The Impact of Renewable Energy Generation on the Spot Market Price in Germany: Ex-Post Analysis using Boosting Method

Alexander Ryota Keeley,[a,b] Ken'ichi Matsumoto,[c,d] Kenta Tanaka,[e] Yogi Sugiawan,[f] and Shunsuke Managi[a]*

ABSTRACT

This study combines regression analysis with machine learning analysis to study the merit order effect of renewable energy focusing on German market, the largest market in Europe with high renewable energy penetration. The results show that electricity from wind and solar sources reduced the spot market price by 9.64 €/MWh on average during the period from 2010 to 2017. Wind had a relatively stable impact across the day, ranging from 5.88 €/MWh to 8.04 €/MWh, while the solar energy impact varied greatly across different hours, ranging from 0.24 €/MWh to 11.78 €/MWh and having a stronger impact than wind during peak hours. The results also show characteristics of the interactions between renewable energy and spot market prices, including the slightly diminishing merit order effect of renewable energy at high generation volumes. Finally, a scenario-based analysis illustrates how different proportions of wind and solar energies affect the spot market price.

Keywords: Renewable energy sources, Electricity spot price, Intermittency, Merit order effect, Boosting.

https://doi.org/10.5547/01956574.41.SI1.akee

1. INTRODUCTION

With the mounting concerns over climate change caused by conventional energy sources such as fossil fuels, making the transition in the electricity supply industry from conventional energy sources to renewable energy (RE) sources has become a critical challenge for society. The European Union (EU)'s RE policy has developed along with the liberalization of the electricity market (Cointe and Nadaï, 2018). Among the countries of the EU, Germany is a leader in terms of its promotion of RE and its ultimate aim of building a sustainable energy system. The share of electricity derived from RE sources in Germany more than doubled over the decade from 2008, strongly led by solar and wind energy generation (German Federal Ministry for Economic Affairs and Energy, 2019), and reached 40.4% of the net electricity generation in 2018 (Fraunhofer ISE, 2019). Germany's

a Urban Institute, Kyushu University, 744 Motooka, Nishi-ku, Fukuoka 819-0395, Japan.
b World Bank, Uchisaiwaicho 2-2-2, Chiyoda-ku, Tokyo 100-001, Japan.
c Graduate School of Fisheries and Environmental Sciences, Nagasaki University, 1-14 Bunkyomachi, Nagasaki 852-8521, Japan.
d Research Institute for Global Change, Japan Agency for Marine-Earth Science and Technology, 3173-25 Showa-cho, Kanazawa-ku, Yokohama, Kanagawa 236-0001, Japan.
e Faculty of Economics, Musashi University, 1-26-1, Toyotama-kami, Nerima-ku, Tokyo 176- 8534, Japan.
f Planning Bureau, National Nuclear Energy Agency of Indonesia, Jl. Kuningan Barat, Mampang Prapatan, Jakarta 12710, Indonesia.
* Corresponding author. E-mail: keeley.ryota.alexander.416@m.kyushu-u.ac.jp.

increasing RE capacity contributes to the country's construction of a sustainable energy system, but the intermittent nature of RE creates challenges in managing the flexibility required in electricity supply and demand. Therefore, investigation of the impact of an increasingly RE-sourced electricity supply on the overall trends and the volatility of the spot market price is important for both future RE policy making and the design of the electricity market.

In Germany, electricity traded at the spot market accounted for 302 TWh in 2015, representing 53% of German electricity consumption. The spot market trading and auctions of electricity are carried out by the European Power Exchange (EPEX). Day-ahead auctions take place at 12 pm each day for the 24 hours of the following day. In these day-ahead auctions, electricity producers offer electricity at their short run marginal cost (SRMC). The SRMC is the cost of production of a unit of electricity in the short-term and mainly consists of fuel, variable operations and management, and CO_2 costs. The offers from the producers are then lined up, beginning with those with the lowest SRMC and running in cost order up to those with the highest SRMC. This price-setting mechanism is called the merit order mechanism. The SRMCs of the RE sources are almost zero, and they are followed by other sources that have higher SRMCs (e.g., nuclear energy, lignite, hard coal, gas and fuel oil plants). Under the merit order mechanism, the addition of further volumes from RE sources with their near-zero SRMC to the offer list is known to cause a reduction in the electricity price, which is called the merit order effect (MOE) (Sensfuß et al., 2008).

Advancing our understanding of the pricing dynamics of the electricity market is of critical importance both for the market participants and for the design of the electricity market, and thus a considerable number of studies have addressed this topic. This study builds upon these preceding studies and aims to advance our understanding of the MOE, with a particular focus on the MOE of electricity from RE sources (both wind and solar) on the spot market price in Germany. As noted by Jónsson et al. (2010), electricity market pricing data typically have complex characteristics such as nonlinearity and nonstationarity that must be taken into careful consideration when conducting such an analysis. As will be discussed in the next section, the most common approach among the studies that have used econometric approaches to investigate the MOE of RE has been to use a regression model with ex-post data. Following these previous studies, this study uses both a linear regression method and a machine learning (ML) approach to investigate the MOE of RE. The main objectives of this study are threefold: first, to estimate the average change in the wholesale price during the period studied (from 19/7/2010 to 18/12/2017) and to investigate how the MOE varies across the hours of the day; second, to analyze the features that are difficult to capture using the linear regression method by using the ML approach; and finally, to perform a scenario-based analysis to examine how different proportions of the wind and solar energies affect the spot market price.

The rest of this paper is structured as follows. In Section 2, before the methodology used in this study is described in detail, the existing studies on the MOE are reviewed. In Section 3, the data used in this study are first presented, followed by a description of the proposed methodology: the generalized least squares (GLS) method and the extreme gradient boosting method. Section 4 then presents the results, beginning with the results of an analysis when using the data as one unique series (2010–2017 analysis), followed by the results of an analysis using the data when separated into 24 hourly series (hourly analysis), and then the results of the scenario-based analysis using the ML approach. Finally, conclusions are presented in Section 5.

2. LITERATURE REVIEW

Existing studies of the MOE can mostly be classified as either simulation-based studies that use both hypothetical and real data or empirical studies that use ex-post data and are generally conducted using econometric models. Most of these earlier studies used simulation-based approaches: Sensfuß et al. (2008) conducted an analysis focused on Germany based on a detailed electricity market simulation platform called the PowerACE Cluster System and their results showed that electricity generation from RE has a considerable impact on the market prices, with an average electricity price reduction of 7.8 €/MWh in 2006. Weigt (2009) also modeled the German electricity market and reported an average price reduction effect for wind generation of approximately 10 €/ MWh between January 2006 and June 2008. The study also showed that the price effect of wind generation increased over time during the study period. Sáenz de Miera et al. (2008) performed a simulation analysis that focused on the Spanish electricity market and showed that wind generation had reduced Spanish electricity prices considerably by −7.08 €/ MWh to −12.44 €/MWh between 2005 and 2007. Another simulation study by Holttinen et al. (2001) focused on Nordpool to investigate the effects of wind generation on market prices. Their study used wind data ranging from 1961 to 1990 to calibrate their model and showed that the model yielded price reductions of 2 €/MWh for each 10 TWh of additional annual wind generation in a 2010 forecast scenario.

With the increasing availability of ex-post data for both the spot market prices and the RE electricity supplies, more recent studies have used econometric approaches to investigate the actual MOE of RE. Among these empirical studies, the most common approach has been to use a regression model with ex-post data. Stating with the German market, Neubarth et al. (2006) used a univariate regression model to investigate the MOE of wind generation on spot prices during the period from 2004 to 2005 and showed that for each additional GW of wind power generated, the spot market price fell by 1.89 €/MWh. Würzburg et al. (2013) pointed out that very limited empirical evidence was available for the MOE in Germany and used a multivariate regression model along with daily averaged data on electricity prices to investigate the MOE of RE (solar and wind power). Their study showed that between 2010 and 2012, RE reduced the electricity spot price on average by 7.6 €/MWh. Cludius et al. (2014), while also focusing on the German market, performed a time-series regression analysis using hourly data on the spot market price, wind and solar generation, and the load, and showed that electricity from wind and solar energy sources caused reductions in the German/Austrian day-ahead spot electricity price of 6 €/MWh in 2010 and 10 €/MWh in 2012. Similar studies have also been conducted while focusing on other countries: Gelabert et al. (2011) focused on the Spanish spot market price, and their ordinary least squares (OLS) estimation results showed that a marginal increase of 1 GWh of electricity from RE is associated with a reduction of approximately 1.9 €/MWh in the wholesale prices during the period studied between 2005 and 2010. Clò et al. (2015) also performed a time-series regression analysis that focused on the impact of wind and solar generation on the Italian spot market price. Their study showed that between 2005 and 2013, wind and solar generation reduced the wholesale electricity prices on average by 4.2 €/MWh and 2.3 €/MWh, respectively. Another more recent study by Quint and Dahlke (2019) investigated the MOE of wind generation while focusing on the Midcontinent Independent System Operator (MISO), which is the largest wholesale electricity market by geographical area worldwide. Their study used several models, including a basic cross-sectional multivariate regression analysis, the Prais-Winsten estimation methods, and a seasonal autoregressive-moving average with exogenous inputs (SARIMAX) model, and showed that each 1 GWh of additional wind generation reduced the wholesale prices in MISO by \$1.4/MWh to \$3.4/MWh.

All these studies focusing on the wholesale electricity markets in various countries and regions have supported the proposition that the acquisition of more electricity from RE sources leads to reduced electricity prices. While studies of this type that used regression models have helped to advance our understanding of the MOE of RE, the existing studies of the MOE have largely focused on estimation of the average change in the wholesale price; however, studies that have investigated how the MOE differs across the hours of the day are scarce. Therefore, to fill this gap, this study investigates both the average change in the wholesale price and also the changes in the MOE across the hours of the day.

Another important feature of this paper lies in its use of the ML approach to investigate the MOE. While a linear regression method is used in this study and most of the previous studies that investigated MOE used its strength in being able to quantify the average MOE, the functional form in a linear regression method is predetermined and this makes it more challenging to capture any unusual features of the data, such as nonlinear relationships between the variables. In contrast to regression modeling, which designs the relationships between the variables using a mathematical equation provided by the modeler, ML is a type of algorithm that can learn from the data without an explicit relationship structure between the variables. Learning the relationship structure, regardless of its functional form, confers the ability to infer many complex and nonlinear relationships, which often leads to high predictive performance. However, this is also what gives a "black box" appearance to ML and makes it difficult to quantify the average MOE. Therefore, an ML approach is used in this study to analyze the features that are difficult to capture using the linear regression method that we also employ, and it is also used to perform a scenario-based analysis to investigate how different proportions of wind and solar generation would affect market prices. ML methods are increasingly being used in economic and financial analysis of the electricity markets (e.g., in price prediction). One of the earliest studies that used ML in economic and financial analysis of the electricity markets was conducted by Conejo et al. (2005) and included prediction of the electricity spot market price using artificial neural networks (ANNs). Papadimitriou et al. (2014) used a support vector machine (SVM)-based prediction model to forecast next-day electricity prices and demonstrated the strength of their SVM method by forecasting electricity prices with high accuracy. The feedforward neural network (FFNN), which offers an advantage in that it does not require complex data preprocessing (e.g., time series decomposition, detrending, and seasonal adjustment), was used by Dudek (2016) in an electricity price forecasting approach. The ensemble method, which is a meta-learning approach that combines multiple weak learner decision trees to formulate strong learners, has also been widely applied to electricity price prediction (see e.g., Mirakyan et al., 2017; Tian et al., 2010). While these studies demonstrated the strength of ML-based approaches in dealing with electricity price data with complex characteristics, most studies that have used ML approaches to analyze the electricity markets have focused on electricity price prediction, but none have used ML to investigate the MOE of RE more closely.

An extreme gradient boosting method, which is a type of ensemble method with greater predictive power and higher interpretability than most conventional ML methods, is used in this study (Carmona, 2019). The XGBoost Explainer R package (Foster, 2017) is then used to provide further improvement in the interpretability of the extreme gradient boosting model by allowing the predictions from the model to be split into the individual impacts of each feature.

3. DATA AND METHODS

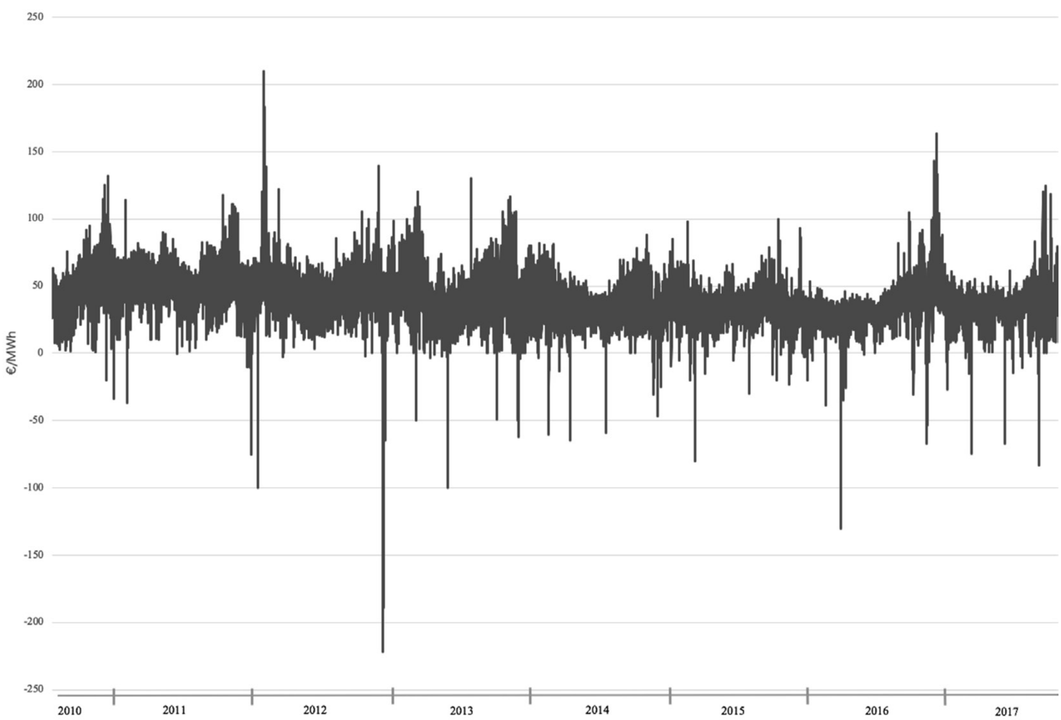
This section describes the data used in this study and provides details of the two estimation methods used: the GLS method and the extreme gradient boosting method

3.1. Data

Until October 2018, the German electricity market formed a joint bidding zone with Austria at EPEX SPOT for both the intraday and day-ahead markets that was the largest market in Europe (with the German part of the market being the larger of the two). Germany and Austria also produce significant amounts of their electricity from wind and solar sources. The majority of the wind and solar capacity is installed in Germany (55,876 MW of wind and 42,396 MW of solar sources in Germany, in contrast to 2,926 MW of wind and 1,404 MW of solar sources in Austria, at the end of 2017). As the largest market with high RE penetration, the German/Austrian spot market is thus a desirable candidate for investigation of the MOE of RE and the results of such a study could provide useful insights that are applicable to other countries aiming for increased RE adoption. Therefore, to analyze the MOE of electricity generated from wind and solar sources, we use hourly data for the day-ahead (spot) market price of the German/Austrian spot market (*Price*) that were obtained from EPEX as the dependent variables. The hourly data for the total load of Germany and Austria (*Load*), as published by the European Network of Transmission System Operators for Electricity (entso-e), and the hourly data for the electricity generated from wind and solar sources during the same hours (*Wind* and *Solar*) that were obtained from the European Energy Exchange (EEX) are used as the explanatory variables. The period of study ranges from 19/7/2010 to 18/12/2017; this study therefore covers the longest time period to date for investigation of the MOE of RE using hourly data of all the published literature on empirical investigation of the MOE.

Figure 1 presents a plot of the spot market price characteristics from 19/7/2010 to 18/12/2017. As the figure shows, some negative prices were recorded among the spot market prices during the study period; this mainly occurs because of system inflexibilities that can lead to periods with excess power. These inflexibilities include renewable generation systems dealing with priority dispatch and production support mechanisms, conventional generation systems facing techno-economic limitations in their output variations, and the must-run conditions of certain power plants for system security reasons (De Vos, 2014). Between 19/7/2010 and 18/12/2017, negative prices were

Figure 1: Time Series of Prices from 19/7/2010 to 18/12/2017



observed 527 times, corresponding to 0.81% of the data. Previous studies that focused on negative prices, such as Genoese et al. (2010), showed that the relationships between RE generation, load, and negative prices differ from the relationships between RE generation, load, and positive prices, which makes it difficult to estimate the MOE accurately when using a linear regression model. However, the main aims of this study are to examine the MOE using a linear regression model that has been widely applied to study of the MOE, to analyze features that are difficult to capture using a linear regression method, and to conduct a scenario-based analysis using an ML approach; therefore, because the negative prices have different characteristics and they consist of less than 1% of the sample data, the negative prices have been taken out of the data.

Table 1 shows the descriptive statistics for the four variables. The mean spot market price was 38.20 €/MWh and ranged from 0 €/MWh to 210.00 €/MWh. When compared with the price variations, the load fluctuations are relatively small. The mean values of the solar and wind powers are 3.40 GW and 6.92 GW, respectively. Because solar power is unavailable during the night, the generated solar power frequently reached zero during this time. Descriptive statistics for the data when separated into 24 hourly series are presented in the Appendix.

Table 1: Descriptive Statistics for the Variables during the Period of Study

	Mean	Standard deviation	Minimum	Maximum
Price (€/MWh)	38.20	15.49	0	210.00
Load (GW)	64.19	11.86	34.74	92.29
Solar (GW)	3.40	5.43	0	28.33
Wind (GW)	6.92	6.02	0.08	37.87
Observations: 64,310				

Table 2 shows the correlation coefficients among the variables under study. The price is correlated with the load (positive) and the generated wind power (negative) to some extent, but the correlation coefficients are not large. Figure 2 shows a histogram of the spot market price. As the histogram shows, the price data distribution is close to a normal distribution.

Table 2: Correlation Coefficients among the Variables

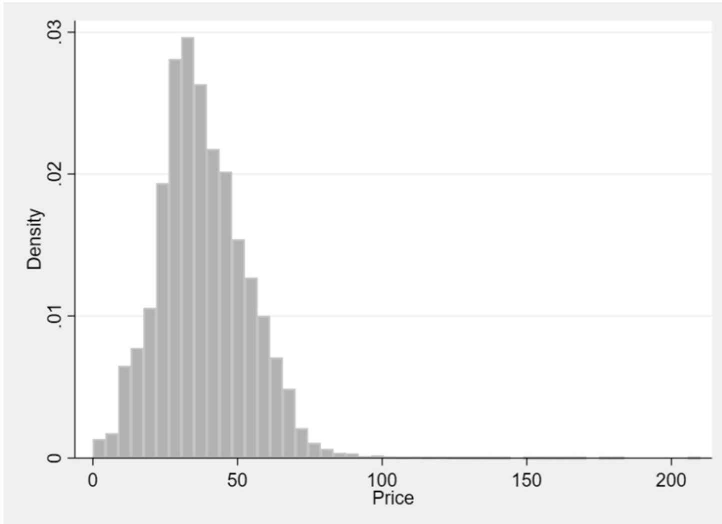
	Price	Load	Solar	Wind
Price	1.00	—	—	—
Load	0.50	1.00	—	—
Solar	–0.08	0.32	1.00	—
Wind	–0.38	0.11	–0.10	1.00

We tested for unit roots in the data for the variables using the Phillips-Perron test. As a result, the null hypothesis of the existence of nonstationarity was rejected with a significance level of 1%.

3.2 Estimation Methods

The aim of this study is to advance our understanding of the MOE of electricity from RE sources (i.e., wind and solar) on the spot market price of the German/Austrian market. To achieve this aim, two approaches are used: the GLS regression method and the extreme gradient boosting method. These analyses are conducted using the data as one unique series (2010–2017 analysis) and using the data separated into 24 hourly series (hourly analysis) to investigate both the average change in the wholesale price and the changes across the hours of the day.

Figure 2: Histogram of EPEX Spot Price (Excluding Negative Prices)



3.2.1 Linear regression approach: GLS

Following the previous studies (Cludius et al., 2014 and Würzburg et al., 2013) on the MOE, to quantify and present the MOE, we first regressed the spot market price with the load (total demand) and the electricity from the solar and wind sources using the OLS method. However, based on application of the Durbin-Watson (DW) statistics and the Breusch-Pagan test to our OLS results, both a positive serial correlation (DW statistics: 0.28) and heteroscedasticity were observed. Therefore, we used the GLS method with Prais-Winsten estimation and calculated the robust standard error (eq. (1)). An important and necessary assumption that is made for the chosen regression methodology is that the short-term electricity demand is perfectly price inelastic; this is the usual assumption made in similar studies that have used regression models to quantify the MOE. To enable the control required for systematic price changes, yearly, monthly, daily, and hourly dummies were also introduced into the model.

$$\begin{aligned} Price_t = \ & \beta_1 Load_t + \beta_2 Solar_t + \beta_3 Wind_t \\ & + \sum_y \beta_y dy_{y,t} + \sum_m \beta_m dm_{m,t} + \sum_d \beta_d dd_{d,t} + \sum_h \beta_h dh_{h,t} + \varepsilon_t \end{aligned} \tag{1}$$

where dy is the year dummy, dm is the month dummy, dd is the date dummy, and dh is the hour dummy. ε is the error term, β_1, β_2, β_3, β_y, β_m, β_d, and β_h are coefficients, t is the specific hour, y is the year, m is the month, d is the date in a particular week, and h is the hour.

The coefficients β_2 and β_3 are estimates of the specific MOEs that show the average reduction in the spot market price per additional GW of electricity obtained from wind or solar sources within a given hour. To estimate the total average MOE, these specific effects are multiplied by the load-weighted average (LWA[1]) of the electricity obtained from wind or solar sources per hour (eq. (2)).

1. The LWA is calculated by multiplying the load in each hour by the power generated from the renewable sources in the same hour, summing up the results acquired over all hours, and then dividing this sum by the total load during the analyzed period.

$$Total\,Merit\,Order\,Effect = \beta_2 LWA(Wind) + \beta_3 LWA(Solar) \tag{2}$$

We apply the same model for the hourly analysis while excluding the hour dummy.

3.2.2 Machine learning approach: Extreme gradient boosting method

To support the analysis using GLS and to perform the scenario-based analysis, this study uses an ML method: the decision trees (DTs) model. To explore the effects of the RE electricity sources (wind and solar) on the spot market price, we use the following empirical relationship (eq. (3)):

$$Price_t = f\left(Load_t, Solar_t, Wind_t,\ dy_{y,t}, dm_{m,t}, dd_{d,t}, dh_{h,t}\right) \tag{3}$$

The model is fitted by growing a number of DTs to create an ensemble of DTs that minimizes both the bias and the variance. For this purpose, we use the extreme gradient boosting method, which is a type of ensemble method that creates an ensemble via an iterative forward stage-wise process that involves fitting of multiple sets of DTs with a gradually increasing focus on observations that were predicted poorly by the previous set of DTs. The final value of this ensemble is then taken from a linear combination of these sets of DTs, thus creating an ensemble that minimizes both bias and variance (Miller et al., 2016).

To control for overfitting, we divided our data into two subsets, i.e., a training set and a test set, with a ratio of 7:3. Our model is then fitted using the training data set to produce the best ensembles that provide the lowest in-sample error, which is shown by the mean absolute percentage error (MAPE) value. After that, we test the performance of our model in prediction of the unobservable data using the test data set and calculate the out-of-sample errors (i.e., the MAPEs) of our ensembles. If the out-of-sample MAPE does not differ significantly from the in-sample MAPE, we can then be assured that our model is not overfitted. However, if the out-of-sample MAPE differs significantly from the in-sample MAPE, we should then suspect model overfitting. To deal with this problem, we iteratively reduce the number of nodes or branches in our DTs model and repeat the procedure until we obtain the optimum DTs model, which has an out-of-sample MAPE that does not differ significantly from the in-sample MAPE. The maximum number of iterations that we use to tune our model is 1000. We also control the learning rate of the iteration process at 0.l and limit the maximum depth of the DTs to 10.

Ensembles of DTs combine hundreds or even thousands of single DTs to build complex models that provide good predictive performance, but these models are often difficult or even impossible to interpret. Therefore, these “black-box” models must be complemented by additional tools to enable exploration of the key features of these models. These features include identification of the most influential variables that affect the outcome variable; comprehension of the marginal effect of a specified independent variable of interest on the predicted outcome while also accounting for the average effects of the other independent model variables; and determination of how a predicted outcome variable would change if the input variables changed.

For this purpose, this work relies on the variable importance plot, the partial dependence plot and the variable breakdown plot, which are all provided by the XGBoost Explainer package (Foster, 2017). The variable importance plot provides a list of the most significant independent variables in descending order based on their drop-out loss. The plot indicates the variables that make significant contributions to the predictive power of the model and also determines the variables that can be excluded from the model. The partial dependence plot visualizes the relationships between the independent variables and the outcome variable to allow us to determine whether the appropriate functional form is monotonic, linear, polynomial or a more complex form. The variable breakdown plot shows the contributions of each variable to the final prediction and indicates how the predicted outcome variable would be altered if the input variables were changed. The variable breakdown plot allows us to differentiate between the effects of wind and solar generation on the electricity market price formation and how changes in the proportions of the RE (wind and solar) sources will affect the spot market price. While maintaining a constant load, we constructed several scenarios using different proportions of wind and solar energy for a selected hour (13:00) and conducted a scenario-based analysis to examine how expected increases in the RE capacity in Germany would affect the spot market price.

4. RESULTS AND DISCUSSION

The following subsections provide the results for an analysis using the data as a unique series (the 2010–2017 analysis) and a second analysis using the data separated into 24 hourly series (the hourly analysis). In both analyses, the results of the GLS regression are introduced first and are followed by those from the extreme gradient boosting method.

4.1 Merit Order Effect—2010–2017 Analysis

Table 3 summarizes the GLS regression results. All the explanatory variables were significant with a 0.1% level. As expected, the load affects the spot market prices positively, while the wind and solar powers both have negative effects. This result is in line with those obtained in previous studies of the MOE (see Section 2). A comparison of the two RE sources shows that electricity generated from solar sources has a slightly stronger effect on the spot market prices than electricity generated from wind sources during the period studied. This is mostly because the solar generation pattern coincides with peaks in demand in Germany, as observed by Frantzen and Hauser (2012). This aspect will be investigated closely in the hourly analysis.

Table 3: GLS Regression Results

	2010–2017
Load	1.23*** (0.013)
Wind	–0.88*** (0.020)
Solar	–0.93*** (0.017)
DW statistic	1.80
R-square	0.54
Observations	64310

Note: Robust standard errors in parenthesis. The results, including all variables, are provided in full in the Appendix.
*** Significance level of 0.1%

Based on the results given above, the total average MOE of the RE sources is then calculated (see Table 4). These results show that during the period under study, the electricity from the wind and solar sources depressed the spot market price by 6.17 €/MWh and 3.47 €/MWh, respectively, which gives a total average MOE for these RE sources of 9.64 €/MWh. Our result for the total average MOE of the RE sources is compatible with the results of previous studies on the MOE on the German/Austrian spot market prices, which ranged from 5.0 €/MWh to 10.13 €/MWh (Cludius et al., 2014; Sensfuß, 2011; and Würzburg et al., 2013).

Table 4: Total MOE of the RE Sources

	2010–2017
LWA of *Wind* (GW)	7.04
LWA of *Solar* (GW)	3.71
MOE of *Wind* (€/MWh)	−6.17
MOE of *Solar* (€/MWh)	−3.47
Total MOE of RE (*Wind* and *Solar*) sources (€/MWh)	−9.64

Note: LWA stands for load-weighted average, as described in Subsection 3.2.

Table 5 shows the predictive performance results for the model that was created using the extreme gradient boosting method. From the five summary statistics, we can see that the model is powerful enough to predict the spot market prices in all data ranges. This can be determined from the predicted values, which show rather good agreement with the actual data in all the sample ranges with the exception of the maximum value, where our model slightly underestimated the price (208.68 €/MWh, with the actual value being 210 €/MWh). Additionally, based on the predictive power evaluation, the overall model performance is very good, with R-squared and correlation values both exceeding 0.99. In terms of the MAPE, our model also demonstrates excellent performance with a MAPE value of well below 0.1 (0.04).

Table 5: Predictive Performance of the Model

Summary statistics	Actual	Predicted
Minimum	0.00	–0.65
1st Quartile	28.06	28.15
Median	36.52	36.53
Mean	38.20	38.22
Quartile	47.91	47.68
Maximum	210.00	208.68
R Square	—	0.991
MAPE	—	0.0379
Correlation	—	0.996

Figure 3 shows the variable importance plots. The most influential variable based on the drop-out loss that determines the spot price for electricity is the Load (i.e., the total demand), which is followed by the electricity from wind, and that generated from solar sources. This result is largely in line with that obtained from the GLS regression, which showed Load, Wind, and Solar as the three most influential variables. With regard to the time dummy variables, years 2011 (y11) and 2012 (y12) were found to have the most influential effects on the price when compared with the other years. In 2011, following the Fukushima Nuclear Disaster that occurred in Japan, Germany shut down nuclear power plants with a capacity of roughly 11 GW, which shifted the entire merit order curve to the left (Bublitz et al., 2017). This nuclear phase-out could be the major reason why 2011 and 2012 show higher impacts on price than the other years.

Based on the results of the partial dependent plot analysis that was conducted for the three most influential variables, i.e., Load, Wind, and Solar, as shown in Figure 4(a) and (b), the Load has an almost linear and positive impact on the spot market price. The figures demonstrate that the electricity from both the wind and solar sources reduces the spot market price and that these sources

Figure 3: Variable Importance Plots

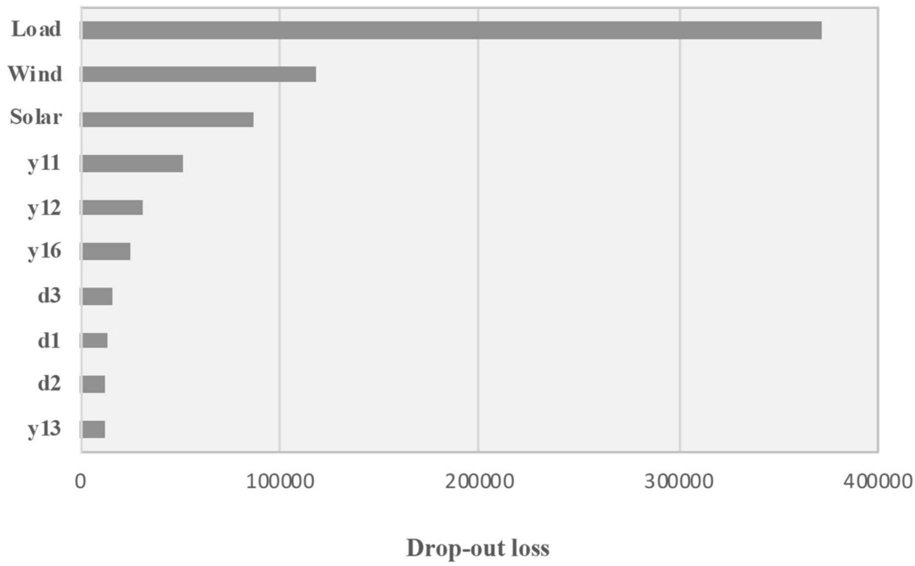
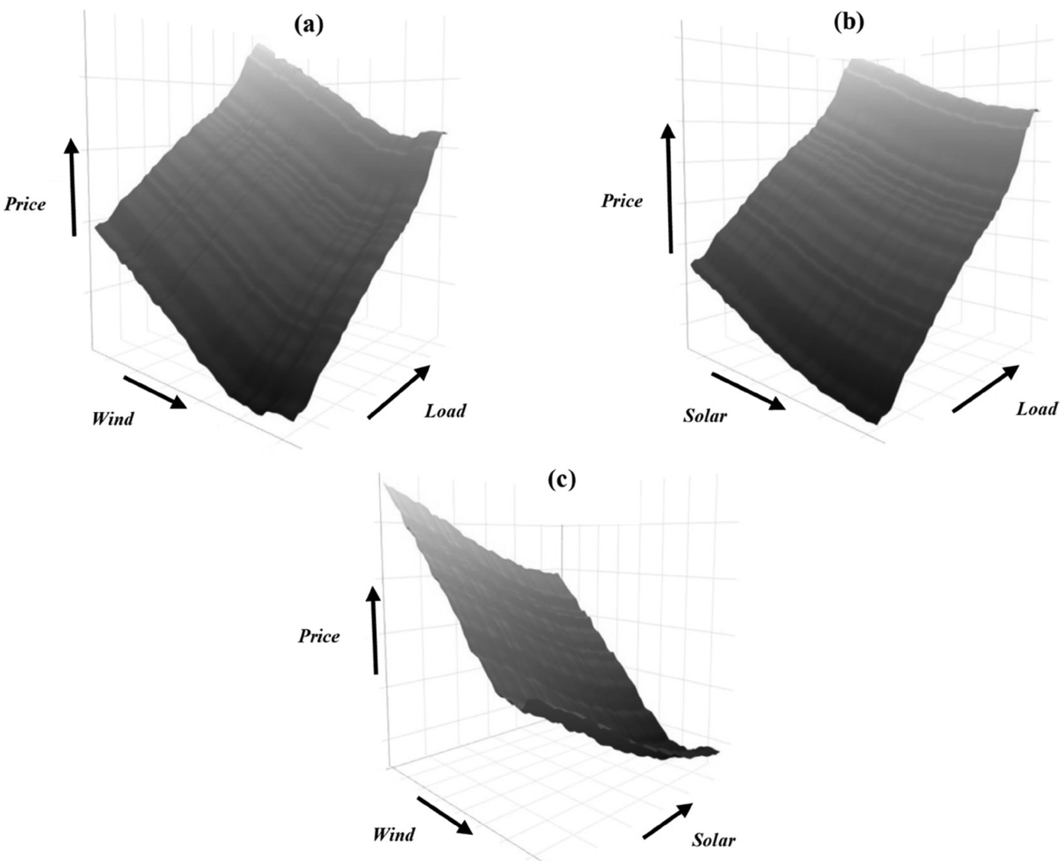


Figure 4: Three-dimensional Partial Dependence Plots



have somewhat linear relationships with price. These results imply that the linear regression method can be used to estimate the MOE accurately to a certain degree while considering the somewhat linear relationships between the three most influential variables and the price. However, it is notable that when the generation volumes are very high for both the solar and wind sources, the MOE of this additional wind and solar penetration diminishes slightly, as indicated by Figure 4(c).

4.2 Merit Order Effect—Hourly Analysis

Table 6 summarizes the results of the GLS regression performed for the hourly analysis. These results show that both the load and the wind sources were significant for all 24 hours with a 0.1% level. Because solar generation did not occur during H1, H2, and H3, it was omitted for these hours. Solar generation becomes statistically significant for H6 and H7 with a 5% level, and is also significant for H8 to H19 with a 0.1% level. When the effects of wind and solar generation are compared, the results show that the effect of solar generation becomes higher during H6, H7, H11, H12, and H13.

Table 6: GLS Regression Results for Each Hour

Hour	*Load*	*Wind*	*Solar*	DW statistic	R-square	Observations
H1	0.37 ***(0.043)	–1.08 ***(0.024)	N/A	2.13	0.67	2,674
H2	0.47 ***(0.045)	–1.11 ***(0.024)	N/A	2.06	0.66	2,654
H3	0.52 ***(0.046)	–1.17 ***(0.025)	N/A	2.07	0.64	2,635
H4	0.48 ***(0.046)	–1.14 ***(0.025)	–2,304.33(23526.35)	2.08	0.62	2,649
H5	0.40 ***(0.040)	–1.10 ***(0.025)	–142.36(113.570)	2.14	0.62	2,659
H6	0.28 ***(0.032)	–0.97 ***(0.025)	–8.13*(3.201)	2.12	0.65	2,671
H7	0.29 ***(0.029)	–0.92 ***(0.028)	–1.40*(0.587)	2.04	0.74	2,658
H8	0.37 ***(0.034)	–1.10 ***(0.040)	–1.03***(0.211)	2.05	0.74	2,677
H9	0.39 ***(0.035)	–1.13 ***(0.037)	–1.06***(0.099)	2.09	0.73	2,692
H10	0.36 ***(0.035)	–1.15 ***(0.035)	–1.14***(0.061)	2.10	0.73	2,695
H11	0.34 ***(0.036)	–1.13 ***(0.031)	–1.16***(0.048)	2.09	0.72	2,690
H12	0.35 ***(0.036)	–1.11 ***(0.023)	–1.17***(0.047)	2.10	0.70	2,691
H13	0.31 ***(0.035)	–1.05 ***(0.027)	–1.09***(0.039)	2.09	0.72	2,684
H14	0.33 ***(0.033)	–1.02 ***(0.026)	–1.02***(0.038)	2.06	0.74	2,678
H15	0.32 ***(0.032)	–1.00 ***(0.026)	–0.97***(0.039)	2.06	0.74	2,669
H16	0.32 ***(0.032)	–0.94 ***(0.024)	–0.88***(0.041)	2.07	0.74	2,670
H17	0.30 ***(0.034)	–0.95 ***(0.025)	–0.82***(0.049)	2.09	0.72	2,678
H18	0.31 ***(0.040)	–1.09 ***(0.032)	–0.79***(0.076)	2.08	0.67	2,699
H19	0.32 ***(0.047)	–1.21 ***(0.036)	–0.77***(0.140)	2.12	0.60	2,701
H20	0.29 ***(0.043)	–1.14 ***(0.031)	–0.34(0.294)	2.16	0.60	2,702
H21	0.24 ***(0.040)	–1.01 ***(0.027)	0.24(0.731)	2.20	0.63	2,701
H22	0.22 ***(0.037)	–0.91 ***(0.024)	2.93(2.926)	2.21	0.63	2,699
H23	0.21 ***(0.037)	–0.94 ***(0.023)	2,071.27(2012.296)	2.21	0.66	2,700
H24	0.30 ***(0.045)	–0.98 ***(0.023)	–119.39(5668.283)	2.13	0.69	2,684

Note: Robust standard errors in parenthesis. For H1, H2, and H3, generation from solar was 0, and thus solar is not used in the analysis for these hours.
*** Significance level of 0.1%; * Significance level of 5%.

Based on the results presented in Table 6, the average MOEs for both wind and solar generation are calculated for each hour, with results as shown in Table 7. These results show that wind had a relatively stable impact across the different hours of the day, ranging from 5.88 €/MWh (H7) to 8.04 €/MWh (H3), while the impact of the solar sources differs greatly across the different hours, ranging from 0.24 €/MWh (H6) to 11.78 €/MWh (H12). When the total MOE is considered, RE had a relatively higher MOE between H9 and H19, with a higher MOE than the total average MOE of RE based on the 2010–2017 analysis, which was 9.64 €/MWh. The RE had a high price reduction effect for H12 and H13 with prices of 19.39 €/MWh and 19.19 €/MWh, respectively, which are approximately double the value of the total average MOE of RE.

Table 7: Total MOE for the RE Sources for Each Hour

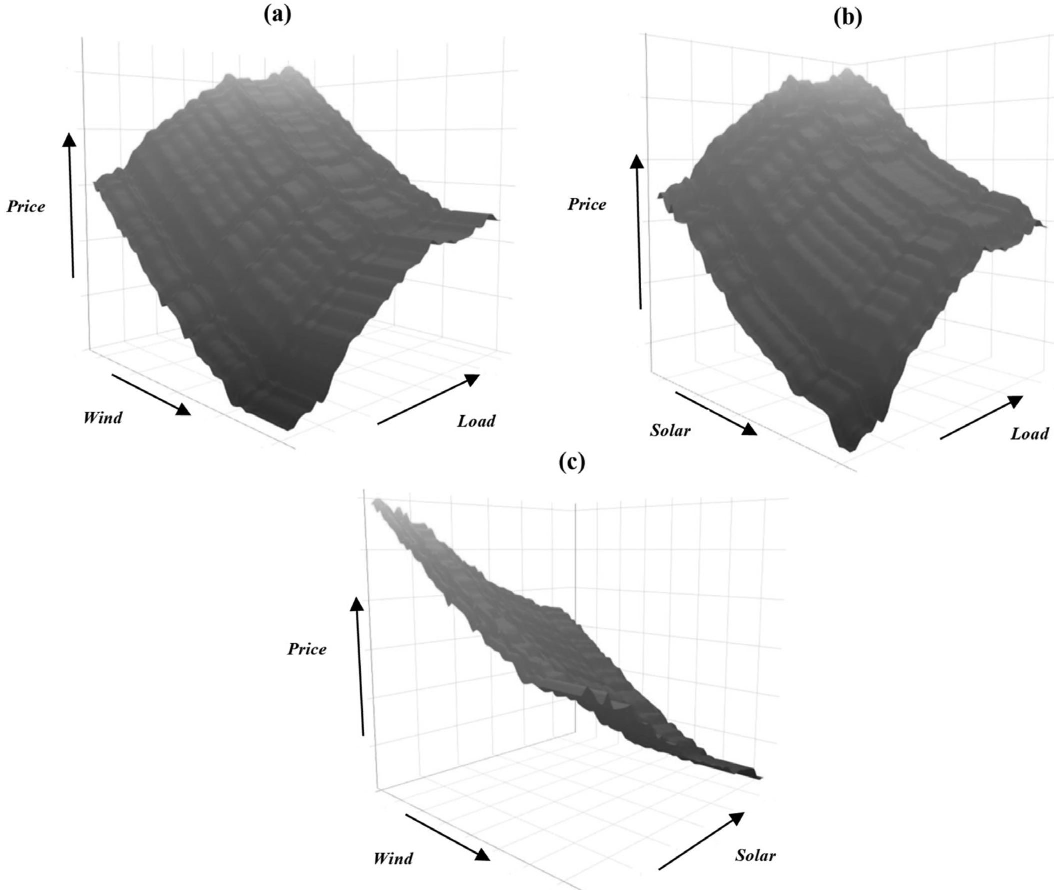
Hour	LWA of *Wind* (GW)	LWA of *Solar* (GW)	MOE of *Wind* (€/MWh)	MOE of *Solar* (€/MWh)	Total MOE of RE (*Wind* and *Solar*) sources (€/MWh)
H1	7.17	0.00	–7.78	N/A	–7.78
H2	6.99	0.00	–7.76	N/A	–7.76
H3	6.85	0.00	–8.04	N/A	–8.04
H4	6.82	0.00	–7.78	N/A	–7.78
H5	6.84	0.00	–7.51	N/A	–7.51
H6	6.91	0.03	–6.70	–0.24	–6.94
H7	6.42	0.37	–5.88	–0.52	–6.40
H8	6.78	1.23	–7.43	–1.26	–8.69
H9	6.60	3.19	–7.48	–3.39	–10.87
H10	6.51	5.84	–7.48	–6.66	–14.14
H11	6.62	8.33	–7.47	–9.68	–17.15
H12	6.87	10.06	–7.61	–11.78	–19.39
H13	7.08	10.79	–7.42	–11.77	–19.19
H14	7.18	10.61	–7.33	–10.78	–18.11
H15	7.20	9.59	–7.21	–9.35	–16.56
H16	7.20	7.87	–6.79	–6.96	–13.74
H17	7.25	5.74	–6.91	–4.70	–11.61
H18	7.34	3.65	–8.03	–2.87	–10.90
H19	7.32	1.90	–8.82	–1.46	–10.28
H20	7.27	0.73	–8.26	N/A	–8.26
H21	7.25	0.17	–7.35	N/A	–7.35
H22	7.33	0.01	–6.64	N/A	–6.64
H23	7.37	0.00	–6.92	N/A	–6.92
H24	7.29	0.00	–7.14	N/A	–7.14

Figure 5 shows the results of the partial dependent plot analysis that was conducted for H13, which is the hour during which both solar and wind generation showed significant impacts on the price. As shown in Figure 5(a) and (b), for H13, the positive impact of the *Load* on the price diminishes along with the increasing demand. The figures show that, similar to the case of the 2010–2017 analysis, the electricity obtained from both wind and solar sources reduces the spot market price, and that these sources have somewhat linear relationships with the price. However, it is notable that the impact of RE, and particularly that of wind, become unresponsive to the price if the share of the RE exceeds a specific threshold, as indicated by the figures. When the results are compared with those of the 2010–2017 analysis (Figure 4), we observe that the relationships between the three most influential variables (i.e., *Load*, *Wind*, and *Solar*) and *Price* are more complex in the hourly analysis, with more apparent thresholds and changes in tendencies, especially for the wind and solar sources when their generation volume is high.

4.3 Scenario-based Analysis—Variables Breakdown

To provide a more detailed analysis of how the wind and solar energies interact with the price, we constructed eight scenarios using different proportions of wind and solar generation for H13, and then conducted a scenario-based analysis using the model developed by the extreme gradient boosting method to examine how the expected increase in the RE capacity in Germany would affect the spot market price.

Figure 5: Three-dimensional Partial Dependence Plots of H13

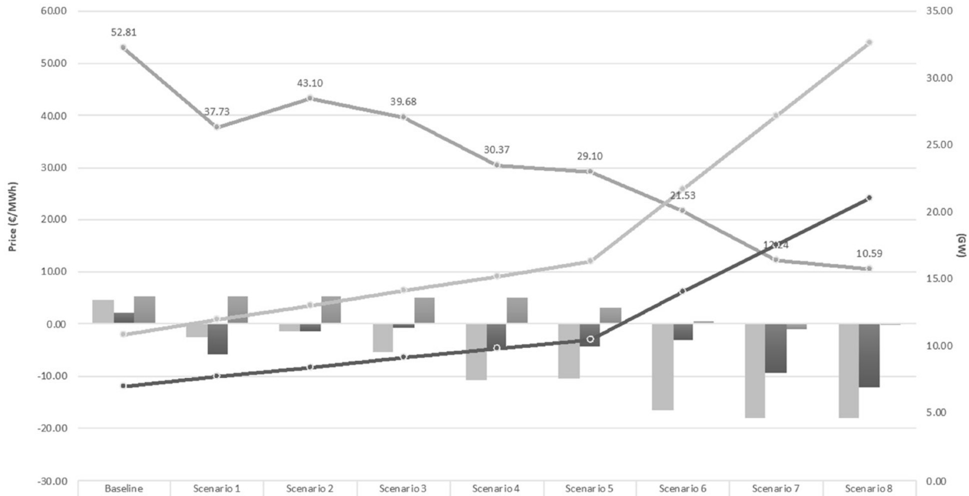


The baseline is the mean value of solar generation, wind generation, and load. While the load is maintained at its mean value for all eight scenarios, the volume of solar and wind generation is increased by 10% of the mean value for scenario 1, and by 20%, 30%, 40%, 50%, 100%, 150%, and 200% for scenarios 2 to 8, respectively. These results illustrated in Figure 6 show that if the volume of RE generation increases by 100% and 200% of the mean value, the spot prices could then be reduced significantly to approximately 20 €/MWh and 10 €/MWh, respectively, for H13. Another notable point from these results is that increased volumes of solar and wind generation tend to reduce the positive impact of the load on the price.

5. CONCLUSIONS

Understanding how the rapidly increasing development of RE affects the spot market price has become an important element of the economic research on RE and the electricity markets and could be helpful in both policy making and planning related to RE, and also in the design of the electricity markets. To gain a deeper understanding of the price reduction effect (i.e., the MOE) of RE on the spot market prices, we have examined the MOEs of wind and solar power on the spot market price of the joint German/Austrian electricity market using the GLS method and the extreme gradient boosting method.

Figure 6: MOE with Different Mixes of Wind and Solar—H13



	Baseline	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8
Solar MOE (left axis)	4.54	-2.55	-1.39	-5.37	-10.63	-10.41	-16.52	-17.96	-17.89
Wind MOE (left axis)	2.21	-5.79	-1.57	-0.67	-4.76	-4.35	-3.20	-9.55	-12.12
Load Contribution (left axis)	5.35	5.35	5.35	5.01	5.05	3.15	0.53	-0.97	-0.11
Estimated Price (left axis)	52.81	37.73	43.10	39.68	30.37	29.10	21.53	12.24	10.59
Volume of Solar (right axis)	10.86	11.95	13.03	14.12	15.21	16.29	21.72	27.16	32.59
Volume of Wind (right axis)	7.01	7.72	8.42	9.12	9.82	10.52	14.03	17.53	21.04

Using hourly data that covered the longest period of study of the MOE, we first showed that, based on the regression analysis, the electricity from the RE (wind and solar) sources reduced the spot market price by 9.64 €/MWh on average during the period from 2010 to 2017. Additionally, by investigating how the impacts of the wind and solar sources vary across the different hours of the day, the study showed that wind sources had a relatively stable impact across the different hours of the day, with prices ranging from 5.88 €/MWh to 8.04 €/MWh, while the impact of solar generation varies greatly across the different hours, ranging from 0.24 €/MWh to 11.78 €/MWh and having a stronger impact than wind generation during the peak hours.

The results from the extreme gradient boosting method have shown further important characteristics of the interactions between RE and the spot market price, including: 1) the somewhat linear interactions of the load and the RE sources with the price, which imply that the linear regression method can estimate the MOE accurately to a certain degree; and 2) the slightly diminishing MOE of the RE sources at high generation volumes, particularly for wind generation. Finally, using a scenario-based variable breakdown analysis, we showed how the different proportions of RE generation change the MOE.

ACKNOWLEDGMENTS

This research is supported by the following Grants in Aid from the Ministry of Education, Culture, Sports, Science and Technology in Japan (MEXT): the Grant in Aid for Specially Promoted Research 26000001; JST CREST JPMJCR15K2; the Integrated Research Program for Advancing Climate Models (TOUGOU program); and JSPS KAKENHI grant number JP18K11754. Any opinions, findings, and conclusions expressed in this material are those of the authors and do not necessarily reflect the views of the MEXT.

REFERENCES

Bublitz, A., D. Keles, and W. Fichtner (2017). "An Analysis of the Decline of Electricity Spot Prices in Europe: Who is to Blame?" *Energy Policy* 107: 323–336. https://doi.org/10.1016/j.enpol.2017.04.034.

Carmona, P., F. Climent, and A. Momparler (2019). "Predicting Failure in the US Banking Sector: An Extreme Gradient Boosting Approach." *International Review of Economics & Finance* 61: 304–323. https://doi.org/10.1016/j.iref.2018.03.008.

Clò, S., A. Cataldi, and P. Zoppoli (2015). "The Merit-Order Effect in the Italian Power Market: The Impact of Solar and Wind Generation on National Wholesale Electricity Prices." *Energy Policy* 77: 79–88. https://doi.org/10.1016/j.enpol.2014.11.038.

Cludius, J., H. Hermann, F.C. Matthes, and V. Graichen (2014). "MOE of Wind and Photovoltaic Electricity Generation in Germany 2008–2016: Estimation and Distributional Implications". *Energy Economics* 44: 302–313. https://doi.org/10.1016/j.eneco.2014.04.020.

Cointe, B. and A. Nadaï (2018). *Feed-In Tariffs in the European Union: Renewable Energy Policy, the Internal Electricity Market and Economic Expertise*. Springer: Berlin. https://doi.org/10.1007/978-3-319-76321-7.

Conejo, A.J., J. Contreras, R. Espinola, and M.A. Plazas (2005). "Forecasting Electricity Prices for a Day-Ahead Pool-based Electric Energy Market." *International Journal of Forecasting* 21(3): 435–462. https://doi.org/10.1016/j.ijforecast.2004.12.005.

De Vos, K., KU Leuven Energy Institute: Heverlee (2014). *Factsheet on Negative Electricity Market Prices. Report.*

Dudek, G. (2016). "Multilayer Perceptron for GEFCom2014 Probabilistic Electricity Price Forecasting." *International Journal of Forecasting* 32(3): 1057–1060. https://doi.org/10.1016/j.ijforecast.2015.11.009.

Foster, D. (2017). "xgboostExplainer: XGBoost Model Explainer." *R package version 0.1.* https://github.com/AppliedDataSciencePartners/xgboostExplainer.

Frantzen, J. and E. Hauser (2012). "Kurzfristige Effekte der PV-Einspeisung auf den Grosshandelsstrompreis." Kurzstudie, Institut für ZukunftsEnergieSysteme (izes).

Fraunhofer ISE (2019). *Net Public Electricity Generation in Germany in 2018*. *Report*. https://www.ise.fraunhofer.de/content/dam/ise/en/documents/News/Stromerzeugung_2018_ 2_en.pdfAnnual.

Gelabert, L., X. Labandeira, and P. Linares (2011). "An Ex-Post Analysis of the Effect of Renewables and Cogeneration on Spanish Electricity Prices." *Energy Economics* 33: S59–S65. https://doi.org/10.1016/j.eneco.2011.07.027.

Genoese, F., M. Genoese, and M. Wietschel (2010). "Occurrence of Negative Prices on the German Spot Market for Electricity and Their Influence on Balancing Power Markets." In IEEE 2010 7th International Conference on the European Energy Market, 1–6. https://doi.org/10.1109/EEM.2010.5558703.

German Federal Ministry for Economic Affairs and Energy (2019). *Zeitreihen zur Entwicklung der erneuerbaren Energien in Deutschland. Report*. https://www.erneuerbare-energien.de/EE/Redaktion/DE/Downloads/zeitreihen-zur-entwicklung-der-erneuerbaren-energien-in-deutschland-1990-2018.pdf;jsessionid=65CFA949366E207CA59C6E9CBB9C9643?__blob=publicationFile&v=20. March 10, 2019.

Holttinen, H., K.O. Vogstad, A. Botterud, and R. Hirvonen. (2001). "Effects of Large Scale Wind Production on the Nordic Electricity Market." *Proceedings of the European Wind Energy Conference*. Copenhagen: Denmark.

International Renewable Energy Agency (IRENA). (2018). *Renewable Capacity Statistics 2018. Report.* IRENA: Abu Dhabi.

Jónsson, T., P. Pinson, and H. Madsen (2010). "On the Market Impact of Wind Energy Forecasts." *Energy Economics* 32(2): 313–320. https://doi.org/10.1016/j.eneco.2009.10.018.

Miller, P.J., G.H. Lubke, D.B. McArtor, and C.S. Bergeman (2016). "Finding Structure in Data using Multivariate Tree Boosting." *Psychological Methods* 21(4): 583. https://doi.org/10.1037/met0000087.

Mirakyan, A., M. Meyer-Renschhausen, and A. Koch (2017). "Composite Forecasting Approach, Application for Next-Day Electricity Price Forecasting." *Energy Economics* 66: 228–237. https://doi.org/10.1016/j.eneco.2017.06.020.

Neubarth, J., O. Woll, C. Weber, and M. Gerecht (2006). "Beeinflussung der spotmarktpreise durch windstromerzeugung." *Energiewirtsch. Tagesfr* 56: 42–45.

Papadimitriou, T., P. Gogas, and E. Stathakis. (2014). "Forecasting Energy Markets using Support Vector Machines." *Energy Economics* 44: 135–142. https://doi.org/10.1016/j.eneco.2014.03.017.

Quint, D. and S. Dahlke (2019). "The Impact of Wind Generation on Wholesale Electricity Market Prices in the Midcontinent Independent System Operator Energy Market: An Empirical Investigation." *Energy* 169: 456–466. https://doi.org/10.1016/j.energy.2018.12.028.

Sáenz de Miera, G., P. del Río, and I. Vizcaíno (2008). "Analyzing the Impact of Renewable Electricity Support Schemes on Power Prices: the Case of Wind Electricity in Spain." *Energy Policy* 36: 3345–3359. https://doi.org/10.1016/j.enpol.2008.04.022.

Sensfuß, F. (2011). "Analysen zum Merit-Order Effekt erneuerbarer Energien Update für das Jahr 2010." *Forschungsbericht*. Fraunhofer Institut für System und Innovationsforschung (ISI).

Sensfuß, F., M. Ragwitz, and M. Genoese (2008). "MOE: A Detailed Analysis of the Price Effect of Renewable Electricity Generation on Spot Market Prices in Germany." *Energy Policy* 36(8): 3086–3094. https://doi.org/10.1016/j.enpol.2008.03.035.

Tian, H., B. Meng, and S. Wang (2010). "Day-Ahead Electricity Price Prediction based on Multiple ELM." *2010 Chinese Control and Decision Conference, IEEE*: 241–244.

Weigt, H. (2009). "Germany's Wind Energy: The Potential for Fossil Capacity Replacement and Cost Saving." *Applied Energy* 86(10): 1857–1863. https://doi.org/10.1016/j.apenergy.2008.11.031.

Würzburg, K., X. Labandeira, and P. Linares (2013). "Renewable Generation and Electricity Prices: Taking Stock and New Evidence for Germany and Austria." *Energy Economics* 40: S159–S171. https://doi.org/10.1016/j.eneco.2013.09.011.

APPENDIX

Table A: Full Results of 2010–2017 GLS Analysis

	2010–2017
Load	1.23*** (0.013)
Wind	–0.88*** (0.020)
Solar	–0.93*** (0.017)
dy11	5.82*** (0.838)
dy12	1.11(0.855)
dy13	–2.84**(0.845)
dy14	–12.52***(0.769)
dy15	–10.77***(0.769)
dy16	–16.11***(0.782)
dy17	–9.19***(0.879)
dm01	–2.86***(0.758)
dm02	–2.53**(0.823)
dm03	–1.31(0.736)
dm04	1.65*(0.725)
dm05	2.41***(0.678)
dm06	2.82***(0.658)
dm07	3.96***(0.651)
dm08	4.12***(0.664)
dm09	3.48***(0.678)
dm10	2.49**(0.727)
dm11	–0.33(0.671)
dm12	N/A
dd01	–1.31***(0.219)
dd02	–0.45(0.245)
dd03	–0.31(0.256)
dd04	–0.13(0.254)
dd05	0.002(0.247)
dd06	1.09***(0.213)
dd07	N/A
dh01	1.79***(0.090)
dh02	2.04***(0.114)
dh03	1.58***(0.129)
dh04	0.23(0.135)
dh05	–0.84***(0.132)
dh06	–1.98***(0.132)
dh07	–2.95***(0.167)
dh08	–1.46***(0.225)
dh09	–1.22***(0.266)
dh10	–1.52***(0.303)
dh11	–2.40***(0.340)
dh12	–2.36***(0.367)
dh13	–2.64***(0.367)
dh14	–3.02***(0.356)
dh15	–3.43***(0.334)
dh16	–3.64***(0.307)
dh17	–3.76***(0.280)
dh18	–1.63***(0.253)
dh19	0.27(0.226)
dh20	0.38*(0.195)
dh21	–0.88***(0.162)
dh22	–1.72***(0.125)
dh23	–0.13(0.087)
dh24	N/A
DW statistic	1.80
R-square	0.54
Observations	64310

Note: Robust standard errors in parenthesis. dm12, dd07, and dh24 are bases for the month, day, and hour dummies, respectively.
*** Significance level of 0.1%; ** Significance level of 1%; * Significance level of 5%.

Table B: Descriptive Statistics for the Variables of Each 24 Hourly Series

		Mean	Standard deviation	Minimum	Maximum
H1	*Price* (€/MWh)	31.03	10.01	0.01	57.32
	Load (GW)	53.49	5.59	39.90	71.85
	Solar (GW)	0	0	0	0
	Wind (GW)	7.04	5.59	0.16	33.96
	Observations: 2,674				
H2	*Price* (€/MWh)	29.02	9.99	0	57.32
	Load (GW)	51.32	5.58	37.83	69.26
	Solar (GW)	0	0	0	0
	Wind (GW)	6.82	5.4	0.16	32.29
	Observations: 2,654				
H3	*Price* (€/MWh)	27.53	10.1	0	57.32
	Load (GW)	50.25	5.58	36.67	69.03
	Solar (GW)	0	0	0	0
	Wind (GW)	6.65	5.29	0.15	32.39
	Observations: 2,635				
H4	*Price* (€/MWh)	26.04	10.01	0	57.32
	Load (GW)	50.19	5.67	36.45	69.03
	Solar (GW)	5.6e-8	2.9e-8	0	0.00015
	Wind (GW)	6.64	5.32	0.14	32.66
	Observations: 2,649				
H5	*Price* (€/MWh)	26.21	9.86	0	57.32
	Load (GW)	51.30	5.95	35.20	68.03
	Solar (GW)	0.00024	0.00091	0	0.019
	Wind (GW)	6.68	5.4	0.14	31.76
	Observations: 2,659				
H6	*Price* (€/MWh)	28.51	9.99	0	57.32
	Load (GW)	54.29	7.07	34.90	71.64
	Solar (GW)	0.03	0.07	0	0.39
	Wind (GW)	6.74	5.56	0.13	32.39
	Observations: 2,671				
H7	*Price* (€/MWh)	35.29	12.41	0	91.21
	Load (GW)	60.77	10.05	34.74	80.27
	Solar (GW)	0.31	0.51	0	2.26
	Wind (GW)	6.69	5.66	0.13	33.86
	Observations: 2,658				
H8	*Price* (€/MWh)	42.82	16.81	0.04	183.49
	Load (GW)	66.46	11.75	35.77	87.83
	Solar (GW)	1.27	1.52	0	6.42
	Wind (GW)	6.64	5.88	0.15	34.47
	Observations: 2,677				
H9	*Price* (€/MWh)	45.28	17.15	0.02	175.55
	Load (GW)	69.66	11.25	36.85	89.8
	Solar (GW)	3.2	2.89	0.003	11.28
	Wind (GW)	6.53	6.09	0.13	35.08
	Observations: 2,692				

(continued)

Table B: Descriptive Statistics for the Variables of Each 24 Hourly Series *(continued)*

		Mean	Standard deviation	Minimum	Maximum
H10	*Price* (€/MWh)	44.58	16.09	0.07	150.1
	Load (GW)	71.28	10.07	39.42	90.26
	Solar (GW)	5.81	4.25	0.03	16.7
	Wind (GW)	6.46	6.22	0.09	35.34
	Observations: 2,695				
H11	*Price* (€/MWh)	43.35	15.94	0.04	151.07
	Load (GW)	72.93	9.52	42.44	91.14
	Solar (GW)	8.3	5.34	0.08	21.31
	Wind (GW)	6.56	6.35	0.09	34.5
	Observations: 2,690				
H12	*Price* (€/MWh)	43.11	16.1	0.02	135
	Load (GW)	74.23	9.09	45.7	91.7
	Solar (GW)	10.02	6.03	0.13	24.2
	Wind (GW)	6.83	6.49	0.08	36.27
	Observations: 2,691				
H13	*Price* (€/MWh)	40.79	15.6	0.73	121.58
	Load (GW)	73.28	9.05	46.98	91.09
	Solar (GW)	10.8	6.43	0.2	26.16
	Wind (GW)	7.02	6.54	0.1	37.12
	Observations: 2,684				
H14	*Price* (€/MWh)	38.89	15.63	0	117.68
	Load (GW)	71.98	9.58	46.97	90.71
	Solar (GW)	10.66	6.59	0.17	26.84
	Wind (GW)	7.12	6.5	0.11	36.93
	Observations: 2,678				
H15	*Price* (€/MWh)	37.69	15.3	0.03	112.21
	Load (GW)	70.6	9.73	45.73	89.65
	Solar (GW)	9.72	6.58	0.11	27.16
	Wind (GW)	7.12	6.39	0.16	36.58
	Observations: 2,669				
H16	*Price* (€/MWh)	37.89	14.85	0.02	117.18
	Load (GW)	69.64	9.71	44.58	89.09
	Solar (GW)	8.04	6.24	0.02	26.84
	Wind (GW)	7.11	6.31	0.15	36.36
	Observations: 2,670				
H17	*Price* (€/MWh)	39.16	14.95	0.06	121.12
	Load (GW)	69.21	9.6	43.31	90.49
	Solar (GW)	5.92	5.37	0.00065	19.68
	Wind (GW)	7.14	6.26	0.15	35.69
	Observations: 2,678				
H18	*Price* (€/MWh)	44.57	17.4	0.07	151.88
	Load (GW)	70.41	9.79	44.17	92.29
	Solar (GW)	3.77	3.94	0	13.39
	Wind (GW)	7.23	6.32	0.16	36.75
	Observations: 2,699				
H19	*Price* (€/MWh)	48.87	17.73	7.45	210
	Load (GW)	70.95	9.42	44.81	91.11
	Solar (GW)	1.97	2.4	0	8.35
	Wind (GW)	7.19	6.28	0.21	37.42
	Observations: 2,701				

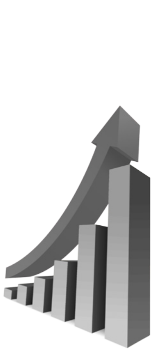
(continued)

Table B: Descriptive Statistics for the Variables of Each 24 Hourly Series *(continued)*

		Mean	Standard deviation	Minimum	Maximum
H20	*Price* (€/MWh)	49.11	15.38	2.16	169.9
	Load (GW)	70.12	8.87	45.4	88.63
	Solar (GW)	0.75	1.09	0	3.88
	Wind (GW)	7.15	6.25	0.25	37.87
	Observations: 2,702				
H21	*Price* (€/MWh)	44.9	12.7	0.23	136.03
	Load (GW)	67.26	7.8	46.89	84.22
	Solar (GW)	0.17	0.31	0	1.24
	Wind (GW)	7.15	6.19	0.27	37.82
	Observations: 2,701				
H22	*Price* (€/MWh)	40.62	10.97	0.11	94.89
	Load (GW)	64.41	6.75	46.4	79.99
	Solar (GW)	0.01	0.03	0	0.14
	Wind (GW)	7.25	6.08	0.26	35.19
	Observations: 2,699				
H23	*Price* (€/MWh)	38.9	10.46	2.59	65.14
	Load (GW)	61.84	6.03	45.99	77.8
	Solar (GW)	0	0	0	0
	Wind (GW)	7.29	5.95	0.19	34.16
	Observations: 2,700				
H24	*Price* (€/MWh)	33.46	9.93	0.04	56.29
	Load (GW)	57.1	5.72	43.04	74.42
	Solar (GW)	0	0	0	0
	Wind (GW)	7.18	5.74	0.17	33.6
	Observations: 2,684				

IAEE

International Association for
ENERGY ECONOMICS



The IAEE is pleased to announce that our leading publications exhibited strong performances in the latest 2019 Impact Factors as reported by Clarivate. The Energy Journal achieved an Impact Factor of 2.394 while Economics of Energy & Environmental Policy saw an increase to 3.217.

Both publications have earned SCIMago Journal Ratings in the top quartile for Economics and Econometrics publications.

IAEE wishes to congratulate and thank all those involved including authors, editors, peer-reviewers, the editorial boards of both publications, and to you, our readers and researchers, for your invaluable contributions in making 2019 a strong year. We count on your continued support and future submission of papers to these leading publications.