission capacity and regional demand-supply balances, directly impacting congestion patterns [28].

The integration of RESs into the Italian electricity generation mix has significantly increased over the past decade. In 2023, total electricity production in Italy was roughly 226,125 GWh. Of this value, 10.4% (23,440 GWh) was from wind energy, 10.5% (23,800 GWh) from solar, and 17.4% (39,422 GWh) from hydro production [29].

As depicted in Figure 3, each zone is accompanied by box plots detailing the distribution of power generation for wind, solar, hydro, and total electricity demand over the period from 2021 to 2023. The red dots on the box plots indicate the mean values for each category.

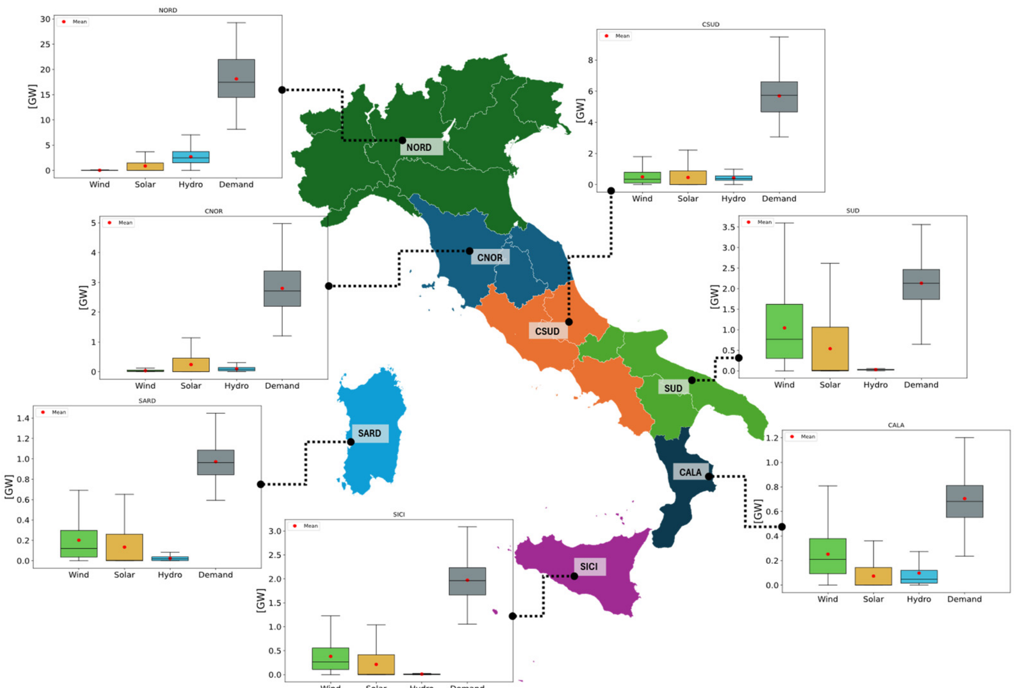

Figure 3. Electricity generation from wind, solar, and hydropower, and electricity demand across different market zones in Italy (2021–2023).

The analysis of power generation and demand across various market zones highlights key extremes. Over the period from 2021 to 2023, the NORD zone has the highest electricity demand (mean: 18,123 MW) and hydropower generation (mean: 2710 MW), while the SARD zone has the lowest hydropower generation (mean: 23 MW). The SUD zone leads in wind power generation (mean: 1044 MW), with the CNOR zone having the lowest (mean: 35 MW). Solar power generation is highest in the NORD zone (mean: 880 MW) and lowest in the SICI zone (mean: 11 MW). The CALA zone has the lowest electricity demand (mean: 705 MW) [30].

Detailed data on the annual averages of wind, solar, and hydro production, as well as load consumption across various electricity market zones in Italy from 2021 to 2023, are provided in Tables A1–A4 in Appendix A.

Figure 4 presents the statistical analysis of the average zonal prices and shows the frequency of the congested hours for each zonal pair when Italian zonal market prices are paired over 1-h intervals annually [28]. The congested hours refer to the time periods when there is a transmission constraint between different zones in the Italian electricity market, leading to price differences between zones. During congested hours, the demand for power flow between zones exceeds the transmission capacity, causing either an increase in price in the importing zone (where demand is high) or a decrease in price in the exporting zone (where supply is high).

Figure 4. Frequency of congested hours: 2021–2023.

Figure 5 illustrates the frequency of positive and negative zonal price differences for various zonal pairs over the three years (from 2021 to 2023) [28]. The graphs on the left and right depict the frequency of positive and negative price differences, respectively.

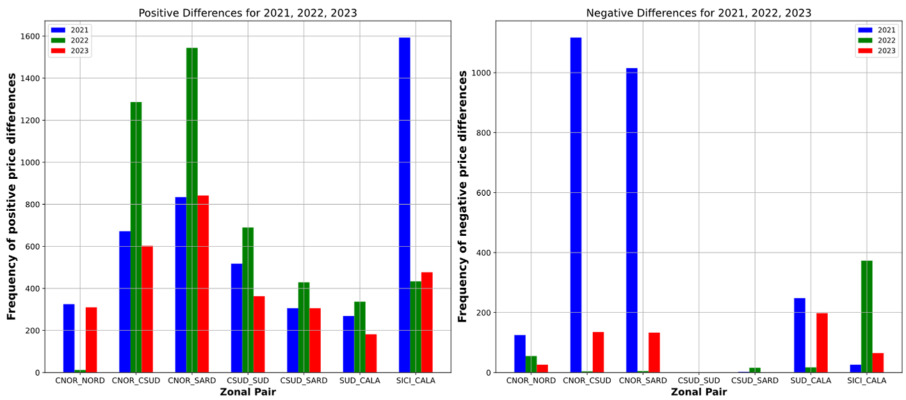

Figure 5. Frequency of positive and negative zonal price differences.

Figure 6 displays the percentage of positive and negative price differences across different zonal pairs over the entire period of 2021 to 2023 [28].

By analyzing the frequency of zonal price differences (Figure 5) alongside the percentages of positive and negative price differences for various paired zones (Figure 6), it is evident that CNOR plays a significant role as an importer in the CNOR-NORD, CNOR-CSUD, and CNOR-SARD pairs. This is demonstrated by the higher percentage of positive price differences compared to negative price differences in these pairs. A detailed description of the statistics for each zonal pair is provided as follows.

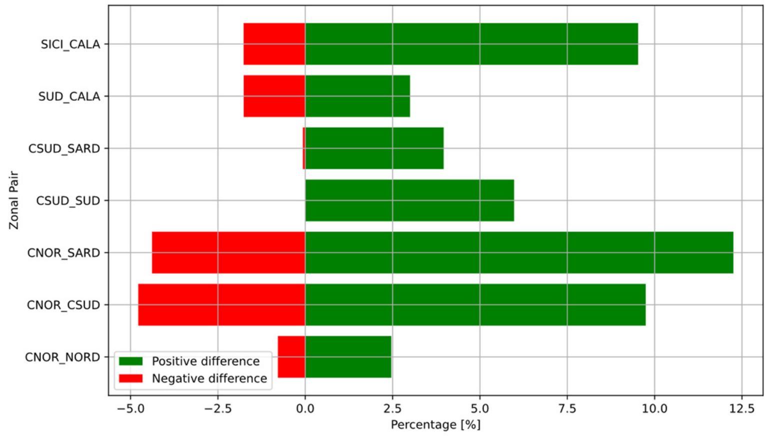

Figure 6. Percentage of positive and negative price difference; 2021–2023.

For the CNOR and NORD pair, there were noticeable fluctuations in the number of congested hours between 2021 and 2023. By examining the average prices and the percentage of positive versus negative price differences, it is evident that CNOR predominantly played the role of an importer (with a 2.5% positive price difference compared to 0.8% negative). As shown in Figure 5, the positive price difference indicating CNOR's imports from NORD significantly dropped in 2022 by 96% relative to 2021. This decrease can be largely attributed to a substantial reduction in hydroelectric generation in the NORD zone (−36%), which led to a decreased electricity flow from NORD to CNOR. Despite this, CNOR consistently maintained its importer role in both 2021 and 2023. Although the generation from traditional sources, such as natural gas power plants, impacts zonal pair congestion, this study focuses on the influence of renewable energy sources.

For the pair CNOR and CSUD, we observe significant changes in the number of congested hours from 2021 to 2023. The data reveals that CNOR has consistently played the role of an importer (9.7% positive price difference vs. 4.8% negative price difference). In 2022, the number of positive price differences surged to 1286 h while negative price differences dropped drastically to 4 h, reflecting an increased dependency of CNOR on CSUD. This coincides with a notable increase in solar generation in CSUD (about 19.5%) and a slight decrease in wind production in CNOR. While the positive price difference hours decreased to 603 in 2023, the negative price difference hours increased to 135, indicating a slight shift but still maintaining CNOR as an importer. This trend is partly due to an increase in wind production in CSUD (19.2%).

For the pair CNOR and SARD, the data from 2021 to 2023 indicates significant fluctuations in congestion patterns, with CNOR predominantly acting as an importer (12.3% positive price difference vs. 4.4% negative price difference). CNOR had 834 positive price difference hours compared to 1015 negative hours, showing a balanced yet slightly higher importation in SARD. Positive price difference hours increased to 1544, while negative hours dropped to 5, highlighting a sharp increase in CNOR's dependency on SARD. This coincides with a significant increase in solar generation in SARD (about 34%) and a decrease in hydro production in CNOR (46.3%).

For the pair CSUD and SUD, the data from 2021 to 2023 shows consistent congestion patterns, with CSUD entirely acting as an importer. Notably, there is a complete absence of negative price differences (0% negative price difference) throughout this period. The persistent zero frequency of negative price differences highlights that SUD does not need to import electricity from CSUD. Despite some fluctuations in the number of congested hours, CSUD consistently imported electricity from SUD throughout the three-year period, underscoring SUD's role as a consistent supplier.

For CSUD-SARD, throughout the period, CSUD consistently imported electricity from SARD, driven by changes in renewable energy generation in both zones, particularly with increased solar production in SARD.

For the pairs SUD-CALA and SICI-CALA, the data from 2021 to 2023 highlights CALA's evolving role in the electricity market. CALA has shown significant fluctuations in its role as both an importer and exporter of electricity. In the SUD-CALA pair, CALA's role shifted markedly over the years. In 2021, CALA was a net exporter to SUD, as evidenced by 248 negative price difference hours compared to 269 positive ones. However, in 2023, CALA became a net importer from SUD, showing 198 negative price difference hours against 182 positive hours. This shift occurred despite CALA's increased solar production (which rose by 54% from 2021 to 2023) and decreased electricity demand (from 722.6 MW in 2022 to 681.7 MW in 2023). The key to understanding this shift lies in the broader generation mix and market dynamics. While CALA increased its solar production, it might have experienced a reduction in other sources of electricity generation, such as gas or other fossil fuel-supplied generation, making it necessary to import more electricity. Additionally, SUD's increased wind production by 16.6% from 2021 to 2023 could have led to a surplus of electricity available for export to CALA. Hence, even with increased local renewable generation and decreased demand, CALA might still have needed to import electricity due to a reduction in other local generation sources.

In the SICI-CALA pair, CALA consistently played the role of a net exporter. In 2021, SICI heavily relied on CALA, reflected by 1593 positive price difference hours and only 26 negative ones. However, 2022 marked a shift towards a more balanced import-export relationship, with 434 positive price difference hours and 373 negative hours. This balance can be attributed to a significant increase in solar production in SICI, which jumped by 10.4% from 2021 to 2022 and 52.7% from 2022 to 2023. This surge in local renewable generation likely reduced SICI's dependency on imports from CALA, leading to a more balanced trade.

Despite the increase in solar generation in SICI after 2022, the trend of CALA exporting to SICI resumed dominance in 2023, with 477 positive price difference hours compared to 65 negative ones. This can be attributed to several factors. Firstly, the increase in solar generation in SICI may not have been sufficient to meet the rising demand or offset other reductions in energy production, such as hydro or wind, in the zone. Additionally, the improved solar generation in CALA, which saw a 54% increase in solar production from 2021 to 2023, likely strengthened its position as a reliable exporter. This increased capacity in CALA would allow it to consistently supply SICI even as SICI's own production rose, especially during periods of high demand or lower local generation in SICI.

Overall, the updated analysis for 2021 to 2023 reveals significant changes in average prices, frequency of congested hours, and price differences across various Italian market zones. These trends indicate shifts in market dynamics, particularly in the high frequency of positive price differences and variations in congested hours, reflecting changing import and export needs between zones. This comprehensive overview of recent trends in the Italian electricity market provides valuable insights for future planning and analysis.

3. Methodology and Data

Unlike black-box methods like artificial neural networks, regression models such as Multinomial Logistic Regression (MLR) effectively model the relationship between independent and dependent variables and have been widely applied in electricity market analysis [31]. The MLR model is employed to estimate the likelihood of various possible outcomes for a categorical dependent variable based on the independent variables. This study employs MLR models as an empirical approach to analyze the inter-zonal congestion between different zonal pairs of the Italian electricity market.

3.1. Multinomial Logistic Regression

The model is an extension of binary logistic regression to handle multiple classes. One key advantage of MLR over linear regression is its fewer stringent assumptions, such as not needing normally distributed residuals or homoscedasticity (equal variance of residuals).

For a response variable y with G categories $(g = 1, 2, 3, \ldots, G)$, the probability that y belongs to category g given the predictor variables x is [32] as follows:

$$P(y = g|x) = \frac{exp(x\vartheta_m)}{\sum_{kl=1}^{G} exp(x\vartheta_l)} \tag{1}$$

where:

ϑ_m: is the coefficient vector for category g
x : is the vector of predictor variables

The model uses one of the categories as the reference category. Assuming the reference category is G. The log-odds of category g relative to the reference category G is as follows:

$$\log \frac{P_r(y = g|x)}{P_r(y = G|x)} = x\vartheta_g \tag{2}$$

For a general MLR model, the equations can be written as follows:

$$\log \frac{P_r(y = g|x)}{P_r(y = G|x)} = \vartheta_{0g} + \vartheta_{1g}x_1 + \vartheta_{2g}x_2 + \cdots + \vartheta_{pg}x_m \tag{3}$$

For each $g = 1, 2, \ldots, G - 1$

Given the advantages of MLR, in this study, the MLR method is utilized to estimate the impact of wind, solar, hydropower generation, and demand on inter-zonal congestion.

The model assumes that the response variable y belongs to one of three distinct categories $(g = 1, 2, 3)$: ① positive price difference $(+1)$, ② negative price difference (-1), and ③ zero price difference (0). The zero price difference (no congestion) category is used as the reference category in the model. Additionally, the model includes a vector of independent variables, which comprises wind, solar, hydropower, generation from other zones, and demand, and these variables are assumed to influence the congestion between $Zone_i$ and $Zone_j$.

Model 1:

$$\begin{aligned} log\frac{P_r(y=+1)}{P_r(y=0)} &= \gamma + \delta_1 Wind_{t,zi} + \delta_2 Solar_{t,zi} + \delta_3 Hydro_{t,zi} + \delta_4 Demand_{t,zi} + \delta_5 Wind_{t,zj} + \delta_6 Solar_{t,zj} \\ &+\delta_7 Hydro_{t,zj} + \delta_8 Demand_{t,zj} + \delta_9 \sum_{k=1,k\neq i,j}^{NZ} Wind_{t,zk} + \delta_{10} \sum_{k=1,k\neq i,j}^{NZ} Solar_{t,zk} \\ &+\delta_{11} \sum_{k=1,k\neq i,j}^{NZ} Hydro_{t,zk} + \delta_{12} \sum_{k=1,k\neq i,j}^{NZ} Demand_{t,zk} + \delta_{13} DH_t + \delta_{14} DD_t + \delta_{15} DM_t + \delta_{16} DY_t + \varepsilon_{t,z} \end{aligned} \tag{4}$$

Model 2:

$$\begin{aligned} log\frac{P_r(y=-1)}{P_r(y=0)} &= \alpha + \beta_1 Wind_{t,zi} + \beta_2 Solar_{t,zi} + \beta_3 Hydro_{t,zi} + \beta_4 Demand_{t,zi} + \beta_5 Wind_{t,zj} + \beta_6 Solar_{t,zj} \\ &+\beta_7 Hydro_{t,zj} + \beta_8 Demand_{t,zj} + \beta_9 \sum_{k=1,k\neq i,j}^{NZ} Wind_{t,zk} + \beta_{10} \sum_{k=1,k\neq i,j}^{NZ} Solar_{t,zk} \\ &+\beta_{11} \sum_{k=1,k\neq i,j}^{NZ} Hydro_{t,zk} + \beta_{12} \sum_{k=1,k\neq i,j}^{NZ} Demand_{t,zk} + \beta_{13} DH_t + \beta_{14} DD_t + \beta_{15} DM_t + \beta_{16} DY_t + \varepsilon_{t,z} \end{aligned} \tag{5}$$

where P_r denotes probability, γ and α are the constant, the coefficient of interests, δ_1 to δ_{12} and β_1 to β_{12} represents the log-odds ratio, and $\sum_{k=1,k\neq i,j}^{NZ} Wind_{t,zk}$ represents the summation of the wind generation in other zone k. To control for the recognized seasonality of electricity prices, the model includes dummy variables indicating hour of the day (DH), day of the week (DD), month of the year (DM), and year (DY).

The log-odds ratio of an event is defined as the probability of the congestion occurring divided by the probability that the congestion will not occur, e.g., δ_1 represents the expected change in the relative risk of being positive price difference versus category no congestion by increasing a unit (1 MWh) in wind generation on the given zone.

3.2. Average Marginal Effects

To have a better explanation of the coefficient, using the average marginal effects can be advantageous. Given the MLR models provided, the marginal effects measure the change in the predicted probability of each category of the dependent variable with respect to changes in the independent variables [33]. Here, we have two models: Model 1 and Model 2, which predict the log-odds of positive and negative price differences, respectively, against the reference category (zero price difference).

Model 1 predicts the log-odds of a positive price difference (+1) relative to zero price difference (0), and Model 2 predicts the log-odds of a negative price difference (-1) relative to zero price difference (0).

The marginal effect of an independent variable x_m on the probability of outcome $y = g$ (where $g \in \{+1\ , -1\}$) is given by the partial derivative of the predicted probability with respect to x_m.

For each category g (positive price difference and negative price difference), the marginal effect is $\frac{\partial P(y=g|x)}{\partial x_m}$. To compute the marginal effects for each predictor x_m, for each category, the following equations are utilized:

For positive price difference (+1):

$$\frac{\partial P_r(y = +1|x)}{\partial x_m} = P(y = +1|x)(1 - P(y = +1|x))\ \delta_m \tag{6}$$

For negative price difference (-1):

$$\frac{\partial P_r(y = -1|x)}{\partial x_m} = P(y = -1|x)(1 - P(y = -1|x))\ \beta_m \tag{7}$$

where:

$P_r(y = +1|x)$ is the predicted probability of a positive price difference
$P_r(y = -1|x)$ is the predicted probability of a negative price difference
δ_m and β_m are the coefficients of the independent variables in Model 1 and Model 2, respectively.

These marginal effects help to understand how a unit (1 MWh) change in each predictor variable (wind, solar, hydropower, and demand in each zone) impacts the probability of observing a positive or negative price difference, holding all other variables constant.

3.3. Input Data

All data, including zonal wind, solar, and hydropower generation, as well as zonal demand, were sourced from the *ENTSO-e* online transparency platform for the period from 2021 to 2024 [30]. Additionally, geographical zonal price data were obtained from *Gestore dei Mercati Energetici (GME)* for the same period [28]. The price difference between the two zones is calculated by subtracting the price of the second zone from the price of the first zone ($Zone_1 - Zone_2$).

The data were collected on an hourly basis, resulting in a comprehensive dataset with no gaps, totaling 26,280 observations (8760 h per year). To account for the seasonality of electricity prices, the model incorporates dummy variables representing the hour of the day (1–24), day of the week (1–7), month of the year (1–12), and year (2021–2023).

Handling cyclical input in MLR models requires appropriately encoding cyclical features to preserve and utilize the cyclical nature effectively in the model. Cyclical input data includes variables like hours of the day, days of the week, and months of the year. These cyclical variables pose a challenge in prediction methods because they lack a natural numerical order (e.g., '1' is not necessarily less than '2' or '3'), which some learning algorithms struggle to interpret correctly [34,35]. To address this issue, various methods can be used to handle such data. One effective approach is trigonometric encoding, where each cyclical variable is mapped onto a circle, placing the lowest value adjacent to the highest value. The transformed values are calculated using cosine and sine trigonometric functions, where x is the original sample, and C_n represents the cycle's period [34]. In this study, we converted the cyclical data (hours of the day, days of the week, and months of the year) using Equations (8) and (9).

$$x_1' = \cos\left(\frac{2\pi x}{C_n}\right) \tag{8}$$

$$x_2' = \sin\left(\frac{2\pi x}{C_n}\right) \tag{9}$$

Having established the MLR models, the associated marginal effects, and input data, the following section presents the analysis results, highlighting the impact of wind, solar, hydropower, and demand on inter-zonal congestion in the Italian electricity market from 2021 to 2023.

4. Results

This section presents the results of the model 1 and model 2, mentioned in the previous section.

Supposing the zonal pair "zone1-zone2", the study aims to investigate how rising various factors, including wind generation, solar generation, hydropower generation, demand in each zone, and the generation in the neighbor zones, influence the probability of experiencing a positive price difference (congestion coming from the first zone; the first zone imports power) or a negative price difference (congestion to the first zone; the second zone imports power).

The empirical strategy involves estimating two econometric models applied to historical data from seven geographical zonal pairs over a three-year period (2021–2023). The seven intergeographic zonal pairs are as follows:

1. CNOR-CSUD
2. CNOR-NORD
3. CNOR-SARD
4. CSUD-SUD
5. CSUD-SARD
6. SICI-CALA
7. SUD-CALA

As previously mentioned, a positive price difference means that the zonal price in the first zone is higher than in the second zone, indicating that the first zone is importing power. On the other hand, a negative price difference suggests that the second zone is importing power.

To analyze the results in detail, we first focus on the outcomes of the CNOR-CSUD model as a sample. This type of interpretation can also be applied to the other pairs. In the second part, we provide a brief description of the model outcomes for the other zonal pairs.

Table 1 presents the results of an MLR analysis examining the influence of various factors on the price differences between two zones, CNOR and CSUD, over the period from 2021 to 2023. The analysis focuses on the impact of wind, solar, hydro generation, and consumer demand in CNOR, CSUD, and other zones on the likelihood of experiencing positive and negative price differences. The figures in the positive price difference column represent the effect of each factor on the probability that the price in CNOR is higher than in CSUD. On the other hand, the negative price difference represents the effect of each factor on the probability that the price in CNOR is lower than in CSUD. The table includes coefficients for each variable, indicating the direction and magnitude of the impact on the likelihood of price differences. Positive coefficients suggest an increase in the likelihood, while negative coefficients suggest a decrease. The asterisks (***, **, *) next to the coefficients denote the statistical significance of the results as follows:

- *** indicates a p-value less than 0.01 (highly significant)
- ** indicates a p-value less than 0.05 (significant)
- * indicates a p-value less than 0.1 (marginally significant)
- Coefficients without asterisks are not statistically significant

Table 1. MLR estimates for a positive and negative price difference in CNOR-CSUD; 2021–2023.

CNOR-CSUD; 2021–2023, Log-Odds Ratio			
	CNOR-CSUD		
	Price Difference	**Price Difference**	
	Positive	**Negative**	
	(1)	**(2)**	
CNOR_Wind	−0.003 *** (−0.020)	0.007 *** (0.018)	
CNOR_Solar	−0.003 *** (−0.016)	0.006 ** (0.016)	
CNOR_Hydro	0.005 *** (0.029)	0.004 *** (0.009)	
CNOR_Demand	0.003 *** (0.017)	−0.005 *** (−0.013)	
CSUD_Wind	0.0003 *** (0.002)	−0.001 *** (−0.003)	
CSUD_Solar	0.001 *** (0.007)	−0.002 * (−0.006)	
CSUD_Hydro	−0.001 *** (−0.007)	0.005 *** (0.012)	
CSUD_Demand	−0.0005 *** (−0.003)	0.002 *** (0.005)	
Other_Wind	0.0004 *** (0.003)	−0.001 *** (−0.002)	
Other_Solar	0.0001 *** (0.001)	−0.0002 ** (−0.001)	
Other_Hydro	−0.001 *** (−0.004)	0.001 *** (0.001)	
Other_Demand	−0.0001 *** (−0.0003)	−0.0001 (−0.0001)	
R^2 values:	*McFadden*	*r2ML*	*r2CU*
	0.36	0.29	0.47

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Marginal effects in parenthesis [%].

The values in parentheses are the marginal effects expressed as percentages, indicating the change in the probability of a positive or negative price difference resulting from a one-unit (1 MWh) increase in each variable.

The table also includes R-squared values (*McFadden*, *r2ML*, *r2CU*), which measure the goodness-of-fit of the model. Higher values indicate a better fit of the model to the observed data.

In the CNOR-CSUD pair, wind generation in CNOR exhibited a distinct impact on inter-zonal congestion. An increase in wind generation in CNOR is associated with a decreased likelihood of a positive price difference (congestion coming from CNOR), indicating that higher wind generation tends to reduce the need for CNOR to import power. Specifically, a one MWh increase in wind generation reduces the probability of a positive price difference by a marginal effect of 0.02%. However, the same increase in wind generation significantly raises the likelihood of a negative price difference, with a marginal effect of 0.018%, indicating that surplus wind power in CNOR contributes to power exports to CSUD.

Wind generation in CSUD also plays a role in congestion dynamics. An increase in CSUD's wind generation has a minimal positive impact on the probability of a positive price difference and a slight negative impact on the probability of a negative price difference. This suggests that wind power in CSUD helps balance the inter-zonal flow to some extent, but the effect is relatively minor compared to CNOR's wind generation.

The analysis reveals that solar generation in CNOR has a similar effect to wind generation. Increased solar power in CNOR reduces the probability of a positive price difference by 0.016% and increases the likelihood of a negative price difference by the same percentage (0.016%). This pattern indicates that solar generation, like wind, contributes to power exports from CNOR to CSUD when generation exceeds local demand.

In CSUD, solar generation shows a modest positive impact on the probability of a positive price difference and a slight negative impact on the probability of a negative price difference. The marginal effects suggest that solar power in CSUD can help mitigate congestion slightly but does not significantly alter the overall congestion pattern between the zones.

Increased hydro generation is associated with a higher likelihood of both positive and negative price differences. Specifically, a one MWh increase in hydro generation increases the probability of a positive price difference by 0.029% and the probability of a negative price difference to a lesser extent compared to the positive price difference (0.009%). This indicates a smaller, but still present, likelihood of CSUD importing power. Operators in CNOR should consider that increasing hydro generation can lead to a higher probability of CNOR importing power.

Conversely, in CSUD, hydro generation reduces the probability of a positive price difference by 0.007% while increasing the likelihood of a negative price difference by 0.012%. The probability reduction of 0.007% for a positive price difference with increased hydro generation in CSUD indicates that additional hydro generation in CSUD makes it less competitive, thereby decreasing CNOR's likelihood of importing power from CSUD. The probability of changes for both price differences (positive and negative) is relatively small. However, the impact on a negative price difference (0.012%) is slightly stronger compared to the impact on a positive price difference (−0.007%). Increasing hydro generation in CSUD has a dual effect of making CNOR less likely to import power from CSUD and making CSUD more likely to import power from CNOR. The latter effect is slightly stronger, indicating that CSUD's increased hydro generation more significantly tilts the balance towards importing power from CNOR. It might have experienced a fluctuation in other sources of electricity generation, such as gas or other fossil fuel-supplied generation.

Consumer demand continues to play a crucial role in inter-zonal congestion dynamics. In CNOR, a 1 MWh increase in demand raises the probability of a positive price difference by 0.017%, indicating a greater likelihood of CNOR importing power to meet local needs. On the other hand, higher demand in CNOR decreases the probability of a negative price difference by 0.013%, suggesting reduced power exports to CSUD when local consumption is high.

In CSUD, higher consumer demand slightly reduces the probability of a positive price difference by 0.003% and increases the likelihood of a negative price difference by 0.005%. This pattern indicates that increased demand in CSUD leads to greater reliance on power imports from CNOR, highlighting the interdependency between the zones.

Generation from other zones also impacts the congestion between CNOR and CSUD. Among the different types of generation from other zones, the total wind generation from the other zones shows the most significant impact on congestion. Specifically, a 1 MWh increase in wind generation in other zones slightly increases the probability of a positive price difference by 0.003% and decreases the likelihood of a negative price difference by 0.002%. This suggests that the power needs in CSUD can also be met by the wind generation elsewhere, reducing the need for CSUD to import power from CNOR, and potentially alleviating congestion in CNOR-CSUD by providing an alternative source of power from the other zones.

The R^2 values for the models are as follows: *McFadden* R^2 is 0.36, *r2ML* is 0.29, and *r2CU* is 0.47. These values provide insight into the explanatorypower of the MLR models used in this analysis. The *McFadden* R^2 value of 0.36 suggests that the model explains 36% of the variability in the outcome variable, which is considered a good fit for models of this type, indicating that the chosen variables significantly contribute to understanding the congestion patterns. The *r2ML* value of 0.29, while slightly lower, still indicates a substantial portion of variability is accounted for by the model. Finally, the *r2CU* value of

0.47 indicates an even stronger explanatory power under the specific conditions considered in this analysis. Overall, these R^2 values demonstrate that the models provide a robust explanation of the factors influencing inter-zonal congestion between CNOR and CSUD. Furthermore, as noted in [36], achieving high R^2 values is challenging when working with large datasets and highly volatile zonal prices. Thus, our model's R^2 reflects a reasonable fit given the volatility and complexity of inter-zonal price dynamics.

The marginal effects for the variables in this study are visualized in the chart below Figure 7.

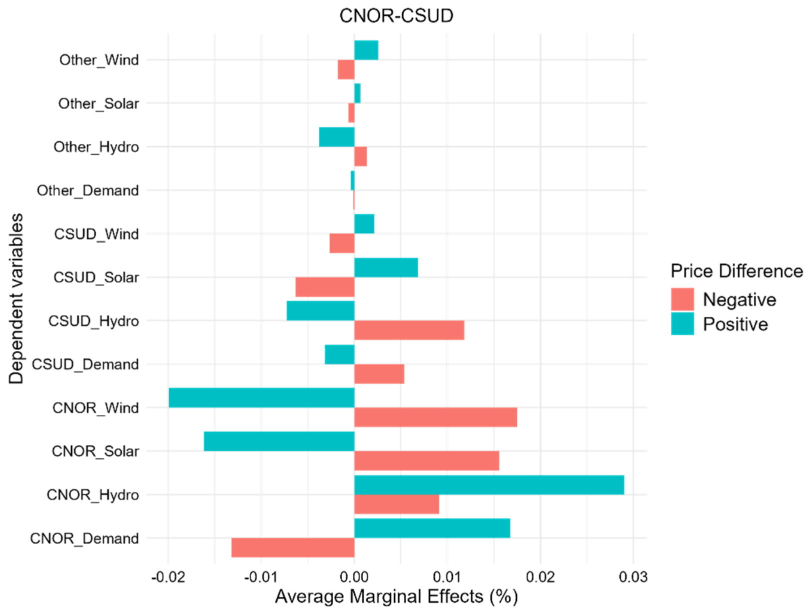

Figure 7. Average marginal effects, CNOR-CSUD; 2021–2023.

The marginal effect of wind generation on positive price differences is −0.02%, indicating that a one MWh increase in CNOR wind generation decreases the probability of a positive price difference by approximately 0.02%. Conversely, the marginal effect on negative price differences is 0.018%, showing an increase in the probability of negative price differences by 0.018%.

Similarly, solar and hydro generation exhibit significant marginal effects on both positive and negative price differences. Solar generation in CNOR reduces the probability of positive price differences by 0.016% and increases the probability of negative price differences by the same value, 0.016%. Hydro generation in the CNOR has the highest positive marginal effect, increasing the probability of positive price differences by 0.029% and negative price differences by 0.009%.

The marginal effects for other variables, including wind, solar, and hydro generation in CSUD, show smaller but notable impacts on congestion. The chart provides a comprehensive visualization of these effects, highlighting the relative influence of each variable on the congestion dynamics between CNOR and CSUD.

The empirical analysis of price differences between other zonal pairs, as depicted in the accompanying charts (Figure 8), highlights several key factors that significantly impact positive and negative price differences.

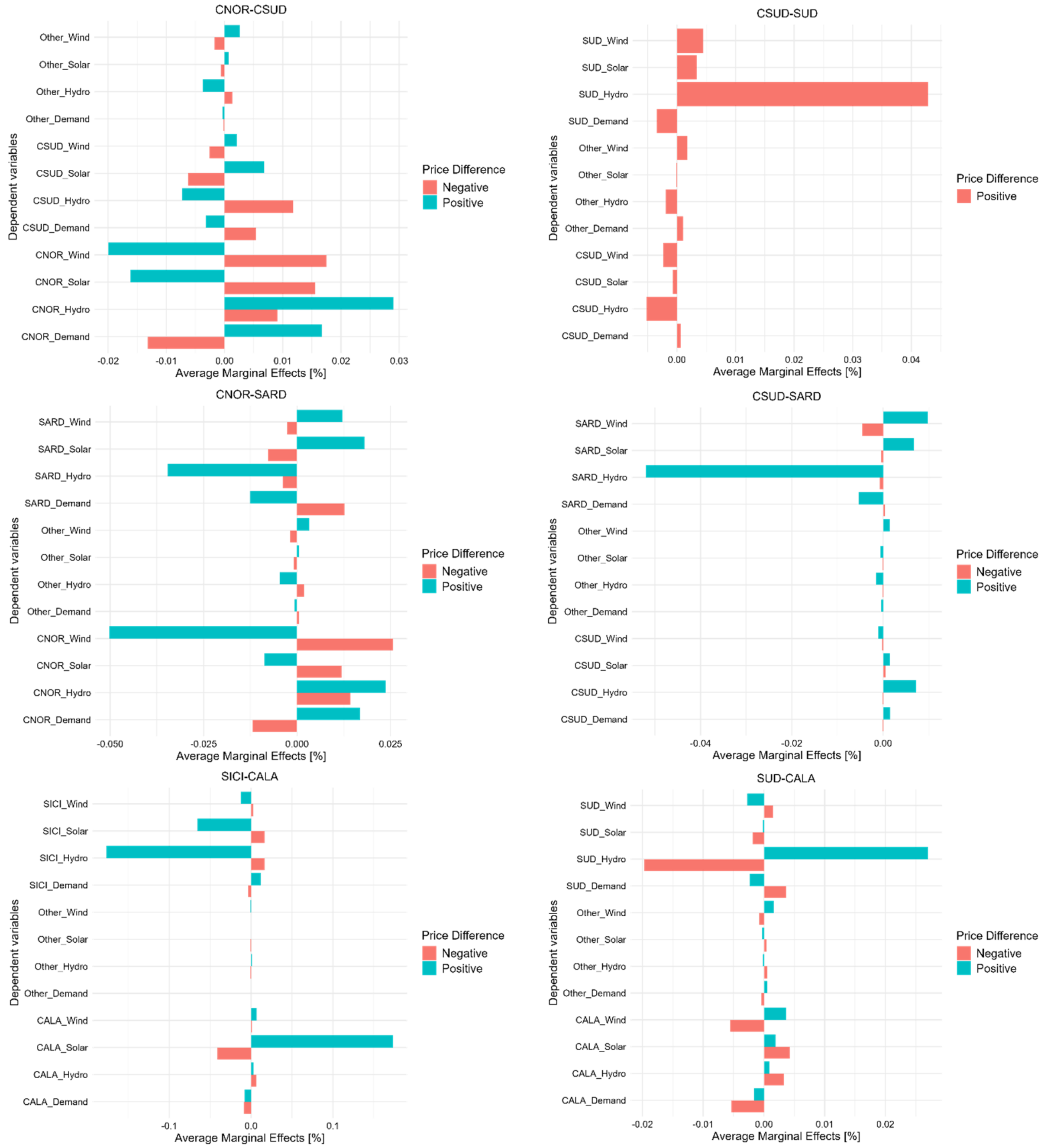

Figure 8. Average marginal effects in the various zonal pairs; 2021–2023.

Appendix B contains Tables A5–A10, which display the outcomes of MLR models for various zonal pairs over the period from 2021 to 2023.

As shown in Figure 8, considering the positive price difference in the CNOR-NORD pair, hydro production in both regions and wind production in NORD are the primary factors influencing congestion. A one MWh increase in CNOR's hydro generation raises the probability of a positive price difference by 0.007%, indicating a higher likelihood of CNOR importing electricity from NORD. Similarly, wind production in NORD increases the likelihood of exports to CNOR by 0.008%, adding to congestion. Solar production in CNOR also plays a role, with a 0.005% increase in the probability of importing from NORD, demonstrating how various renewable energy sources collectively impact congestion dynamics.

Turning to the CNOR-SARD pair, wind and hydro production in CNOR, along with hydro production in SARD, significantly affect congestion. Wind production in CNOR decreases the probability of congestion by 0.050%, as increased local wind generation reduces the need for imports from SARD. Conversely, an increase in CNOR's hydro production raises the congestion probability by 0.024%. Additionally, a rise in CNOR's demand has a marginal effect of 0.017% on increasing congestion.

For the CSUD-SARD pair, solar and hydro production in both regions, along with wind production in SARD, are key congestion factors. In SARD, a one MWh increase in solar generation raises the likelihood of importing from CSUD by 0.007%. CSUD's demand also contributes to congestion with a marginal effect of 0.002%. In contrast, SARD's hydro production mitigates congestion by reducing the need for exports to CSUD by 0.052%.

The CSUD-SUD pair shows consistent congestion patterns from 2021 to 2023, with CSUD mainly as an importer. Notably, SUD has never imported electricity from CSUD during this period. Wind production in CSUD reduces congestion by 0.002%, as local wind generation meets more of the demand. Similarly, hydro production in CSUD alleviates congestion by decreasing the probability of importing from SUD by 0.005%.

In the SICI-CALA pair, solar production in CALA significantly increases congestion as SICI imports electricity. A one MWh increase in CALA's solar generation raises the likelihood of SICI importing by 0.173%. However, solar and hydro production in SICI, with marginal effects of -0.066% and -0.177%, respectively, reduce the need for imports from CALA, thus alleviating congestion. Wind production in SICI also helps by reducing the likelihood of importing from CALA by 0.013%. SICI's demand slightly decreases exports to CALA, mitigating congestion, while CALA's demand increases the likelihood of importing electricity, contributing to congestion.

In the SUD-CALA pair, wind and hydro production in SUD and wind and solar production in CALA impact congestion significantly. Wind production in SUD alleviates congestion by reducing the probability of importing from CALA by 0.003%. However, SUD's hydro production increases congestion likelihood by 0.027%. SUD's demand has mixed effects: it reduces the need for imports from CALA by 0.002% but increases the probability of CALA importing electricity by 0.004%, contributing to congestion.

Although the primary focus of our analysis has been on the generation and demand within each zonal pair, it is important to note that the impact of generation and demand from other zones is also considerable and statistically significant. The MLR results highlight that while the marginal effects of wind, solar, and hydro production from other zones are generally lower compared to the same zones within the zonal pairs, their influence on congestion cannot be overlooked. For instance, in the CNOR-CSUD pair, the wind and hydro production from other zones show significant impacts, with marginal effects of 0.003% and -0.002%, respectively. Similarly, in the CNOR-NORD pair, other zones' hydro production has a significant positive effect on the negative price difference, with a marginal effect of 0.003%. These findings indicate that even though the local generation and demand within the pairs have more pronounced effects on congestion, the contributions from surrounding zones are non-negligible and play a critical role in the overall congestion dynamics.

5. Conclusions

The empirical analysis of the Italian electricity market over the entire period of 2021 to 2023 reveals that demand and RESs generation have distinct impacts on inter-zonal congestion. Utilizing a multinomial regression model, the study finds that increased local RESs generally reduce the likelihood of congestion for importing regions but increase it for exporting zones. Specifically, higher wind and solar production in importing zones like CNOR and CSUD alleviates congestion by reducing the need for imports. Conversely, in exporting zones, such as NORD and CALA, increased RESs production can exacerbate congestion on exit due to higher export volumes. Hydropower production demonstrates similar trends on some zonal pairs, where increased local production raises the probability of causing congestion in exporting zones but helps mitigate it in importing zones. The rise in local demand generally increases congestion in importing regions by driving up the need for imports and slightly reduces congestion in exporting regions by lowering exports of RESs. Besides the impact of local generation and demand within each zonal pair, the influence of generation and demand from other zones is also statistically significant. Although their marginal effects are generally lower, the contributions from surrounding zones are crucial in understanding overall congestion dynamics.

The policy implications of this study are significant. The findings offer valuable insights for investors and decision-makers on optimal locations for RESs to minimize congestion issues, particularly in exporting zones. Promoting renewable energy growth in importing zones tends to create a more balanced system, which is crucial for transmission system operators (TSOs) and policymakers aiming to enhance grid stability and efficiency. However, the expansion of intermittent renewable supplies, such as wind and solar, must be carefully managed. While these sources generally reduce congestion costs and spot prices, unchecked growth could lead to significant congestion problems, especially in exporting zones. To facilitate a smooth energy transition, market mechanisms should be designed to enhance efficiency by encouraging the installation of new RESs power plants in areas where they have the most positive impact. As a result, these research outcomes can aid in structuring an efficient zonal market and promoting high RESs penetration through sustainable and operational renewable policies.

These insights are applicable not only to the Italian electricity market but also to wholesale electricity markets in other EU countries with similar market structures and data availability. Future research is essential to deepen the understanding of RESs integration and congestion. It can explore various pathways, such as assessing the impact of intermittent RESs at specific penetration levels on congestion and considering the degree of zonal price differences among market zones.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Conflicts of Interest: The author declares no conflicts of interest.

Appendix A

Table A1. Annual average of wind generation across various electricity market zones in Italy over the period from 2021 to 2023.

Zone	2021 [MW]	2022 [MW]	2023 [MW]
CALA	251.2	249.2	256.6
CNOR	37.8	30.9	36.4
CSUD	477.0	460.8	549.2
NORD	13.0	21.4	56.4
SARD	201.5	186.6	217.3
SICI	396.8	360.3	382.6
SUD	991.4	985.8	1156.1

Table A2. Annual average of solar generation across various electricity market zones in Italy over the period from 2021 to 2023.

Zone	2021 [MW]	2022 [MW]	2023 [MW]
CALA	61.2	66.2	94.5
CNOR	216.4	252.9	253.0
CSUD	403.7	482.6	491.0
NORD	820.5	884.2	936.8
SARD	105.1	140.9	156.4
SICI	169.6	187.4	286.2
SUD	522.7	551.0	541.5

Table A3. Annual average of hydro production across various electricity market zones in Italy over the period from 2021 to 2023.

Zone	2021 [MW]	2022 [MW]	2023 [MW]
CALA	86.8	94.5	113.6
CNOR	127.1	68.2	99.5
CSUD	504.3	338.1	442.4
NORD	3203.0	2062.1	2865.0
SARD	29.5	21.9	17.2
SICI	9.5	15.8	8.0
SUD	34.4	25.7	27.1

Table A4. Annual average of load consumption across various electricity market zones in Italy over the period from 2021 to 2023.

Zone	2021 [MW]	2022 [MW]	2023 [MW]
CALA	709.9	722.6	681.7
CNOR	2839.5	2854.3	2705.1
CSUD	5700.6	5789.1	5609.7
NORD	18,546.4	18,295.6	17,527.2
SARD	1007.1	985.8	923.0
SICI	1989.3	1955.7	1972.6
SUD	2227.6	2069.7	2099.9

Appendix B. MLR Results

Table A5. MLR models estimates for a positive and negative price difference in CNOR-NORD;2021–2023.

CNOR-NORD; 2021–2023, Log-Odds Ratio			
	CNOR-NORD		
	Price Difference	**Price Difference**	
	Positive	**Negative**	
	(1)	**(2)**	
CNOR_Wind	0.0004 (0.001)	0.010 *** (0.006)	
CNOR_Solar	0.003 ** (0.005)	0.003 *** (0.002)	
CNOR_Hydro	0.004 *** (0.007)	0.006 *** (0.004)	
CNOR_Demand	−0.001 *** (−0.002)	−0.0003 (−0.0002)	
NORD_Wind	0.005 *** (0.008)	−0.018 *** (−0.011)	
NORD_Solar	0.0002 (0.0004)	−0.0001 (−0.0001)	
NORD_Hydro	0.001 *** (0.002)	−0.0005 *** (−0.0003)	
NORD_Demand	−0.0003 *** (−0.001)	0.0004 *** (0.0002)	
Other_Wind	−0.001 *** (−0.001)	0.001 *** (0.0004)	
Other_Solar	−0.001 *** (−0.002)	0.0004 *** (0.0002)	
Other_Hydro	−0.001 ** (−0.001)	0.005 *** (0.003)	
Other_Demand	0.001 *** (0.001)	−0.002 *** (−0.001)	
R^2 values:	*McFadden*	*r2ML*	*r2CU*
	0.35	0.10	0.39

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Marginal effects in parenthesis [%].

Table A6. MLR models estimates for a positive and negative price difference in CNOR-SARD;2021–2023.

CNOR-SARD; 2021–2023, Log-Odds Ratio			
	CNOR-SARD		
	Price Difference	**Price Difference**	
	Positive	**Negative**	
	(1)	**(2)**	
CNOR_Wind	−0.007 *** (−0.050)	0.010 *** (0.026)	
CNOR_Solar	−0.001 *** (−0.009)	0.005 *** (0.012)	
CNOR_Hydro	0.003 *** (0.024)	0.006 *** (0.014)	
CNOR_Demand	0.002 *** (0.017)	−0.005 *** (−0.012)	
SARD_Wind	0.002 *** (0.012)	−0.001 *** (−0.003)	
SARD_Solar	0.002 *** (0.018)	−0.003 *** (−0.008)	
SARD_Hydro	−0.005 *** (−0.035)	−0.002 (−0.004)	
SARD_Demand	−0.002 *** (−0.013)	0.005 *** (0.013)	
Other_Wind	0.0004 *** (0.003)	−0.001 *** (−0.002)	
Other_Solar	0.0001 ** (0.0005)	−0.0004 *** (−0.001)	
Other_Hydro	−0.001 *** (−0.005)	0.001 *** (0.002)	
Other_Demand	−0.0001 *** (−0.001)	0.0002 *** (0.0005)	
R^2 values:	*McFadden*	*r2ML*	*r2CU*
	0.33	0.29	0.45

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Marginal effects in parenthesis [%].

Table A7. MLR models estimates for a positive and negative price difference in CSUD-SARD;2021–2023.

CSUD-SARD; 2021–2023, Log-Odds Ratio			
	CSUD-SARD		
	Price Difference	**Price Difference**	
	Positive	**Negative**	
	(1)	**(2)**	
CSUD_Wind	−0.0003 *** (−0.001)	−0.003 (−0.0002)	
CSUD_Solar	0.0005 ** (0.002)	0.010 *** (0.001)	
CSUD_Hydro	0.002 *** (0.007)	−0.0003 (−0.00002)	
CSUD_Demand	0.001 *** (0.002)	−0.002 *** (−0.0001)	
SARD_Wind	0.003 *** (0.010)	−0.084 *** (−0.005)	
SARD_Solar	0.002 *** (0.007)	−0.007 * (−0.0004)	
SARD_Hydro	−0.017 *** (−0.052)	−0.012 *** (−0.001)	
SARD_Demand	−0.002 *** (−0.005)	0.008 ** (0.0004)	
Other_Wind	0.0005 *** (0.001)	0.0005 (0.00003)	
Other_Solar	−0.0002 *** (−0.001)	−0.002 *** (−0.0001)	
Other_Hydro	−0.0005 *** (−0.002)	−0.0002 (−0.00001)	
Other_Demand	−0.0001 *** (−0.0004)	0.001 *** (0.00004)	
R^2 values:	*McFadden*	*r2ML*	*r2CU*
	0.28	0.09	0.31

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Marginal effects in parenthesis [%].

Table A8. MLR models estimates for a positive and negative price difference in CSUD-SUD;2021–2023.

CSUD-SUD; 2021–2023, Log-Odds Ratio			
	CSUD-SUD		
	Price Difference		
	Positive		
CSUD_Wind	−0.001 *** (−0.002)		
CSUD_Solar	−0.0002 (−0.001)		
CSUD_Hydro	−0.001 *** (−0.005)		
CSUD_Demand	0.0002 ** (0.001)		
SUD_Wind	0.001 *** (0.004)		
SUD_Solar	0.001 *** (0.003)		
SUD_Hydro	0.011 *** (0.043)		
SUD_Demand	−0.001 *** (−0.003)		
Other_Wind	0.0004 *** (0.002)		
Other_Solar	−0.00002 (−0.0001)		
Other_Hydro	−0.0005 *** (−0.002)		
Other_Demand	0.0003 *** (0.001)		
R^2 values:	*McFadden*	*r2ML*	*r2CU*
	0.35	0.14	0.40

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Marginal effects in parenthesis [%].

Table A9. MLR models estimates for a positive and negative price difference in SICI-CALA;2021–2023.

SICI-CALA; 2021–2023, Log-Odds Ratio			
	SICI-CALA		
	Price Difference	**Price Difference**	
	Positive	**Negative**	
	(1)	**(2)**	
SICI_Wind	−0.002 *** (−0.013)	0.002 *** (0.002)	
SICI_Solar	−0.009 *** (−0.066)	0.011 *** (0.017)	
SICI_Hydro	−0.026 *** (−0.177)	0.010 ** (0.017)	
SICI_Demand	0.002 *** (0.012)	−0.002 *** (−0.004)	
CALA_Wind	0.001 *** (0.007)	0.001 * (0.001)	
CALA_Solar	0.025 *** (0.173)	−0.026 *** (−0.041)	
CALA_Hydro	0.001 ** (0.003)	0.004 *** (0.006)	
CALA_Demand	−0.001 *** (−0.008)	−0.006 *** (−0.009)	
Other_Wind	−0.0001 *** (−0.001)	−0.0002 *** (−0.0003)	
Other_Solar	0.00001 (0.0001)	−0.0003 *** (−0.0005)	
Other_Hydro	0.0002 *** (0.001)	−0.001 *** (−0.001)	
Other_Demand	−0.00003 *** (−0.0002)	0.0002 *** (0.0002)	
R^2 values:	*McFadden*	*r2ML*	*r2CU*
	0.19	0.13	0.25

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Marginal effects in parenthesis [%].

Table A10. MLR models estimates for a positive and negative price difference in SUD-CALA;2021–2023.

SUD-CALA; 2021–2023, Log-Odds Ratio			
	SUD-CALA		
	Price Difference	Price Difference	
	Positive	Negative	
	(1)	(2)	
SUD_Wind	−0.001 *** (−0.003)	0.001 *** (0.002)	
SUD_Solar	−0.0001 (−0.0002)	−0.001 *** (−0.002)	
SUD_Hydro	0.011 *** (0.027)	−0.013 ** (−0.020)	
SUD_Demand	−0.001 *** (−0.002)	0.002 *** (0.004)	
CALA_Wind	0.001 *** (0.004)	−0.004 *** (−0.006)	
CALA_Solar	0.001 (0.002)	0.003 ** (0.004)	
CALA_Hydro	0.0004 (0.001)	0.002 *** (0.003)	
CALA_Demand	−0.001 *** (−0.002)	−0.004 *** (−0.005)	
Other_Wind	0.001 *** (0.002)	−0.001 *** (−0.001)	
Other_Solar	−0.0001 *** (−0.0003)	0.0003 *** (0.0005)	
Other_Hydro	−0.0001 ** (−0.0002)	0.0004 *** (0.001)	
Other_Demand	0.0002 *** (0.0005)	−0.0003 *** (−0.0004)	
R^2 values:	*McFadden*	*r2ML*	*r2CU*
	0.23	0.09	0.27

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Marginal effects in parenthesis [%].

References

1. Gelabert, L.; Labandeira, X.; Linares, P. An Ex-Post Analysis of the Effect of Renewables and Cogeneration on Spanish Electricity Prices. *Energy Econ.* **2011**, *33*, S59–S65. [CrossRef]
2. Clò, S.; Cataldi, A.; Zoppoli, P. The Merit-Order Effect in the Italian Power Market: The Impact of Solar and Wind Generation on National Wholesale Electricity Prices. *Energy Policy* **2015**, *77*, 79–88. [CrossRef]
3. Quint, D.; Dahlke, S. The Impact of Wind Generation on Wholesale Electricity Market Prices in the Midcontinent Independent System Operator Energy Market: An Empirical Investigation. *Energy* **2019**, *169*, 456–466. [CrossRef]
4. Csereklyei, Z.; Qu, S.; Ancev, T. The Effect of Wind and Solar Power Generation on Wholesale Electricity Prices in Australia. *Energy Policy* **2019**, *131*, 358–369. [CrossRef]
5. Cludius, J.; Hermann, H.; Matthes, F.C.; Graichen, V. The Merit Order Effect of Wind and Photovoltaic Electricity Generation in Germany 2008–2016: Estimation and Distributional Implications. *Energy Econ.* **2014**, *44*, 302–313. [CrossRef]
6. Woo, C.-K.; Horowitz, I.; Moore, J.; Pacheco, A. The Impact of Wind Generation on the Electricity Spot-Market Price Level and Variance: The Texas Experience. *Energy Policy* **2011**, *39*, 3939–3944. [CrossRef]
7. Würzburg, K.; Labandeira, X.; Linares, P. Renewable Generation and Electricity Prices: Taking Stock and New Evidence for Germany and Austria. *Energy Econ.* **2013**, *40*, S159–S171. [CrossRef]
8. Figueiredo, N.C.; da Silva, P.P. The "Merit-Order Effect" of Wind and Solar Power: Volatility and Determinants. *Renew. Sustain. Energy Rev.* **2019**, *102*, 54–62. [CrossRef]
9. Benhmad, F.; Percebois, J. Photovoltaic and Wind Power Feed-in Impact on Electricity Prices: The Case of Germany. *Energy Policy* **2018**, *119*, 317–326. [CrossRef]
10. Macedo, D.P.; Marques, A.C.; Damette, O. The Role of Electricity Flows and Renewable Electricity Production in the Behaviour of Electricity Prices in Spain. *Econ. Anal. Policy* **2022**, *76*, 885–900. [CrossRef]
11. Grohnheit, P.E.; Sneum, D.M. Calm before the Storm: Market Prices in a Power Market with an Increasing Share of Wind Power. *Energy Policy* **2023**, *179*, 113631. [CrossRef]
12. Zhang, R.; Ni, M.; Shen, G.Q.P.; Wong, J.K.W. An Analysis on the Effectiveness and Determinants of the Wind Power Feed-in-Tariff Policy at China's National-Level and Regional-Grid-Level. *Sustain. Energy Technol. Assess.* **2019**, *34*, 87–96. [CrossRef]
13. Halužan, M.; Verbič, M.; Zorić, J. The Crowding out of Conventional Electricity Generation by Renewable Energy Sources: Implications from Greek, Hungarian, and Romanian Electricity Markets. *Environ. Sci. Pollut. Res.* **2023**, *30*, 120063–120084. [CrossRef] [PubMed]

14. Myrvoll, T.; Undeli, P. Assessing the Impact of NordLink on Day-Ahead Prices in NO2 and Germany: A Quantile Regression Approach. Master's Thesis, Norwegian School of Economics, Bergen, Norway, 2022.
15. Titz, M.; Pütz, S.; Witthaut, D. Identifying Drivers and Mitigators for Congestion and Redispatch in the German Electric Power System with Explainable AI. *Appl. Energy* **2024**, *356*, 122351. [CrossRef]
16. Zhang, Q.; Li, X.; Liu, X.; Zhao, C.; Shi, R.; Jiao, Z.; Liu, J. Data-Driven Risk Assessment Early-Warning Model for Power System Transmission Congestions. In Proceedings of the 2022 12th International Conference on Power, Energy and Electrical Engineering (CPEEE), Shiga, Japan, 25–27 February 2022; pp. 201–206.
17. Liao, S.; Liu, Y.; Xu, J.; Jia, L.; Ke, D.; Jiang, X. Data-Driven Real-Time Congestion Forecasting and Relief With High Renewable Energy Penetration. *IEEE Trans. Ind. Inform.* **2024**, 1–18. [CrossRef]
18. Yang, L.; Zou, B. Research on Cross-Border Electricity Price Spread Model of Nordic Power Market. In Proceedings of the 2019 IEEE 3rd International Electrical and Energy Conference (CIEEC), Beijing, China, 7–9 September 2019; pp. 210–216.
19. Unger, E. Renewable and Conventional Energy Sources, Cross-Border Interactions, and Electricity Prices Within the Nord Pool Market. Ph.D. Dissertation, Faculty of Civil and Environmental Engineering, University of Iceland, Reykjavik, Iceland, 2018.
20. Hosseini Imani, M.; Bompard, E.; Colella, P.; Huang, T. Impact of Wind and Solar Generation on the Italian Zonal Electricity Price. *Energies* **2021**, *14*, 5858. [CrossRef]
21. Bindu, S.; Olmos, L.; Ávila, J.P.C. The Devil in the Details: The Factors Determining the Selection of Intrazonal Congestion Management Methods across Europe. *Heliyon* **2024**, *10*, e26610. [CrossRef]
22. Ardian, F.; Concettini, S.; Creti, A. Renewable Generation and Network Congestion: An Empirical Analysis of the Italian Power Market. *Energy J.* **2018**, *39* (Suppl. 2), 3–40. [CrossRef]
23. Anbazhagan, S.; Kumarappan, N. Day-Ahead Deregulated Electricity Market Price Forecasting Using Recurrent Neural Network. *IEEE Syst. J.* **2012**, *7*, 866–872. [CrossRef]
24. Imani, M.H.; Andani, M.T.; Andani, H.T. Clustering of Electricity Price: An Application to the Italian Electricity Market. In Proceedings of the 2023 IEEE Texas Power and Energy Conference (TPEC), College Station, TX, USA, 13–14 February 2023; pp. 1–6.
25. Han, L.; Peng, Y.; Li, Y.; Yong, B.; Zhou, Q.; Shu, L. Enhanced Deep Networks for Short-Term and Medium-Term Load Forecasting. *IEEE Access* **2018**, *7*, 4045–4055. [CrossRef]
26. Imani, M.H.; Bompard, E.; Colella, P.; Huang, T. Predictive Methods of Electricity Price: An Application to the Italian Electricity Market. In Proceedings of the 2020 IEEE International Conference on Environment and Electrical Engineering and 2020 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe), Madrid, Spain, 9–12 June 2020; pp. 1–6.
27. Gianfreda, A.; Parisio, L.; Pelagatti, M. The Impact of RES in the Italian Day–Ahead and Balancing Markets. *Energy J.* **2016**, *37*, 161–184. [CrossRef]
28. GME-Gestore Dei Mercati Energetici. Available online: https://www.mercatoelettrico.org/EN/ (accessed on 20 July 2024).
29. TERNA S.p.A. Available online: https://www.terna.it/en/electric-system/transparency-report/energy-balance (accessed on 1 August 2024).
30. ENTSO-E. Available online: https://www.entsoe.eu/ (accessed on 22 July 2024).
31. Imani, M.H.; Bompard, E.; Colella, P.; Huang, T. Data Analytics in the Electricity Market: A Systematic Literature Review. *Energy Syst.* **2023**, 1–35. [CrossRef]
32. Hedeker, D. A Mixed-effects Multinomial Logistic Regression Model. *Stat. Med.* **2003**, *22*, 1433–1446. [CrossRef]
33. Davezies, L.; D'Haultfoeuille, X.; Laage, L. Identification and Estimation of Average Marginal Effects in Fixed Effects Logit Models. *arXiv* **2021**, arXiv:2105.00879.
34. Imani, M.H.; Bompard, E.; Colella, P.; Huang, T. Forecasting Electricity Price in Different Time Horizons: An Application to the Italian Electricity Market. *IEEE Trans. Ind. Appl.* **2021**, *57*, 726–5736. [CrossRef]
35. Vamplew, A.A.P. Encoding and Decoding Cyclic Data. *S. Pac. J. Nat. Sci* **1998**, *16*, 54–58.
36. Zarnikau, J.; Tsai, C.H.; Woo, C.K. Determinants of the Wholesale Prices of Energy and Ancillary Services in the US Midcontinent Electricity Market. *Energy* **2020**, *195*, 117051. [CrossRef]