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Determinants of Electricity Prices in Turkey: An Application of Machine Learning and Time Series Models

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Abstract: The study compares the prediction performance of alternative machine learning algorithms and time series econometric models for daily Turkish electricity prices and defines the determinants of electricity prices by considering seven global, national, and electricity-related variables as well as the COVID-19 pandemic. Daily data that consist of the pre-pandemic (15 February 2019–10 March 2020) and the pandemic (11 March 2020–31 March 2021) periods are included. Moreover, various time series econometric models and machine learning algorithms are applied. The findings reveal that (i) machine learning algorithms present higher prediction performance than time series models for both periods, (ii) renewable sources are the most influential factor for the electricity prices, and (iii) the COVID-19 pandemic caused a change in the importance order of influential factors on the electricity prices. Thus, the empirical results highlight the consideration of machine learning algorithms in electricity price prediction. Based on the empirical results obtained, potential policy implications are also discussed.

Keywords: electricity prices; global factors; national factors; prediction; machine learning; time series econometrics; Turkey

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1. Introduction

Both developing and developed countries aim to provide a higher quality of life to their citizens [1]. Although the gross domestic product is not a good indicator of societal well-being [2,3], government policy usually focuses mainly on economic indicators because there is a high correlation between economic indicators and stability [4].

Stability in economic and financial indicators helps reduce uncertainty and improve well-being in an economy. There are many factors that affect the stability of economic and financial indicators, and energy is one of the most important ones that influence both production and consumption capabilities in an economy. Almost all economic and social well-being indicators are affected by the availability and affordability of energy.

Electricity prices affect both production and consumption [5]. The recent pandemic has underlined the notion that access to clean and affordable energy is a basic human right. Therefore, fluctuations in electricity prices cannot be ignored when it comes to economic and social stability.

Electricity can also be regarded as a commodity traded in markets in many countries, including Turkey [6]. Investors are also participating in electricity derivatives markets. Hence, electricity prices affect more economic actors than consumers and producers of electricity.

In general, the stability of electricity prices is crucial for all economic actors. Depending on the lacking proper infrastructures and investments, emerging countries may be suffering

from high volatility in energy prices. As an emerging country, Turkey has highly volatile electricity prices, of which the progress of Turkish Lira (TRY) denominated electricity prices in Turkey over recent years, as presented in Figure A1.

To achieve sustainable and stable electricity prices, the influential factors on electricity prices should first be well understood. In this context, not only energy market fundamentals but also global and national factors as well as financial and macroeconomic factors should be considered. Moreover, as a recent crisis and black-swan case [7], the world is facing the COVID-19 pandemic, which influences both economic and social dynamics in every economy [8]. There are approximately 162 million confirmed cases and 3.4 million deaths as of 14 May 2021 in the world, and 5.1 million confirmed cases and 44 thousand deaths as of 14 May 2021 in Turkey [9]. The COVID-19 pandemic has caused a deterioration in all indicators and areas with no exception. Therefore, the pandemic should also be taken into account when stability in energy markets is examined. Moreover, countries are taking various measures to mitigate the negative impacts of the COVID-19 pandemic [10]. These precautions should also be considered in assessing stability in electricity prices.

In the literature, researchers have mainly focused on electricity demand, e.g., [5,6,11–16], and a limited number of studies have directly considered electricity prices around the pandemic, e.g., [17–21]. In this study, we investigate the prediction performance of alternative machine learning and time series models for electricity prices and identify the important determinants of electricity prices for Turkey. In addition to market fundamentals, we consider global and national factors and the COVID-19 pandemic in our models. We take Turkey as a case study because it is an emerging economy with highly volatile electricity prices. In the analysis, we include a total of seven variables, and daily data for two sub-periods that consist of the pre-pandemic (15 February 2019–10 March 2020) and the pandemic (11 March 2020–31 March 2021) periods. In addition, we apply various time series econometric as well as machine learning algorithms because some studies have stated that machine learning algorithms can perform better [21,22]. By following up such an approach, we aim to examine the effect of the selected variables on electricity prices, which are hypothesized in the following part of the study by benefitting from the current literature. The findings reveal that (i) machine learning algorithms have better prediction performance than time series models for both periods, (ii) renewable sources are the most influential factor for Turkish electricity prices; and (iii) the COVID-19 pandemic caused a change in the relative importance of electricity price determinants. Hence, the validity of the hypothesis is confirmed.

This study makes three important contributions to the literature. First, to the best of our knowledge, this is a leading study in the current literature that compares the prediction performance of alternative machine learning and time series models for the Turkish electricity market using high-frequency (i.e., daily) data. Although there are studies on developed countries, including Italy [18], Germany [19], Spain [23], and the United Kingdom [24], emerging countries such as Turkey have not been comprehensively examined yet. Second, we show that the COVID-19 pandemic changes the relative importance of electricity price determinants. This implies that stability policies of tranquil times may not work during crisis periods, such as pandemics. Third, we account for global and domestic factors such as oil prices, volatility, foreign exchange (FX) rates, renewable sources, and monetary policy indicators and assess their relative importance in determining electricity price stability.

This study consists of five sections. After the introduction, the relevant literature is examined in Section 2, and the variables used in the analysis are summarized. The research objectives, data, and methodology are explained in Section 3. The results of empirical analysis including the comparison of empirical models, variable importance, and the results of the best model are presented in Section 4. The discussion and policy implications are presented in Section 5. Finally, Section 6 concludes.

2. Literature Review

The main focus of the literature is on the demand side of electricity markets. There are also several studies on the determinants of electricity prices. These studies have considered various factors, such as raw material prices, FX rate, renewable sources, volatility, etc. In what follows, we provide a brief discussion of these studies from the perspective of determinants used.

Global factors take place in the first group of studies. One of the main determinants of electricity prices considered in the literature is raw material prices. Although there are a variety of sources that are used for electricity production, oil prices appear the most significant indicator for electricity markets. For this reason, we include oil prices as a determinant in line with the studies of [6,13,16,25–30]. It is expected that electricity prices increase while oil prices increase because the cost of electricity production increases as well. We consider Brent crude oil prices as oil prices because this type of oil is used in Turkey and expect a positive relationship between oil prices and electricity prices.

H_1: *OIL has a statistically significant positive impact on EP at a 95% of confidence level.*

References [6,15,26] found that the volatility in financial asset markets has a significant impact on energy markets. Hence, we also include volatility in this study. Although there are a variety of volatility indicators, the volatility (VIX) index is the most used variable to capture global risk perceptions. For this reason, we include the VIX index as a determinant. It is expected that electricity prices increase while the VIX index increases because the cost of production increases with risk perceptions. We expect a positive relationship between the VIX index and electricity prices.

H_2: *VIX has a statistically significant positive impact on EP at a 95% of confidence level.*

National factors, such as the strength of the local currency, also play an important role in electricity price determination. References [26,28] included FX rates as a determinant and find that they are significant. In line with these findings, we include the United States Dollar (USD)/TRY FX rate in the study because USD is the most used FX in the world [31]. It is expected that electricity prices increase while FX rates increase because the cost of electricity production increases. We expect a positive relationship between FX rates and electricity prices.

H_3: *USDTRY has a statistically significant positive impact on EP at a 95% of confidence level.*

In addition, we include some financial indicators in the context of national factors by considering that electricity can also be used as an alternative investment vehicle. For this reason, we consider the stock market index of Turkey (e.g., XU100 index) [32,33]. It is expected that electricity prices increase while the XU100 index increases because they can be viewed as alternative investments, and we expect a positive relationship between the XU100 index and electricity prices.

H_4: *XU100 has a statistically significant positive impact on EP at a 95% of confidence level.*

Moreover, money emission by the central bank can be influential because the emission amount can affect the prices of any commodities through liquidity. In addition, including such an indicator is important because most countries have used monetary policy measures to mitigate the negative economic impacts of the COVID-19 pandemic [10]. Hence, we include the TRY emissions by the central bank of the Republic of Turkey (CBRT). It is expected that electricity prices increase while emission amount increases because demand for commodities increases in response to higher liquidity as well. We expect a positive relationship between emission amount and electricity prices.

H_5: *EMISSION has a statistically significant positive impact on EP at a 95% of confidence level.*

The electricity market variables take place in the third group of studies. In this group, the consumption amount of electricity and share of renewable sources in total

electricity production is observed. References [6,15,16,34] included the supply and demand of electricity in their studies. Naturally, we expect a positive relationship between electricity demand and electricity prices.

H_6: *DEMAND has a statistically significant positive impact on EP at a 95% of confidence level.*

Using renewable sources can significantly decrease electricity prices. References [5,34–36] used renewable sources as a determinant in their studies. Following these studies, we include renewable sources and expect a negative relationship between renewable sources usage and electricity prices because it is expected that electricity prices decrease while renewable use increases.

H_7: *RENEW has a statistically significant negative impact on EP at a 95% of confidence level.*

Moreover, the impact of the COVID-19 pandemic is also considered since it affects both economic and social indicators. The COVID-19 pandemic has been considered by various studies in the literature [10,33,37,38]. In line with these studies, we also account for the pandemic. We expect a positive relationship between the pandemic and electricity prices because the pandemic affects indicators adversely.

H_8: *COVID-19 has a changing effect in importance order of influential factors on EP.*

The current studies have used either econometric techniques like Autoregressive Distributed Lag (ARDL), causality & cointegration (Granger, Johansen), Generalized Autoregressive Conditional Heteroskedastic (GARCH), Generalized Method of Moments (GMM), Nonlinear Autoregressive Distributed Lag (NARDL), Regression (Dynamic Ordinary Least Squares-DOLS, Fully Modified Ordinary Least Squares-FMOLS, Ordinary Least Squares-OLS), or machine learning algorithms (Artificial Neural Network-ANN). On the other hand, since studies about working on the prediction performance of electricity prices before and during the pandemic using machine learning algorithms are limited in the literature, different machine learning algorithms' performances are tested and compared to classical econometric models in this study. Moreover, there is no such study for Turkey in the current literature. This study attempts to add to this limited literature by examining the relative importance of global, national, and electricity market fundamentals as well as the COVID-19 pandemic for electricity prices in Turkey, and by comparing the prediction performance of econometric models and machine learning algorithms. Our results may have important implications for other emerging economies.

In total, seven independent variables as well as the COVID-19 pandemic are included in the analysis with benefiting from the literature. Table 1 summarizes the details of these variables.

Table 1. The description of the variables.

Group	Variable	Symbol	Description	Relation
Dependent	Electricity Prices	EP	Spot Electricity Prices (TRY/MWh)	
Global	Oil Prices	OIL	Brent Crude Oil Prices (USD/Barrel)	+
	Volatility	VIX	Volatility Index	+
National	Foreign Exchanges	USDTRY	USD/TRY FX Rate	+
	Stock Market Index	XU100	XU100 Price Index	+
	Central Bank Emission	EMISSION	Amount of Money Issued by CBRT	+
Electricity Related	Electricity Consumption	DEMAND	Electricity Consumption (MWh)	+
	Renewable Electricity	RENEW	Share of Renewable Energy in Electricity Production (%)	-

3. Data and Methods

3.1. Data

The sample period ranges from 15 February 2019 to 31 March 2021. The first COVID-19 case was determined on 11 March 2020 in Turkey. Hence, the beginning of the pandemic was used to divide data into sub-periods. For this reason, data regarding the pandemic period started on 11 March 2020, and there were 266 observations until 31 March 2021 for this sub-period. We extended the date back to have the same number of observations, namely to 15 February 2019, for the pre-pandemic sub-period. As a result, the data was split into two sub-periods, the pre-pandemic period (15 February 2019–10 March 2020) and the pandemic period (11 March 2020–31 March 2021), and each period had 266 observations. Moreover, we used the last 26 observations in each period for out-of-sample performance evaluation.

Data for all variables were gathered from the Ministry of Health of Turkey [9], Bloomberg [39], CBRT [40], and Energy Exchange Istanbul [41]. Moreover, a business day-based dataset for all variables was used because the study focused on the progress of the electricity prices in both the pre-pandemic and pandemic period.

3.2. Methodology

As depicted in Figure 1, the methodology of this research consists of seven steps as follows: (i) collecting raw data from four different sources, (ii) combining the data to reach the final dataset that is ready to analyze for the pre-pandemic and the pandemic periods, (iii) analyzing descriptive statistics, (iv) conducting time series models to predict electricity prices, (v) creating the train/test design of the machine learning models, (vi) comparing the results of time series models versus machine learning models, and finally (vii) interpreting the results of the best performing model on the electricity prices.

3.2.1. Extreme Gradient Boosting (XGB) Algorithm

XGB is an ensemble machine learning method based on a tree boosting algorithm, which was proposed by the authors of [42]. To optimize the loss function, the XGB algorithm uses not only the first derivative but only the second derivative of this function. The gradient boosting method can improve the effectiveness and flexibility of the model for both prediction and classification problems.

For a given dataset D that has m features and n samples $D = \{(x_i, y_i) : i = 1, 2, \ldots, n, x_i \epsilon R^m, y_i \epsilon R\}$, the objective function is expressed in Equation (1).

$$obj(\phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \quad (1)$$

where l represents the loss function, k is the number of trees, and f_k is the kth tree in the model. According to Taylor's expansion of the objective function, the second-order Taylor of the loss function after the kth iteration was obtained. Therefore, the loss function was calculated to avoid overfitting as given below [43]:

$$\sum_{i=1}^{n} \left[l\left(y_i, \hat{y}^{k-1}\right) + g_i f_k(x_i) + \frac{1}{2} h_i f_k^2(x_i) \right] + \Omega(f_k) \quad (2)$$

$$\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^{T} w_j^2 \quad (3)$$

In Equations (2) and (3), T is the total number of leaf nodes and w is the score of each leaf node. g_i and h_i show the first- and second-order derivatives of each sample, respectively [44].

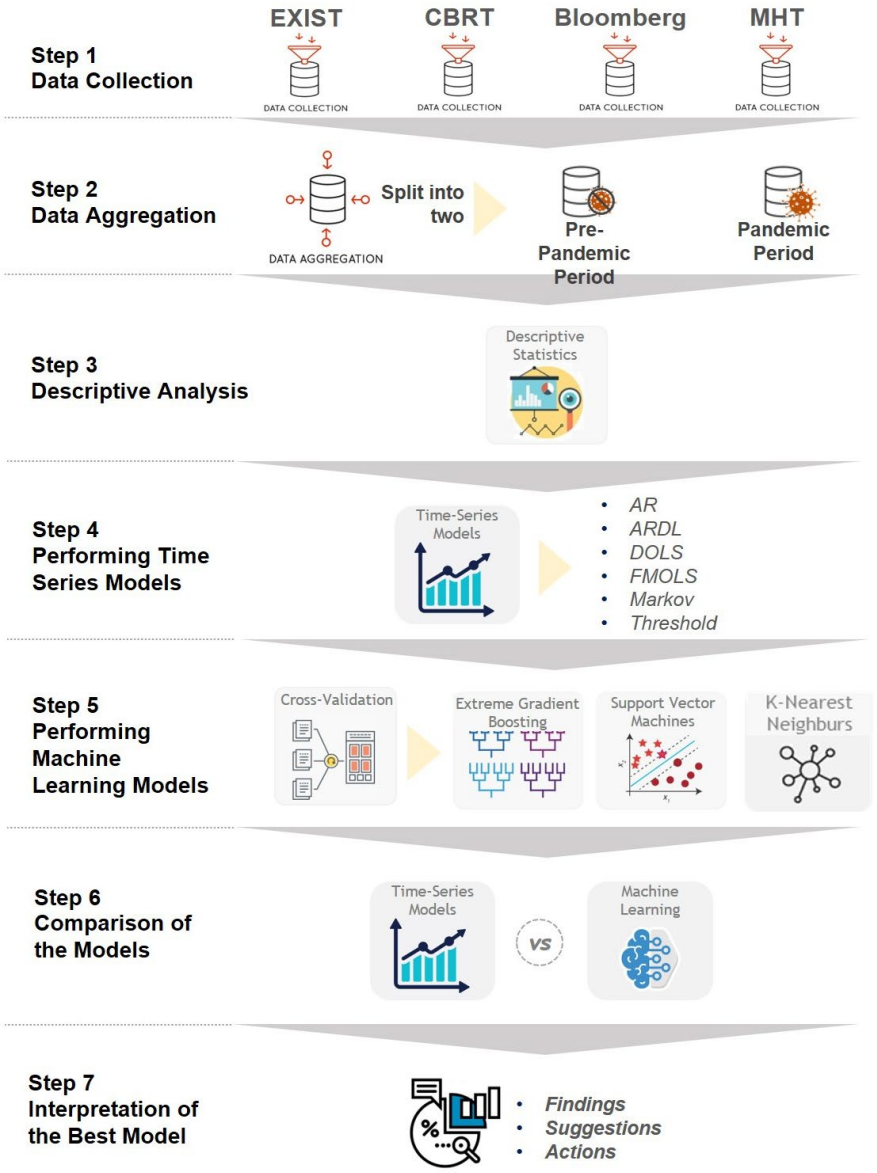


Figure 1. The methodology flowchart.

3.2.2. Model Construction and Performance Evaluation

In the machine learning methods, training and testing samples were determined based on the repeated cross-validation methodology to improve the accuracy of the model. Herein, 10-fold with a 5-repeat validation approach was performed to reach the final model, which was named the in-the-sample period. Furthermore, the last 26 observations in both the pre-pandemic and the pandemic periods are were into consideration as an out-of-sample period to evaluate the prediction performance of all models. Measuring the model performance in both in-the-sample (train and test) and out-of-sample confirmed the reliability of the model.

The model performance was evaluated based on the root mean squared error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE). The lower values of these statistics indicated that the difference between the actual and predicted values was relatively small. The formulations of the model performance statistics are given in Equations (4)–(6) below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (4)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| * 100 \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (6)$$

where y_i, $\hat{y}_i$, and n represent the observed values of the dependent variable, predictions of the dependent variables, and the number of observations, respectively.

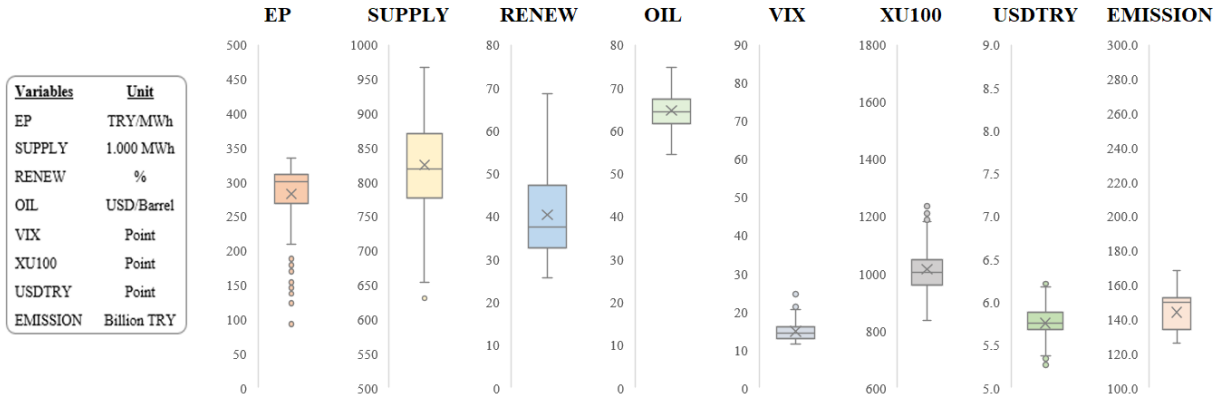
4. Empirical Analysis

4.1. Descriptive Statistics

The first stage of the analysis is to examine the distribution of the variables using common descriptive statistics and a box-plot approach. Figures 2 and 3 depict the basic statistics and the distributions of the variables used in the study for the pre-pandemic and the pandemic periods.

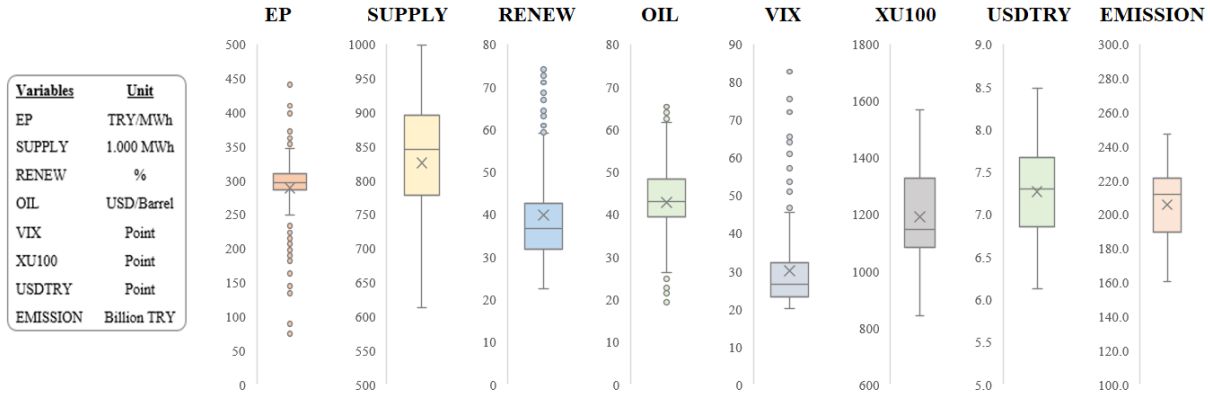
In the pre-pandemic period, the mean and standard deviation of the electricity price were 282.4 and 44.1, respectively. In addition, the electricity price had a left-skewed distribution with few outliers. On the other hand, independent factors generally had no outliers and the coefficient of variation values were lower than 15 (except for renewable energy), which means that there was no strong variation in the independent factors in the pre-pandemic period. It is not surprising to have a high variation relative to the mean for renewable energy since it depends on weather conditions.

As presented in Figure 3, contrary to the pre-pandemic period, the number of outliers in electricity price, renewable electricity, oil prices, and the volatility index was relatively higher in the pandemic period, which states that the volatility of the aforementioned factors increased. The standard deviations and variations relative to the mean were all above their pre-pandemic levels, reflecting the increased uncertainty due to the pandemic. Furthermore, the average values of the oil prices, volatility index, stock market index, foreign exchanges, and CBRT emission amount in the pre-pandemic period significantly changed in the pandemic period, while the average value of electricity prices stayed stable at the 280–209 level. This descriptive finding is strong evidence that the factors that influence the electricity price should be examined as separate periods for the pre-pandemic and pandemic periods.



	EP	SUPPLY	RENEW	OIL	VIX	XU100	USDTRY	EMISSION
Mean	282.4	824,840.0	40.3	64.6	14.8	1014.6	5.8	144.1
Standard Deviation	44.1	59,951.8	9.9	4.1	2.3	83.5	0.2	9.5
Coefficient of Variation	15.6	7.3	24.7	6.3	15.4	8.2	3.3	6.6
Minimum	92.8	630,426.7	25.7	54.5	11.5	836.8	5.3	126.3
Q_{25}	268.7	777,176.9	32.9	61.6	12.9	960.2	5.7	133.9
Median	299.7	818,883.2	37.4	64.3	14.3	1003.4	5.8	149.9
Q_{75}	310.9	870,567.0	47.1	67.2	16.0	1048.4	5.9	152.3
Maximum	334.8	966,757.8	68.5	74.6	24.6	1235.6	6.2	168.4

Figure 2. Descriptive statistics in the pre-pandemic period (15 February 2019–10 March 2020).



	EP	SUPPLY	RENEW	OIL	VIX	XU100	USDTRY	EMISSION
Mean	288.0	831,371.2	39.8	42.8	30.1	1191.1	7.3	205.5
Standard Deviation	46.5	89,943.6	12.0	9.7	11.3	195.0	0.5	18.7
Coefficient of Variation	16.1	10.8	30.2	22.6	37.5	16.4	6.7	9.1
Minimum	74.4	614,183.1	22.4	19.3	20.0	842.5	6.1	160.6
Q_{25}	285.5	780,456.2	31.8	39.4	23.1	1083.1	6.9	189.7
Median	295.7	856,526.3	36.6	42.9	26.4	1146.0	7.3	211.8
Q_{75}	310.0	901,386.5	42.6	48.2	32.2	1326.3	7.7	221.0
Maximum	440.3	998,058.0	74.0	65.4	82.7	1569.4	8.5	247.2

Figure 3. Descriptive statistics in the pandemic period (11 March 2020–31 March 2021).

4.2. Comparison of Empirical Models

In the study, seven different time series-based and three machine learning-based methodologies were used to predict electricity prices. The performance of the models used in the study was evaluated based on the goodness-of fit-statistics, which are RMSE, MAE, and MAPE. The model performance statistics are given in Tables 2 and 3 in both the pre-pandemic and the pandemic periods.

Table 2. Prediction performance comparison of models in the pre-pandemic period.

Group	Model	RMSE	MAE	MAPE
Time Series Econometrics [1]	AR	20.373	17.152	5.783
	ARDL	17.664	12.644	4.435
	DOLS	17.556	14.093	4.885
	FMOLS	17.251	12.686	4.451
	MARKOV	16.269	12.711	4.418
	THRESHOLD	32.764	19.195	6.742
	OLS	18.805	16.412	5.609
Machine Learning Algorithms [1]	SVM	17.463	11.535	3.230
	XGB	17.503	12.051	3.234
	k-NN	21.518	13.419	4.699

[1] To save space and not to extend the article too much, the mentioned methods are not discussed broadly. Detailed information concerning these models can be found in [45,46] for time series econometric models and [10,21,47–49] for machine learning algorithms.

The obtained results of the model performed in the pre-pandemic period revealed that the Support Vector Machines (SVM) and XGB algorithms relatively outperformed other models. Although the RMSE values of ARDL, DOLS, and FMOLS, the SVM, and XGB algorithms were close to each other, the MAE and MAPE values of the machine learning models were relatively lower than time series models. Since the k-Nearest Neighbors (k-NN) algorithm was only better than the Threshold model, it is not a good alternative to econometric models to predict electricity prices.

The results of the pandemic period in terms of model comparison statistics were similar to the pre-pandemic period. In the pandemic period, all machine learning algorithms had

significantly better performance than the time series models considering the RMSE, MAE, and MAPE statistics.

Table 3. Prediction performance comparison of alternative models in the pandemic period.

Group	Model	RMSE	MAE	MAPE
Time Series Econometrics	AR	29.470	22.902	7.048
	ARDL	57.661	52.451	16.580
	DOLS	55.655	50.962	16.117
	FMOLS	57.566	52.550	16.621
	MARKOV	55.405	50.052	15.770
	THRESHOLD	35.457	30.701	9.571
	OLS	62.184	57.018	18.050
Machine Learning Algorithms	SVM	21.056	14.810	2.490
	XGB	21.208	15.052	4.383
	k-NN	25.639	17.439	5.429

According to Tables 2 and 3, machine learning models provide superior prediction performance than time series models for both the pre-pandemic and pandemic periods. After we found that machine learning models produced superior predictions than time series models, we compared the out-of-sample performance of the alternative machine learning algorithms to determine the best-performing model. The out-of-sample performance of machine learning models is presented in Table 4.

Table 4. The Out-of-Sample Period Performance of Machine Learning Algorithms.

Period	Model	In-the-Sample			Out-of-Sample		
		RMSE	MAE	MAPE	RMSE	MAE	MAPE
Pre-Pandemic Period	XGB	17.503	12.051	3.234	15.512	11.819	4.076
	SVM	17.463	11.535	3.230	18.858	15.463	5.291
	k-NN	21.518	13.419	4.699	25.228	18.485	6.700
Pandemic Period	XGB	21.056	14.810	2.490	21.641	16.580	5.145
	SVM	21.208	15.052	4.383	25.452	21.934	6.849
	k-NN	25.639	17.439	5.429	19.421	14.179	4.376

As presented in Table 4, the performances of the XGB and SVM algorithms are very close to each other in the pre-pandemic period. On the other hand, when the model is performed for the out-of-sample period to validate the model, it is seen that the XGB algorithm has significantly superior performance to the SVM algorithm. In addition, the performance comparison of all models in the pandemic period was analyzed. Similar to the results of the pre-pandemic period, the XGB algorithm was selected as the suitable model based on minimum RMSE, MAE, and MAPE statistics in both in-the-sample and out-of-sample periods.

4.3. Variable Importance

Variable importance analysis was used to determine the most influencing factor on the target variable to make a prioritization of the actions. The result of the variable relative importance analysis is presented in descending order in Figure 4. According to the literature, since the impacts of the different lag-orders of the electricity price have a significant impact on the electricity prices, the 1-day (EP_1), 1-week (EP_7), and 2-week (EP_14) lags of the electricity prices were included in the model [50,51].

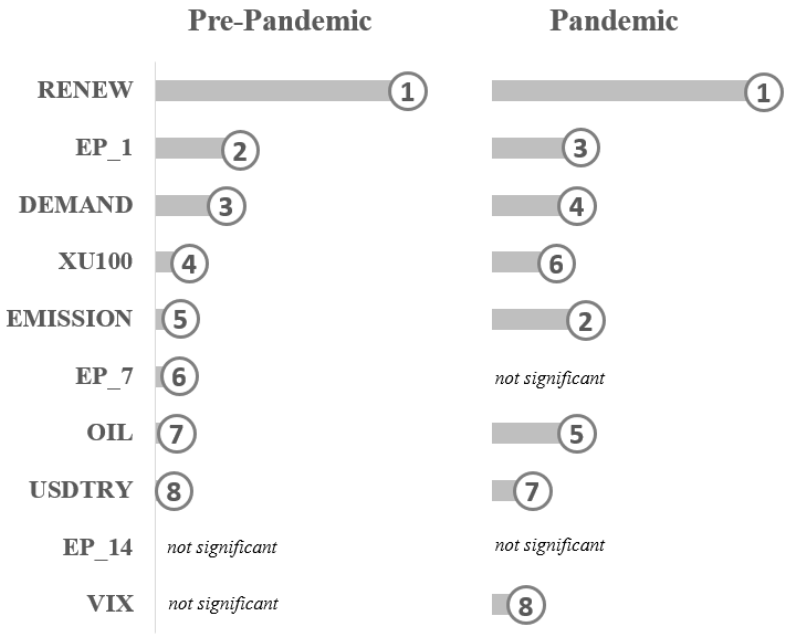


Figure 4. Variable importance analysis of the XGB algorithm.

The most influencing factor affecting electricity prices is renewable electricity in both periods. The second and third most important factors, which are the 1-day lag of electricity price and electricity consumption in the pre-pandemic period, had almost equal importance. Furthermore, the impacts of other factors were relatively lower than renewable electricity, the 1-day lag of electricity price, and electricity consumption. In addition, the 2-week lag between electricity price and the volatility index did not have a statistically meaningful impact. Compared to the pre-pandemic period, most of the factors had a slightly increased impact on electricity prices, except for renewable energy in the pandemic period. In this period, 1- and 2-week lag orders of electricity prices had no impact on the electricity prices. In addition, the importance of oil prices and CBRT money emissions significantly increased.

The single effect, interaction effects, and thresholds of the independent factors on electricity prices are visualized in Figures 5 and 6. The thresholds show statistically significant changes in electricity prices over the independent factors. Furthermore, interaction effects show the co-impact of independent factors on the change in electricity prices. In addition, the x-axis represents the values of independent variables, while the y-axis represents the estimated values of the dependent variable in Figures 5 and 6.

As presented in Figure 5, the electricity prices increased as the electricity consumption, oil prices, the volatility index, and CBRT emission amount increased. These findings, as expected, are consistent with the literature, e.g., [13,15,16,21,29,30,32,34]. The critical thresholds of the aforementioned factors were determined as 750,000, 70, 14, and 135, respectively. These critical thresholds are important because it means that electricity prices are significantly increased in areas where electricity consumption, oil prices, the volatility index, and CBRT emission amount are above these critical thresholds. This is why policymakers should create ready-to-action plans based on these thresholds.

On the other hand, there was a strong negative correlation between renewable electricity and electricity prices, which is similar to the results of studies in the literature, e.g., [5,34–36]. In addition, the critical threshold of renewable electricity was around 50, and electricity prices were at a lower level when the stock market index and foreign exchanges were between 925–1150 and 5.70–5.90, respectively. The interaction effects between the 1-day lag of electricity prices versus electricity consumption, renewable electricity, and the stock market index were statistically significant. In addition, the following interaction effects were statistically significant: electricity consumption versus renewable electricity, electricity consumption versus the stock market index, and renewable electricity versus the

stock market index. To sum up, these findings show that not only individual impact but also interaction effects are taken into consideration by policymakers to estimate or decline the electricity price because of the nexus between variables used in the study.

As given in Figure 6, similar to the pre-pandemic period, electricity prices increased as electricity consumption, oil prices, the stock market index, and CBRT emission amount increase. Similar to the results of the pre-pandemic period, electricity prices decreased as renewable electricity increased. There were clear critical thresholds in a few independent factors in the pandemic period as well. These thresholds for the 1-week lag of electricity prices, electricity consumption, oil prices, the volatility index, the stock market index, and CBRT emission amount increase were 320, 850,000, 64, 28, 1.525, and 180, respectively. Similar to the results obtained from the pandemic period, we observed a 1-day lag of electricity prices versus renewable electricity, the stock market index, and foreign exchanges. In addition, the following interaction effects were statistically significant: renewable electricity versus the stock market index, renewable electricity versus foreign exchanges, and foreign exchanges versus the stock market index. Compatible with the results obtained from the pre-pandemic period, the nexus between electricity prices and independent factors is consistent with the literature during the pandemic period.

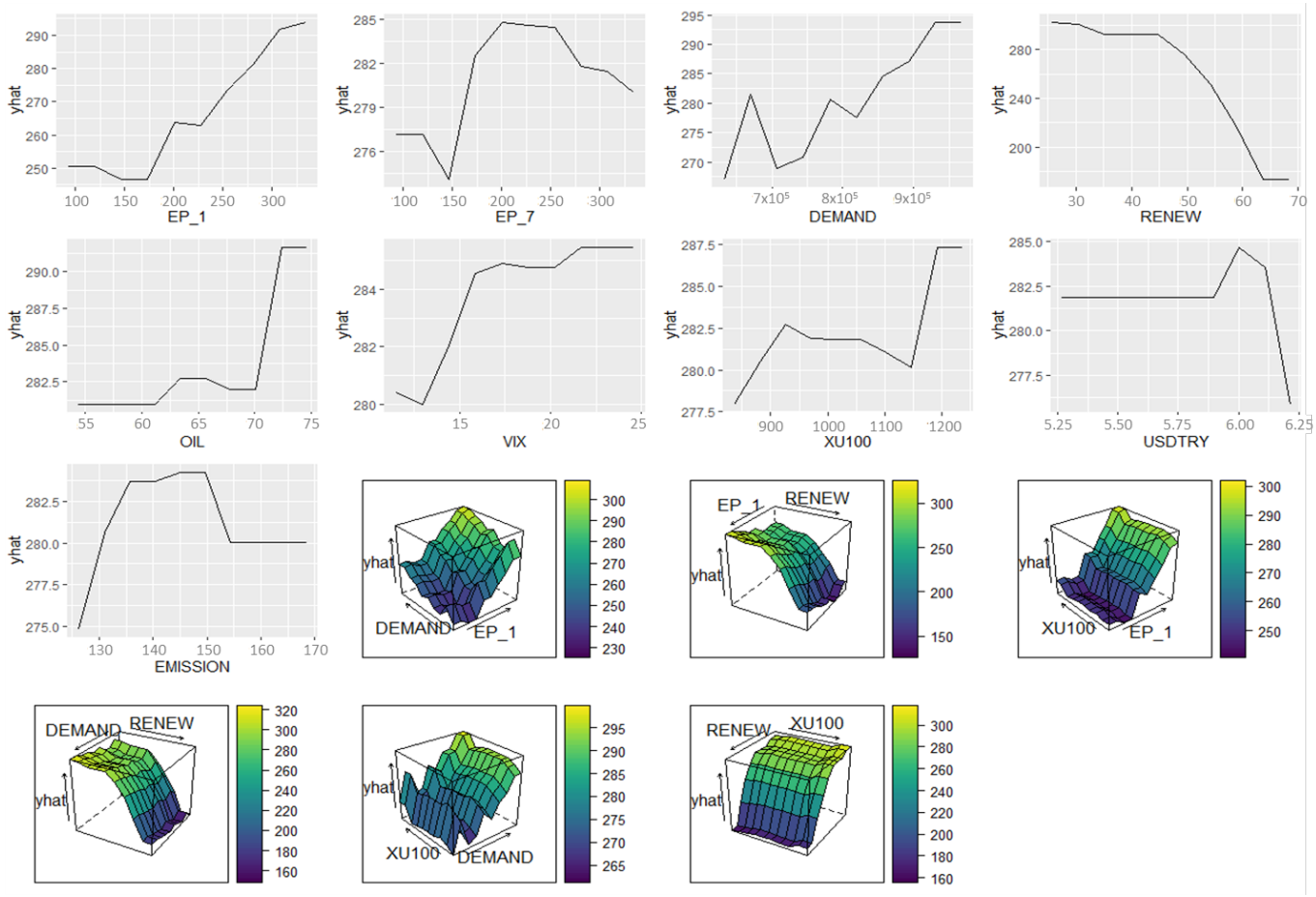


Figure 5. Single and interaction effects of independent variables in the pre-pandemic period.

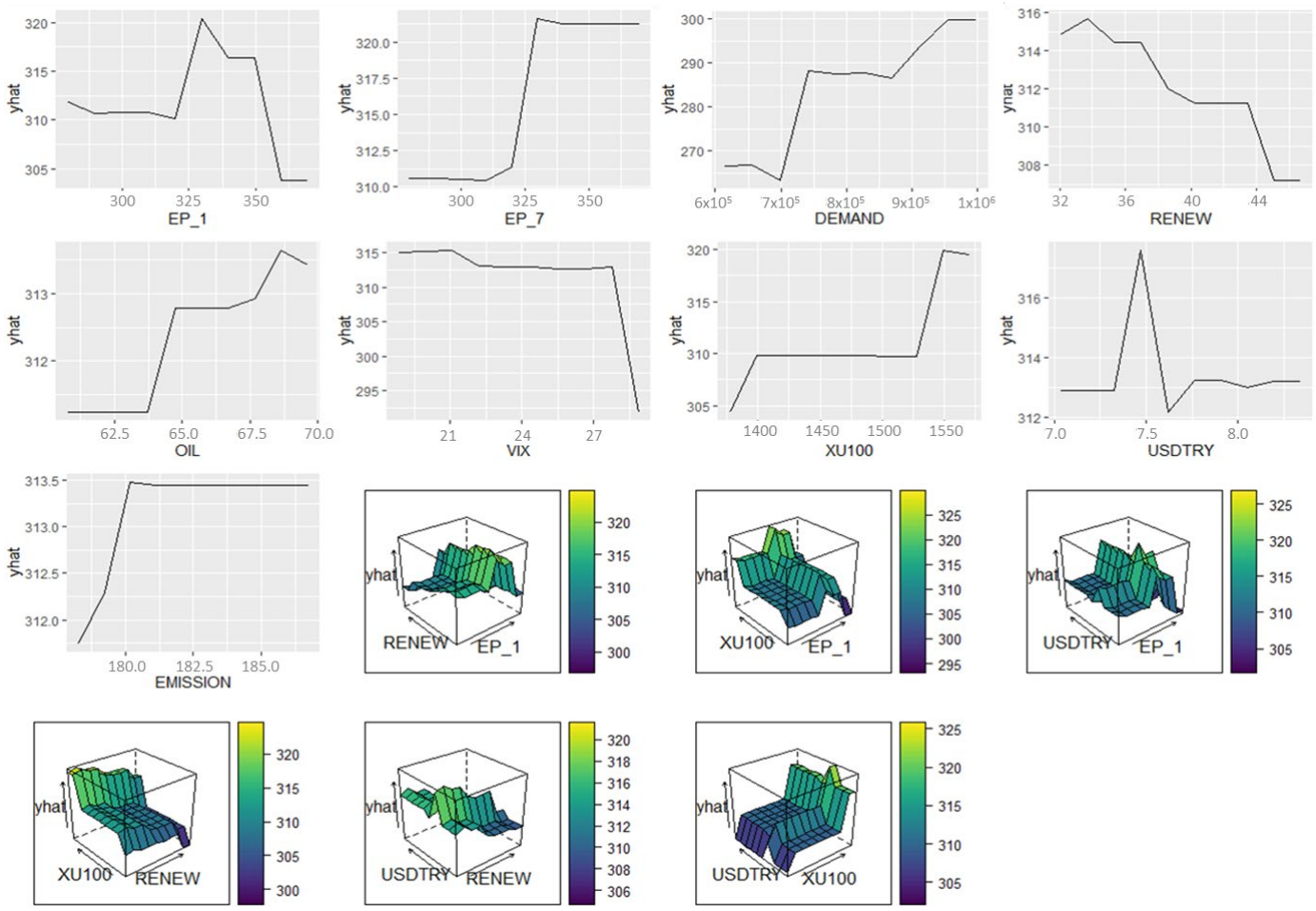


Figure 6. Single and interaction effects of independent variables in the pandemic period.

4.4. Results of the Best Machine Learning Model

The actual versus the predicted values of the electricity prices in both in-the-sample and out-of-sample periods are given in Figures 7 and 8.

Figure 7 depicts that the ability of the XGB algorithm in predicting the electricity prices in the pre-pandemic period is at a satisfactory level (R^2: 85%), especially in sudden increases and decreases. The performance of the model in the out-of-sample period is quite satisfactory as well.

It is evident from the results obtained that the prediction ability of the XGB algorithm is also at a satisfactory level (R^2: 80%) during the pandemic period. Hence, it is concluded that the XGB algorithm can predict electricity prices based on the results of both in-the-sample and out-of-sample periods for predicting electricity prices.

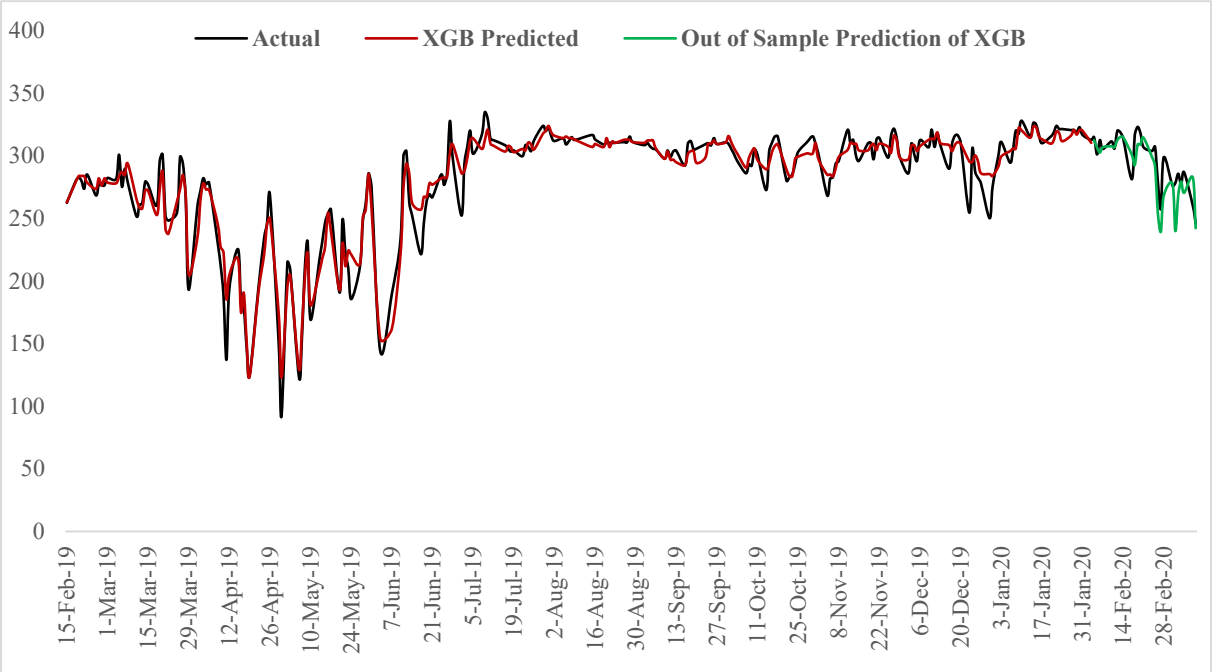


Figure 7. Actual and predicted values in the pre-pandemic period.

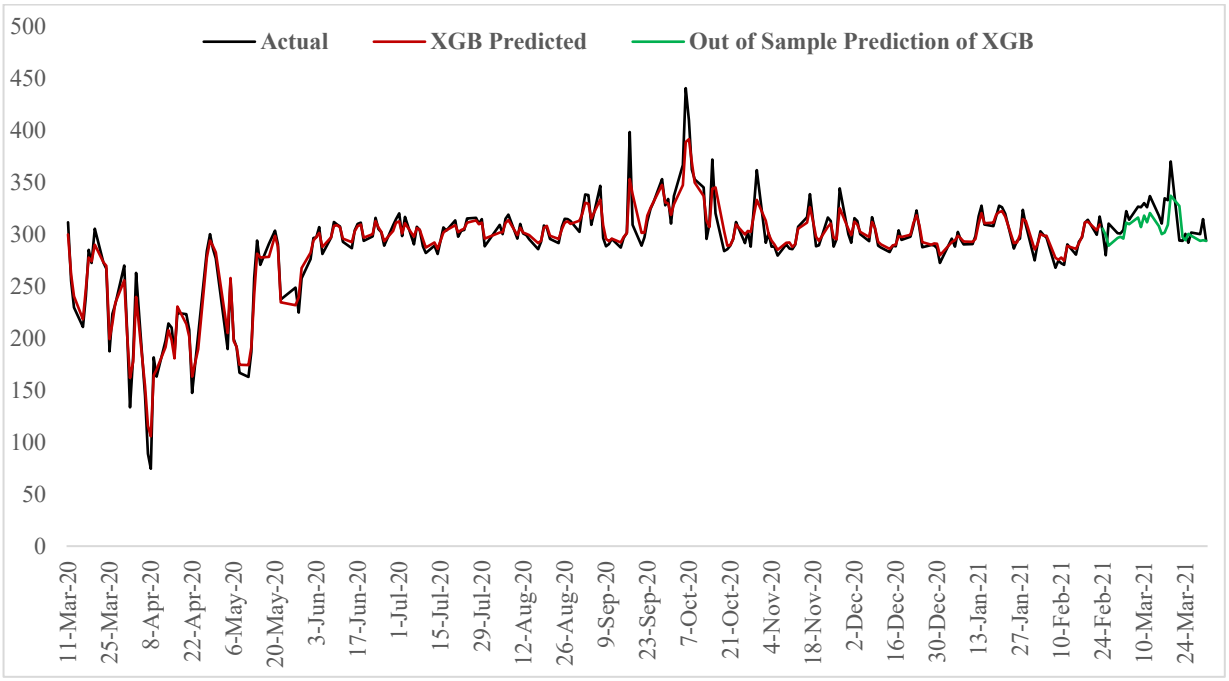


Figure 8. Actual and predicted values in the pandemic period.

5. Discussion and Policy Implications

By following the proposed methodology and making a comparison between time series econometrics and machine learning algorithms, we found that machine learning algorithms provided better prediction performance for electricity prices. Specifically, the Extreme Gradient Boosting (XGB) algorithm provided the best results. Hence, we completed the detailed analysis with the XGB algorithm.

The use of renewable sources emerged as the most important determinant in both periods. However, the relative importance of other influential factors varied across periods.

Electricity demand, XU100 index, emission amount, oil prices, USD/TRY FX rates had corresponding importance following renewable sources usage, whereas the VIX index did not have an impact in the pre-pandemic period. However, renewable energy was followed by emission amount, electricity demand, oil prices, XU100 index, USD/TRY FX rates, and VIX index in the pandemic period, respectively. It seems that electricity prices responded more to global factors (i.e., oil price, VIX index) and domestic monetary and economic (i.e., money emissions, XU100, FX) stances during the pandemic.

The results of the Extreme Gradient Boosting (XGB) algorithm showed that oil prices, VIX index, USD/TRY FX rates, stock market index, emission amount, and electricity demand had a positive relationship with the electricity prices, whereas the share of renewable energy had a negative relationship in both periods. Hence, the empirical results obtained reveal that the hypotheses included in the study are validated. These results are consistent with the current literature, e.g., [5,15,16,21,32,52–54].

The empirical results suggest that the following policies are appropriate. First, Turkey should focus on increasing the share of renewables in electricity production to increase the affordability of electricity. This would improve the greenhouse gas emission performance of the country as well.

After renewable sources, Turkey should concentrate on electricity consumption as an important factor in the electricity prices. In this regard, Turkey can increase electricity production to meet the demand and improve energy efficiency. For this, Turkey should take into account the rebound effect and develop incentive schemes for renewable energy investments.

The government cannot ignore the effects of stock market developments and money emissions on electricity prices. As variable importance shows, the importance of emission increased in the pandemic period, whereas the importance of XU100 index decreased. Issuing money to mitigate the negative economic impacts of a pandemic leads to rising electricity prices, which may crowd out the initial impact by raising production costs.

The COVID-19 pandemic caused a change in the relative importance of electricity price determinants. Thus, this dynamic change must be followed closely to understand the potential impacts of government policies until the end of the pandemic. It may be fruitful for future research to repeat this analysis in the post-pandemic period.

Last but not least, machine learning algorithms have better prediction performances than time series econometric models. Policymakers and market participants can benefit from these tools to improve their forecasts to design better policies and strategies.

The findings in this study can help Turkish authorities improve stability in the electricity market. Producers, consumers, and investors will benefit from this stability. Turkish policymakers have access to high-frequency data that are not available to the public, and machine learning algorithms can help them utilize these data more effectively.

6. Conclusions

This study identifies the relative importance of electricity price determinants and compares the prediction performance of alternative machine learning and time series models in Turkey. In this context, seven global, national, and electricity-related variables were used. In addition, daily data for two sub-periods, the pre-pandemic (15 February 2019–10 March 2020) and the pandemic (11 March 2020–31 March 2021) periods, were included.

According to our results, machine learning algorithms had better prediction performances than time series econometric models. In addition, according to out-of-sample prediction performance, the XGB algorithm yielded the best results in both periods. XGB results showed that the share of renewables in electricity production was the most important determinant, and the pandemic caused a change in the relative importance of determinants. It is important to keep track of these changing dynamics throughout the pandemic to correctly anticipate the potential impacts of global and local factors on electricity prices. The results obtained from the XGB are consistent with the expectations and the current literature.

The results highlight the importance of renewable energy share for electricity prices, the pandemic's role in the changing importance of the variables, and the better performance of machine learning algorithms in electricity price prediction. This analysis can be repeated by government authorities using high-frequency data, which are not available to the public, to illuminate the path for a more stable electricity market in Turkey.

Although this study makes a comprehensive empirical examination, unfortunately, it has some limitations. In this context, continuing this line of research in other emerging countries can be fruitful in understanding the drivers of electricity price stability during natural crises. A comparative study between highly and less affected countries by the COVID-19 pandemic can be beneficial. In addition, including more factors and using different indicators, which were not included in this study, can be considered in new studies to either validate the results of this study or obtain different insights regarding electricity prices. Moreover, different time series econometric models, mixed models considering the unobserved heterogeneity in the data, and machine learning algorithms not included in this study can be applied in forthcoming studies.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

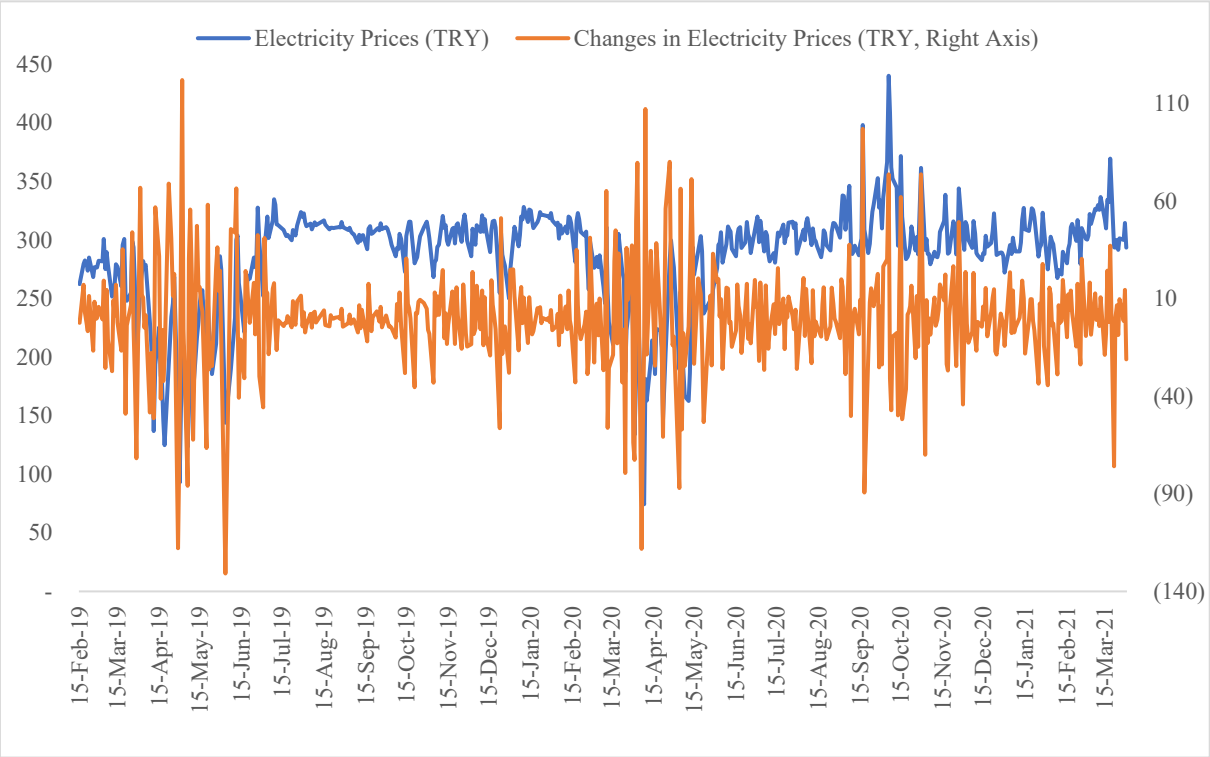


Figure A1. The progress of electricity prices in Turkey.

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