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SPECIAL FEATURE: ORIGINAL ARTICLE

Managing Climate Risks for a Sustainable Future: Adaptation Strategies and Resilience Building

The impact of weather changes on the supply and demand of electric power and wholesale prices of electricity in Germany

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Abstract
Weather conditions critically affect electricity demand. Recently, weather changes have also affected the electricity supply because renewable energy sources have been diffused. Some studies have revealed that weather conditions affect electricity supply or demand. However, few studies have revealed the integrated effects of weather changes on the electricity supply, demand, and market prices. This study aims to reveal the regional weather impact on the German electricity spot market based on combined hourly weather and electricity market data using structural equation modeling. Our results reveal that weather changes affect both demand and supply. First, the effect of weather on electricity supply differs in each state. Our estimation results show a more complex effect of an increase in solar radiation. Second, the electricity demand is also affected by weather conditions, particularly by temperature. Additionally, regional differences in weather conditions create a complex structure of electricity supply and demand. Our results indicate that extreme weather events in specific areas have a significant impact on the electricity market price.

Keywords Renewable energy · Weather effect · Electricity market · Structural equation modeling

Introduction

Climate change is one of the most important issues faced in every country. Every country aims to mitigate carbon dioxide (CO_2) emissions by transitioning to new energy sources, and use of renewable energy sources is encouraged to tackle the problem. Almost all developed countries have employed diffusion policies for renewable energy, such as subsidies, tax rebates, and feed-in tariffs (FITs). FITs provide each household with a large economic incentive to diffuse renewable energy sources in each country that employs this policy.

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Previous studies have shown that FITs encourage the diffusion of solar power generation in many countries (Tanaka et al. 2017; Popp et al 2011). FIT and other diffusion policies have been introduced in developed countries. Thus, the share of renewable energy sources has increased in such countries. Increases in the share of electricity generated by renewable energy have affected the structure of the electricity market.

In the aftermath of the liberalization of the electricity market in the European Union, various factors have affected electricity prices. Recently, with the promotion of electricity generated by various sources of renewable energy (e.g., solar and wind power), the generation of electricity from renewable energy sources has negatively affected electricity prices (i.e., reducing electricity prices), which is often referred to as the merit order effect. For example, Cludius et al. (2014) employed a time series regression analysis using hourly data on spot market prices, wind and solar generation, and load. Their study showed that electricity from wind and solar energy sources caused reductions of German/Austrian day-ahead spot electricity prices of 6 € per MWh in 2010 and 10 € per MWh in 2012. Keeley et al. (2020) analyzed the impact of solar and wind power on the German electricity spot market using a machine learning technique. Their study showed that wind power had a relatively stable impact across different hours of the day (ranging from 5.88 € per MWh to 8.04 € per MWh), while the impact of solar power differed greatly across different hours (ranging from 0.24 € per MWh to 11.78 € per MWh) and was stronger than that of wind during peak hours. These studies reveal that renewable energy sources have an impact on the German electricity market.

However, previous studies did not reveal any weather effects on wholesale electricity spot prices. Weather conditions strongly affect solar and wind power generation, but they also affect electricity demand (e.g., the demand for electricity increases during hot summer and cold winter months). There are complicated relationships among electricity prices, electricity demand, renewable power generation, and weather conditions. As climate change produces more serious climatic conditions, understanding the influence of weather on electricity markets will become increasingly important. For example, Perera et al. (2021) estimate how much future climate variation and extreme events will affect the energy system in Sweden. Their study reveals that uncertainties in renewable energy potential and demand can lead to a significant performance gap as a result of future climate variations and a decreased power supply reliability due to extreme weather events. Therefore, we need to further consider the potential impact of weather on the electricity market to construct a stable electricity supply for the future.

Against this background, the current study aims to construct an integrated model to reveal how weather changes affect electricity demand and supply and spot trading prices in Germany. Finally, we clarify the impact of weather on the price formation of the German electricity spot market (German/Austria day-ahead spot market). To reveal the complex weather effect on electricity demand and supply, we apply generalized structural equation modeling (SEM) to analyze the impact of weather and renewable energy on the German wholesale electricity market. Additionally, we aim to reveal a detailed regional effect of weather change based on state weather data in Germany.

This study comprises five sections. In "Background and literature review", we review previous literature related to the current analysis. In "Data", we introduce the data we use in the analysis. In "Analysis method", the details of the data analyzed in this study are introduced and our analysis method using generalized SEM is explained. The estimation results are presented in "Results". In "Discussion and conclusion", we summarize and discuss the results.

Background and literature review

An increase in renewable energy has become an important policy issue because every country needs to mitigate CO_2 emissions to prevent climate change. At the same time, the electricity demand of almost all countries tends to increase. Therefore, forecasting of the electricity supply from renewable energy sources is needed to sustain a stable energy system. Das et al. (2018) reviewed previous studies related to forecasting photovoltaic power generation and model optimization. Their paper concluded that solar irradiance strongly correlates with electricity generation from solar PV. Additionally, their paper pointed out that temperature has a certain amount of impact on PV power output, although the correlation between temperature and the amount of electricity generated by PV power is not high.

Some researchers have recently employed deep or machine learning for renewable energy forecasting. Wang et al. (2019) reviewed the related literature and concluded that this new forecasting method improves the forecasting of renewable energy supply. However, weather changes also critically affect electricity demand. Many previous studies have aimed to reveal the impact of weather changes on electricity demand. For example, Blázquez et al. (2013) revealed that the number of heating- and cooling-degree days had a significant positive correlation with the residential electricity demand in Spain between 2000 and 2008. In particular, their study revealed the higher sensitivity of electricity demand on cold days than on hot days. This result implies that Spanish households are not widely using electric heating systems. Cassarino et al. (2018) aimed to reveal how much social and weather conditions affect the national electricity demand in the European region and determine the electricity demand effect of temperature change using two-threshold regression to capture the different effects of cool and hot days. Their study found that the historical European electricity demand strongly correlates with temperature.

A few studies have aimed to reveal the effect of weather change on both electricity supply and demand. Staffell and Pfenninger (2018) constructed a model that included the impacts of weather on electricity supply and demand in the UK. Their simulated results for 2030 showed that overnight demand in winter and midday demand in summer become approximately zero due to rapidly increasing solar PV and wind power installation resulting from the CO_2 reduction policy. They remarked that the UK faces difficulty in planning energy management in the near future.

These previous studies revealed that weather is an important factor affecting both electricity demand and supply. Although many previous studies have revealed the effect of weather conditions on electricity demand and supply, few studies have constructed an integrated model that considers weather effects on the electricity demand, supply, and market outcome. For example, Jasiński (2020) constructed a forecasting model that considered weather impacts on electricity supply and demand using deep neural networks. Their study concluded that including weather variables in the model improves the prediction accuracy of spot electricity prices.

Table 1 Data sources and variable details

Variable	Definition (data source)	Unit	Time scale of data
Electricity market data			
Price	Wholesale electricity price	€/MW	Hourly
	(The German electricity market formed a joint bidding zone with Austria at EPEX SPOT for both the intraday and day-ahead markets)		
Load	Total load of electricity	GW	Hourly
	(The European Network of Transmission System Operators for Electricity (ENTSO-E))		
Wind	Amount of the electricity supply that is generated by wind power	GW	Hourly
	(Hourly data from the European Energy Exchange (EEX))		
Solar	Amount of the electricity supply that is generated by solar power	GW	Hourly
	(Hourly data from the EEX)		
Weather data			
Temperature	Lowest atm level (WFDEI Meteorological Forcing Data)	Degrees Kelvin	Every 3 h
Solar radiation	Short wave radiation (WFDEI Meteorological Forcing Data)	W/m^2	Every 3 h
Wind speed	Lowest atm level (WFDEI Meteorological Forcing Data)	m/s	Every 3 h

Data

In this study, we analyzed the weather effect on the electricity market in Germany. To achieve the research objective, we combined electricity market data and weather data. The definition of each variable is summarized in Table 1.

Electricity market data

We obtained electricity market data from Germany from the following sources: electricity prices were obtained from the European Power Exchange (EPEX). The total load was obtained from the European Network of Transmission System Operators for Electricity (ENTSO-E). The electricity supply generated by solar and wind power was obtained from the European Energy Exchange (EEX).

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, which formed the largest market in Europe (with the German portion of the market being the largest). Germany and Austria also produce significant amounts of electricity from wind and solar sources. The International Renewable Energy Agency (IRENA) reported that most of the wind and solar capacity was installed in Germany (55,876 MW of wind and 42,396 MW of solar sources, in contrast to 2,926 MW of wind and 1,404 MW of solar sources in Austria at the end of 2017) (IRENA 2018). Thus, as the largest market with a high renewable energy penetration, the German/Austrian spot market is ideal for investigating the weather effects on electricity prices. The results of this study could provide useful insights that could be applicable to other countries aiming to increase their adoption of renewable energy. Therefore, to analyze the effects of weather changes on the market price, we used hourly data for the day-ahead (spot) market price of the German/Austrian spot market (*Price*) obtained from EPEX as the dependent variable.

To understand the effect of the change in electricity demand on the spot price, we used hourly data for the total load of Germany and Austria (*Load*), as published by the ENTSO-E, as an independent variable. Additionally, we used hourly data for the electricity supply from wind and solar sources during the same hours (*Wind* and *Solar*) that were obtained from the EEX. These variables were used as independent variables to capture the changes on the supply side caused by solar and wind power electricity generation. The study period was from January 1, 2010, to December 28, 2016, which was the longest duration for investigating the weather effects on electricity supply and demand using hourly data. The study period depended on the period of weather data. To adjust the time span difference between the market and weather data, we combined the data at 3 h intervals. We explain in more detail how to combine the market and weather data in section of "Weather data". Table 2 shows the summary statistics of the variables used in the market data.[1]

Weather data

The weather data (i.e., temperature, solar radiation, and wind speed) were obtained from the Research Data Archive (WFDEI Meteorological Forcing Data). The WFDEI Meteorological

[1] In Table 2, the minimum value of *Price* was -221.94. In December 2012, the German electricity spot market experienced negative prices because of a low electricity demand and an excessive electricity supply from renewable energy. In particular, the spot market price was recorded as -221.94 per MWh on December 25, 2012.

Table 2 Summary statistics of electricity market data

Variable	Unit	Observation	Mean	SD	Min	Max
Load	GW	18,824	63,751.4	11,730.32	34,480	91,110.5
Solar	GW	18,824	3262.117	5240.062	0	26,491.25
Wind	GW	18,824	6572.64	5756.044	86.55	32,811.75
Price	€ per MW	18,824	38.067	16.502	– 221.94	210

Forcing Data consist of geographical mesh data (0.5° × 0.5° from the 0.25°E to 359.75°E longitude and 89.75°S to 89.75°N latitude) covering the entire globe every 3 h. These data were obtained from the National Center for Atmospheric Research (Weedon et al. 2018). From this dataset, we used temperature (Kelvin, lowest atm level), wind speed (m/s: meters per second, lowest atm level), and solar radiation (W/m^2: watts per square meter, shortwave radiation) for this analysis.

Generally, a timely change in temperature is an important factor influencing electricity demand in real time. Therefore, temperature affects the hourly electricity load and price. Increases in solar radiation encourage the generation of electricity by solar PV systems. Thus, solar radiation affects the supply of electricity from solar power to the market. Finally, timely changes in solar radiation affect market prices in real time. Real-time changes in wind speed also affect the supply side of the electricity market. Increases in wind speed encourage the generation of electricity by wind power generators.

In this study, we used the average weather indices of each German state as the independent variables to classify the differences in each state's weather effects on the electricity demand and supply. We mapped the state boundaries based on the mesh size of the WFDEI Meteorological Forecasting Data. Then, we classified the weather data mesh that belongs to each state. For example, 26 meshes were classified within the state of Brandenburg. After classifying each weather data mesh, we calculated each state's average weather indices (12 states).[2] In this classification of the areas, we considered some states as single state areas due to difficulties in identifying state lines. For example, Berlin is considered to be part of Brandenburg. In addition, we treat Freie Hansestadt Bremen and Freie Hansestadt Hamburg as part of Niedersachsen and Schleswig–Holstein, respectively. In these cases, we could not identify the state boundaries because the mesh size of the weather data was too large to determine which data belonged to which state. Additionally, Rheinland–Pfalz and Saarland could not be separated for the same reason. The mesh overlapped between these two states in nearly all areas. Thus, we considered these states as a single area (state) for this study.

In this analysis, we combined electricity market data and weather data from 2010 to 2016. The electricity market data consisted of hourly data. In contrast, the weather data consisted of data measured every 3 h. To adjust for this time gap, we integrated the electricity market data and weather data every 3 h. Table 3 lists the average weather index variables in each state.[3]

Analysis method

Overview of SEM

The SEM is a multivariate method used to test hypotheses regarding the influence of interacting variables. For the convenience of explanation, we set up a hypothetical case in which the variables y^1, y^2, and y^3 are correlated, as shown in Fig. 1.[4] A single straight arrow represents a causal relation.[5] In Fig. 1, y^1 is an explanatory (independent) variable for y^2, and y^1 directly affects y^2. The impact of the direct path is captured by β_{12}. Additionally, Fig. 1 shows that y^3 has a direct path to y^2. The impact of the path is captured by β_{32}. However, the value of y^3 depends on y^1. In short, y^1 directly affects y^2 and has an indirect effect through y^3. In Fig. 1, we define the impact of the direct path from y^1 to y^3 as β_{13}. If we consider the indirect path y^1 through y^3 to y^2, the impact can be calculated by multiplying β_{13} by β_{32}.

In the simplified SEM in Fig. 1, we assume the following general linear model:

$$\gamma = \gamma\beta + \varepsilon. \tag{1}$$

In this model, γ is the data matrix, ε is the error term, and β shows the free parameter that includes the paths of interacting variables (β_{12}, β_{13}, and β_{32}). Instead of minimizing the sum of squared errors, the free parameters are estimated using the sample covariance structure of the data.

[2] Appendix 1 shows a map of the sample states in this study.

[3] More detailed summary statistics for the weather data are shown in Appendix 2.

[4] An explanation of the SEM is provided in Harrison et al. (2007).

[5] In this model, we suppose each weather variable does not affect the other. The correlation coefficient between solar radiation and wind speed is 0.068. The correlation coefficient between wind speed and temperature is – 0.0846. We found that solar radiation and temperature correlate (the correlation coefficient between temperature and solar radiation is 0.3962). However, we do not consider the pass coefficient between temperature and solar radiation because of the German weather situation.

Table 3 Average value of each weather data group

Area	State	*Temperature* (Kelvin)	*Radiation* (W/m^2)	*Wind speed* (m/s)
Northern	Schleswig–Holstein	282.9391	123.232	4.2384
	Niedersachsen	283.1042	123.4838	3.8499
	Mecklenburg–Vorpommern	283.1101	124.6516	3.9480
Eastern	Brandenburg	283.5459	127.4437	3.5620
	Freistaat Sachsen	283.0252	131.2479	3.4073
	Sachsen–Anhalt	283.2724	128.8412	3.5112
	Freistaat Thüringen	282.4133	131.5657	3.3000
Western	Hessen	283.1005	130.4966	3.2825
	Nordrhein–Westfalen	283.2715	126.3736	3.7314
	Rheinland–Pfalz and Saarland	283.8011	132.3109	3.3174
Southern	Baden–Württemberg	283.2089	135.0828	2.7395
	Freistaat Bayern	282.4045	133.4902	2.7245

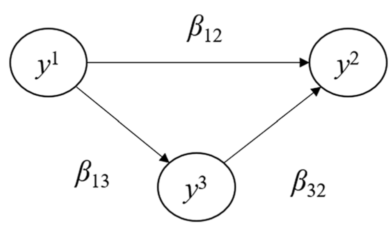

Fig. 1 Example of a simple SEM

Practically, an objective function is constructed from the sampled and implied covariance, which is optimized with respect to the parameters. The maximum likelihood fitting function is defined to estimate the parameters as follows:

$$F_{ML} = \log[\Sigma(\theta)] + \mathrm{tr}\left(S\Sigma^{-1}(\theta)\right) - \log[S] - p, \tag{2}$$

where p represents the number of variables, S represents the observed covariance matrix, and $\Sigma(\theta)$ shows the implied covariance matrix.

Generalized SEM analysis

To estimate the relationship between electricity prices, renewable energy power supply (i.e., solar and wind power), and weather conditions, we applied generalized SEM. This estimation model is deemed appropriate, given the complexity of the relationships among the variables. Solar activity affects both the demand and supply of electricity. Based on the discussion of previous studies and the correlation coefficient between each variable, we set up an estimation model. Figure 2 shows the path diagram used in this study.[6] The figure shows *Price* as the dependent variable. In contrast, the variables for the total electricity load (*Load*), amount of electricity supply from solar power (*Solar*), and wind power generation (*Wind*) capture the direct effect of electricity demand and supply change in the spot market. The average temperature (*Temperature*), solar radiation (*Radiation*), and wind speed (*Wind speed*) are independent variables that capture the indirect weather effect on the electricity price through *Load*, *Solar*, and *Wind*.

Temperature is an important factor that influences the electricity demand. The peak and off-peak demand for electricity could be correlated to the temperature change. Therefore, we applied *Temperature* as an independent variable for *Load*. The amount of solar radiation is the most important factor influencing the amount of electricity generated by the solar PV system. In addition, the amount of electricity generated is determined by the wind speed surrounding the wind power station. Therefore, we defined the amount of solar radiation and wind power as the independent variables for the amount of electricity supplied by *Solar* and *Wind*. Finally, we defined *Load*, *Solar*, and *Wind* as the independent variables for the wholesale electricity *Price* in this model. *Wind* and *Solar* captured the effects on the supply side of the renewable energy sources. In short, an estimated parameter of these variables shows the merit order effect of renewable energy. In contrast, *Load* was the variable that showed the total demand change of the market.

In Fig. 2, the market electricity data represent only the aggregated demand (*Load*) and supply (*Solar* and *Wind*) amount of electricity because we could not classify how much the electricity demand and supply of the spot market occurred from each area. Additionally, *Price* was only one index in the spot market. In contrast, the weather data (*Temperature*, *Radiation*, and *Wind speed*) were state-level data in this study. In short, we used the average weather indices of each state to reveal how much each region's weather conditions affect the total electricity supply and demand on the

[6] This model included error term when we estimate the pass coefficient between each weather variable, *Load*, *Solar*, and *Wind*.

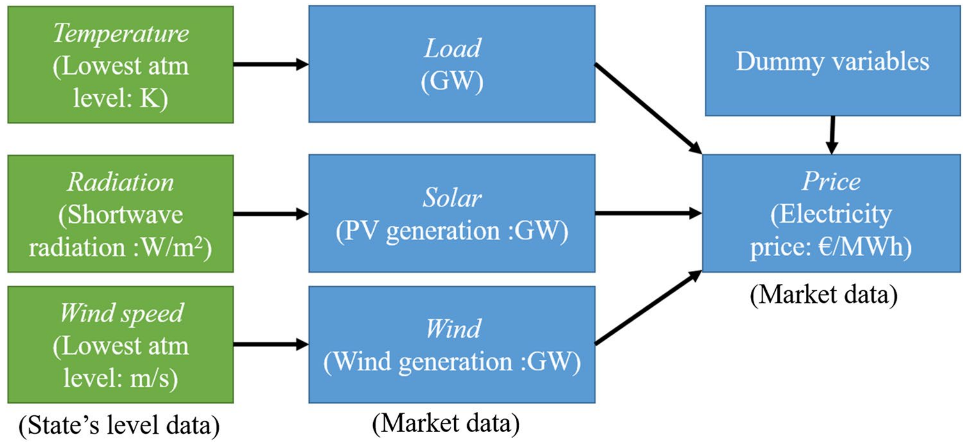

Fig. 2 Model depicting variables relevant to *Price*

spot market. In SEM, each area's weather indices are standalone, independent variables for *Load*, *Solar*, and *Wind*. Basically, we set up 12 path coefficients between the *Load* and each area's average value of *Temperature*. Additionally, 12 path coefficients between other market data (*Solar* and *Wind*) were set up with other weather indices (*Radiation* and *Wind speed*). These path coefficients can reveal how each state's weather conditions affect electricity supply and demand on the spot market.

We also included dummy variables for hours, days of the week, and months as independent variables to consider the electricity supply and demand changes by season and days of the week. These data formed a time series from July 19, 2010, to December 28, 2016. The resolution of our dataset was 3 h, so it was consistent with that of the data for weather conditions. The total number of observations in this estimation was 18,824.

Table 4 Estimated impact of each state's temperature on the total load

Area	State	Coefficient	SD
Northern	Schleswig–Holstein	– 1010.198***	145.1302
	Niedersachsen	4185.498***	250.6756
	Mecklenburg–Vorpommern	– 2023.799***	169.4301
Eastern	Brandenburg	2151.56***	265.5903
	Freistaat Sachsen	– 1446.922***	162.7478
	Sachsen–Anhalt	– 961.8349***	261.562
	Freistaat Thüringen	1718.986***	260.2186
Western	Hessen	– 3408.474***	222.2909
	Nordrhein–Westfalen	– 2670.862***	192.604
	Rheinland–Pfalz and Saarland	3382.437***	183.9022
Southern	Baden–Württemberg	– 1647.884***	135.4027
	Freistaat Bayern	1621.99***	143.5924
Constant		94,265.91***	3538.569

The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Results

Temperature impact of the electricity demand

The estimated results of the pass coefficient between each state's average temperature and total load are listed in Table 4.[7] The coefficients in this table indicate that the amount of electricity demand (total load) changes if a state's temperature increases by 1 °K. This table shows that the impact of temperature is different for each state. For example, Mecklenburg–Vorpommern and Schleswig–Holstein are in the northern area of Germany. This area is classified as a west coast, marine climate zone. Its temperature is lower in summer and higher in winter. Germany's temperature is lower than that of other countries. The cold winter tends to increase the electricity demand. Therefore, our results show that an increase in temperature decreases the electricity demand during winter for the area.

In the case of Mecklenburg–Vorpommern, the estimation result shows that the total electricity load decreases by approximately 2023 GW with an increase of 1 °K. We suspect that the increase in temperature in Freistaat Sachsen and Sachsen–Anhalt tends to decrease the total load for the same reason. The minimum average temperature of these states is lower than in other states. In these states, temperature increases can prevent bitter cold winters. Therefore, the average temperature of these states showed a negative correlation with the total load. However, the average temperature in some states showed a positive correlation with the total load. Almost all the states with a positive correlation between the average temperature and total load had higher maximum temperatures than the other states. For example,

[7] Estimation results of generalized SEM did not produce goodness-of-fit indices, such as a comparative fit index (CFI) and a goodness-of-fit index (GFI). We only reported this model's Akaike information criterion (AIC) and Bayesian information criterion (BIC) values. Our estimation results show an AIC = 1,263,392 and a BIC = 1,265,831.

Table 5 Estimated impact of solar radiation on each state's electricity supply from solar power

Area	State	Coefficient	SD
Northern	Schleswig–Holstein	29.9189***	2.4974
	Niedersachsen	− 22.0693***	4.1838
	Mecklenburg–Vorpommern	− 34.3395***	3.6083
Eastern	Brandenburg	32.0644***	6.0898
	Freistaat Sachsen	− 29.8871***	3.6067
	Sachsen–Anhalt	− 2.4199	4.3705
	Freistaat Thüringen	35.4378***	4.7295
Western	Hessen	− 29.5288***	4.1710
	Nordrhein–Westfalen	24.0072***	3.0096
	Rheinland–Pfalz and Saarland	7.4711***	2.7208
Southern	Baden–Württemberg	16.4565***	1.6318
	Freistaat Bayern	− 9.8301***	1.7717
Constant		986.6939***	23.2536

The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Rheinland–Pfalz and Saarland had higher average, minimum, and maximum temperatures than other states. Therefore, the estimated coefficient of these states increased.

Impact of solar radiation and wind speed on the electricity supply

Table 5 shows the pass coefficient between each state's solar radiation and electricity supply from solar power to the market. The coefficients in this table indicate the amount of electricity supply change if a state's solar radiation increases by 1 W/m^2. The table shows that the estimated coefficient of certain states is negative. Normally, the amount of electricity generated from solar PV increases when solar radiation increases. We propose two explanations of why our estimation produced these results.

First, some studies mention that excessively high solar radiation decreases the amount of electricity that is generated by solar PV. However, such a technological problem may have a limited impact on our results. For example, the pass coefficient of Mecklenburg–Vorpommern is significantly negative compared to that of the other states. In short, 1 W/m^2 increase in solar radiation decreases the electricity supply from solar PV to the market by approximately 34 GW in Mecklenburg–Vorpommern. The summary statistics (Table 3) show that the state's average radiation value is not higher than that of the other states. If the state faces nearly the same technological constraints, the estimated coefficient of Mecklenburg–Vorpommern will not become negative. Second, we can suppose that each state differs in the cost of electricity generation by solar PV. The cost of generating electricity by solar PV depends on weather conditions and several processes and technological constraints (e.g., grid, diffusion level, and scale of the PV system). If one state faces a higher cost of electricity generation through solar power, the generating company cannot sell that electricity for some time because other states that have a cost advantage in the electricity market can sell more electricity at a less expensive price. In this case, the increase in solar radiation increases the amount of electricity sold by other states. In contrast, an inefficient generator tends to use the electricity generated by solar PV for self-consumption. In this case, the amount of electricity supplied to the market declines since the state has a disadvantage in terms of the cost-effectiveness of electricity that is generated by solar power.

We cannot explain the apparent gap in the cost-effectiveness of solar generation between each state. However, states with a higher average solar radiation tend to increase the supply amount of electricity generated by solar power in their area. For example, the southern states of Baden–Württemberg and Freistaat Bayern have a rich solar power capacity and receive more solar radiation than other areas. In 2016, the solar capacity in Baden–Württemberg was 5,393 MW (the second highest capacity of all states). Freistaat Bayern had 11,637 MW (the highest capacity of all states) in the same year. In this area, Baden–Württemberg receives more solar radiation than Freistaat Bayern, although the latter state's solar capacity is larger than that of the former state. Both states already have a sufficient scale effect. Thus, the difference in solar radiation is the most important factor determining the cost-effectiveness of solar power in those states. In fact, the pass coefficient in Baden–Württemberg is positive. In contrast, the pass coefficient in Freistaat Bayern is negative. Thus, our estimation results in Table 5 imply the differences in cost-effectiveness between each state in each area.

Table 6 shows the pass coefficient between each state's wind speed and electricity supply from wind power to the market. The coefficients in this table indicate the amount of electricity supply changes if a state's wind speed increases by 1 m/s. In this table, the average wind speed for almost all states showed a positive pass coefficient with the electricity supply from wind power. These results imply that wind power can be a basic electricity source if each state's surplus electricity generated from wind power can be supplied to the wholesale market. Additionally, the value of the estimated coefficients demonstrates a trend similar to the amount of installed wind power capacity for each state. For example, the coefficients of Niedersachsen and Schleswig–Holstein are larger than those of other states. These states have a high installed capacity for wind power, particularly offshore wind power. Offshore wind power has the competitive advantage of a lower generating cost compared to other renewable energy (Soares-Ramos et al. 2020). Therefore, the electricity supply from the states to the market strongly increases when the wind speed increases in the states.

Although the wind capacity is not high in Freistaat Bayern compared to other states, the estimated pass coefficient

Table 6 Estimated impact of each state's wind power on the electricity supply from wind power

Area	State	Coefficient	SD
Northern	Schleswig–Holstein	855.8021***	58.6562
	Niedersachsen	836.422***	109.0853
	Mecklenburg–Vorpommern	109.0718	77.7091
Eastern	Brandenburg	473.9572***	126.3078
	Freistaat Sachsen	421.051***	75.4960
	Sachsen–Anhalt	309.1065**	120.7361
	Freistaat Thüringen	− 790.7166***	116.6529
Western	Hessen	− 215.3195**	106.2773
	Nordrhein–Westfalen	533.9378***	82.7977
	Rheinland–Pfalz and Saarland	− 81.77933	76.3945
Southern	Baden–Württemberg	200.643***	58.8215
	Freistaat Bayern	695.7228***	70.9896
Constant		− 5763.684***	68.4361

The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

of the states is relatively large. This is because there are differences in climatic conditions from north to south Germany. In the northern area, the correlation coefficients between each state are significantly high.[8] For example, the correlation coefficient is 0.919 between Niedersachsen and Schleswig–Holstein in our study. However, the correlation coefficient of Schleswig–Holstein is 0.4929. These results imply that alternative relationships occur between northern and southern areas. When electricity generated by wind power declines in the northern area due to weather changes (such as declining wind speeds), the wind speed increases in the southern area. In this case, wind power in the southern area increases. A declining electricity supply in the northern area has a large impact on the market; in short, the electricity price increases. Therefore, wind power generators in the southern area have a greater incentive to sell electricity when the electricity supply from the northern area declines. Thus, the electricity supply generated by solar power increases in the southern area, although it does not have a high wind power generating capacity.

The pass coefficients of Hessen and Freistaat Thüringen show negative values in Table 6. These states have seasonal effects. In other areas, the wind speed increases in summer and winter. These seasons require more electricity consumption. In both of the above-mentioned states, the wind speed increases in another season when the total electricity demand decreases in the market. These states have a lower incentive to supply electricity that is generated by wind power. Therefore, their coefficients show a negative correlation with the dependent variable.

[8] Appendix 3 shows the correlation coefficient between each state's weather index.

Table 7 Estimated impact of *Load, Solar* and *Wind* for market price

Independent variable	Coefficient	SD
Load	0.0007***	2.59×10^{-5}
Solar	−0.0016***	2.39×10^{-5}
Wind	−0.0013***	1.41×10^{-5}

Note: The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Total impact of electricity demand and supply based on weather conditions

Table 7 shows the estimated pass coefficients between the independent variables (*Load*, *Solar*, and *Wind*) and the dependent variable (*Price*). These coefficients show how much the electricity market price changes as electricity demand and supply change. The pass coefficient from *Load* is positive and has a significant relationship with *Price*. This coefficient means that an increase of 1 GWh in total load increases the spot electricity market price in Germany by 0.0007 € per MWh. Conversely, the pass coefficients of *Solar* and *Wind* show a negative relationship with the dependent variable. In short, the amount of electricity supply from renewable energy sources decreases the electricity spot trading price. In the case of the electricity supply from solar PV, increasing the electricity supply from solar PV by 1 GW decreases the electricity trading price to approximately 0.0016 € per MWh. Additionally, increasing the electricity supply from wind power by 1 GW decreases the electricity trading price to approximately 0.0013 € per MWh. Table 2 shows that the amount of electricity supply from wind power is approximately twice as much as that from solar PV on average. Therefore, the negative impact of wind power on the electricity market is more significant than that of solar PV. These results are in line with those of previous studies (Cludius et al. 2014; Keeley et al. 2020). An increase in supply causes a downward shift in the supply curve of the wholesale market. A shift in the supply curve decreases the electricity price.

Based on the overall estimation, we discussed how weather conditions affect the wholesale market price. The total indirect effect of each state's weather conditions was calculated by the summation of the pass coefficients. Additionally, the total indirect effect of weather conditions and each direct factor (i.e., *Load*, *Solar*, and *Wind*) were calculated by multiplying the pass coefficient of the total indirect effect by the direct effect. For example, in the case of temperature, we calculated the summation of the path coefficient between *Temperature* and *Load* as − 109.5029 (indirect effect). Additionally, the summation of the path coefficient between *Load* and *Price* was calculated as 0.000665 (direct effect). Therefore, the total effect of *Temperature* on the market price became − 0.00728 (− 109.503 × 0.000665). In short, our estimation results indicated that if the temperature in all states increased by 1 °K, the spot market price decreased to 0.00728€ per MWh.

The average temperature in Germany is not high, although the minimum temperature is lower than that of other countries. The peak demand for electricity occurs during the cold winter months. Therefore, the total effect of the temperature was negative in this estimation.

We can also calculate the effects of solar radiation and wind speed on the electricity price. The total indirect effect of solar radiation was approximately 19.701 GW supplied by solar power. If the average solar radiation increased by 1% (1.2902 W/m^2) in all states, the total effect was − 0.0396 € per MWh. In contrast, the total indirect effect of wind speed was 3347.899. If the average wind power increased by 1% (0.0347 m/s) in all states, the total effect was -0.1546 € per MWh.

Discussion and conclusion

This study aimed to reveal the effect of weather changes on the electricity supply and demand of the wholesale electricity market in Germany. We constructed an hourly time series dataset with weather data and electricity market data. We estimated the impact of weather changes on the electricity spot wholesale market using SEM based on this dataset. The estimation results had significant findings for understanding weather effects on the electricity market.

First, the effect of weather on the electricity supply differs in each state. Generally, increases in solar radiation increase the electricity supply from solar PV to the market. Our estimation results show a more complex effect of increased solar radiation. In short, the increase in solar radiation in certain states decreases the electricity supply generated by solar PVs. In our study, the correlation coefficients of temperature between each state are significantly high (approximately 0.9). Also, the correlation coefficients of solar radiation between each state are high. These results imply that the amount of electricity supplied from solar power is affected by changes in weather conditions, as well as by complex factors caused by the electricity trading system and regional differences in renewable energy sources. In contrast, nearly all the states can increase their electricity supply from wind power if the wind speed increases. However, the electricity supply to the spot market is affected by differences in climate zones and each state's capacity for wind power generation.

Second, electricity demand is also affected by weather conditions and, particularly, by temperature. Our results show that an increase of 1 °K decreases the spot electricity market price by approximately 0.0728 € per MWh. This result indicates that the total electricity consumption increases during winter in Germany. The German Environment Agency (2015) reported that climate change will soon increase the average temperature by 0.5 °C (which will occur over 2021–2050). A temperature increase of up to 2 °C in northern Germany and 2.5 °C in southern Germany is possible. Additionally, the agency mentioned that the largest temperature increase is expected in winter rather than summer. These forecasts imply that the climate change effect is different for each region and has the potential to dramatically change the structure of electricity demand. Our results show that the increase in the temperature effect for each region is complex. We must analyze the effect more thoroughly to plan for sustainable electricity use in Germany.

Our estimation results show that weather changes have an impact on the electricity spot market price in Germany. The estimated impact of weather is not large by itself. However, this impact cannot be ignored. This is because the impact occurs during each hour of trading. The effect of the weather changes hourly and daily. Therefore, the accumulated impact is not statistically insignificant.

Our results imply that we must not ignore rapid weather changes affecting the electricity market. As the severity of climate change increases, the occurrence of extreme weather is increasing. Extreme weather has occurred around the globe from 2020 to 2021. The Institute for Energy Research (2021) commented that extreme weather events, particularly the severe cold in winter, caused a critical spike in electricity market prices in Europe and Asia. For example, Spain registered its coldest temperature on record at − 35.6 °C, and several areas of the country were under at least 18 inches of snow and had record-breaking snowfalls. The electricity price in Spain increased to nearly €95 per MWh. This price change was 123% more than the prices of the previous week and nearly 3 times higher than the 2020 average price. Hagfors et al. (2016) defined extreme prices and counted price spike occurrences. They revealed 564 price spikes (387 positive spikes and 177 negative spikes) between January 2010 and May 2014 in the Germany spot electricity market. These price spike increases are projected to occur due to the severity of impending climate change. Some researchers have already discussed climate change effects on electricity prices (Bartos and Chester 2015). A new model that can analyze integrated effects between the market and weather changes is increasingly important.

Our model is one of the trials to consider how weather change in a detailed area affects the electricity market price. However, we can improve the model more. For example, we do not care here about the effect of temperature on the electricity supply from solar power. In some areas, the temperature may have a negative impact on the electricity supply from solar power (Staffell and Pfenninger 2018). In future tasks, we need to care about more complex weather conditions when we estimate the impact of their condition on the market impact. Additionally, previous studies have already revealed that change in the economic and institutional situations related to climate change cause change in electricity demand. For example, climate change will increase large scale disasters in many places. Previous studies found that such a disaster discourages economic growth (Onuma et al. 2021). Discouragement of economic growth critically affects the electricity demand. Also, climate policies, such as FIT, make it more complex for consumers' electricity use situation (Tanaka et al. 2022). Therefore, our future task will be to construct a more robust estimation of electricity market price, including several factors related to climate change.

Appendix 1

See Fig. 3.

Fig. 3 The map of sample states of weather data in this study

Appendix 2

See Table 8.

Table 8 Summary statistics of weather variables

	Variable	Observation	Mean	SD	Min	Max
Temperature	Schleswig–Holstein	18,824	282.939	7.283	258.109	307.973
	Niedersachsen	18,824	283.104	7.423	256.041	309.579
	Mecklenburg–Vorpommern	18,824	283.110	7.727	255.164	308.519
	Brandenburg	18,824	283.546	8.290	254.482	310.105
	Freistaat Sachsen	18,824	283.025	8.562	252.962	310.081
	Sachsen–Anhalt	18,824	283.272	8.196	254.329	309.862
	Freistaat Thüringen	18,824	282.413	8.254	253.243	308.835
	Hessen	18,824	283.101	7.963	256.356	309.746
	Nordrhein–Westfalen	18,824	283.272	7.408	257.659	309.729
	Rheinland–Pfalz and Saarland	18,824	283.801	7.821	259.327	310.612
	Baden–Württemberg	18,824	283.209	8.171	257.266	310.300
	Freistaat Bayern	18,824	282.405	8.323	255.240	308.959
Radiation	Schleswig–Holstein	18,824	123.232	189.674	0	832.323
	Niedersachsen	18,824	123.484	188.835	0	849.538
	Mecklenburg–Vorpommern	18,824	124.652	191.098	0	851.228
	Brandenburg	18,824	127.444	194.004	0	864.523
	Freistaat Sachsen	18,824	131.248	199.937	0	887.453
	Sachsen–Anhalt	18,824	128.841	196.186	0	870.702
	Freistaat Thüringen	18,824	131.566	200.243	0	879.568
	Hessen	18,824	130.497	199.333	0	871.445
	Nordrhein–Westfalen	18,824	126.374	193.830	0	861.768
	Rheinland–Pfalz and Saarland	18,824	132.311	201.493	0	876.894
	Baden–Württemberg	18,824	135.083	203.882	0	888.766
	Freistaat Bayern	18,824	133.490	199.688	0	897.431
Wind speed	Schleswig–Holstein	18,824	4.238	1.858	0.426	13.841
	Niedersachsen	18,824	3.850	1.734	0.438	13.409
	Mecklenburg–Vorpommern	18,824	3.948	1.727	0.486	13.053
	Brandenburg	18,824	3.562	1.625	0.466	12.268
	Freistaat Sachsen	18,824	3.407	1.674	0.315	13.451
	Sachsen–Anhalt	18,824	3.511	1.691	0.249	14.377
	Freistaat Thüringen	18,824	3.300	1.643	0.255	14.151
	Hessen	18,824	3.283	1.647	0.290	13.489
	Nordrhein–Westfalen	18,824	3.731	1.789	0.425	13.877
	Rheinland–Pfalz and Saarland	18,824	3.317	1.686	0.222	13.055
	Baden–Württemberg	18,824	2.739	1.330	0.354	10.876
	Freistaat Bayern	18,824	2.725	1.257	0.401	11.923

Appendix 3

Correlation coefficient between weather data in each state.

Appendix 3.1

See Table 9.

Table 9 Correlation coefficient between solar radiation in each state

State number	Name of state	1	2	3	4	5	6	7	8	9	10	11
1	Schleswig–Holstein	1	–	–	–	–	–	–	–	–	–	–
2	Niedersachsen	0.984	1	–	–	–	–	–	–	–	–	–
3	Mecklenburg–Vorpommern	0.979	0.969	1	–	–	–	–	–	–	–	–
4	Brandenburg	0.954	0.960	0.985	1	–	–	–	–	–	–	–
5	Freistaat Sachsen	0.925	0.941	0.951	0.986	1	–	–	–	–	–	–
6	Sachsen–Anhalt	0.955	0.972	0.973	0.992	0.986	1	–	–	–	–	–
7	Freistaat Thüringen	0.935	0.961	0.949	0.973	0.984	0.990	1	–	–	–	–
8	Hessen	0.935	0.968	0.936	0.946	0.946	0.967	0.982	1	–	–	–
9	Nordrhein–Westfalen	0.952	0.986	0.940	0.937	0.927	0.955	0.957	0.982	1	–	–
10	Rheinland–Pfalz and Saarland	0.923	0.952	0.920	0.925	0.925	0.943	0.958	0.990	0.977	1	–
11	Baden–Württemberg	0.901	0.923	0.907	0.922	0.933	0.937	0.959	0.968	0.934	0.970	1
12	Freistaat Bayern	0.907	0.928	0.920	0.943	0.962	0.955	0.977	0.962	0.951	0.931	0.983

Appendix 3.2

See Table 10.

Table 10 Correlation coefficient between wind speed in each state

State number	Name of state	1	2	3	4	5	6	7	8	9	10	11
1	Schleswig–Holstein	1										
2	Niedersachsen	0.895	1									
3	Mecklenburg–Vorpommern	0.915	0.831	1								
4	Brandenburg	0.816	0.840	0.931	1							
5	Freistaat Sachsen	0.677	0.780	0.773	0.926	1						
6	Sachsen–Anhalt	0.788	0.899	0.848	0.953	0.947	1					
7	Freistaat Thüringen	0.652	0.828	0.694	0.834	0.923	0.938	1				
8	Hessen	0.606	0.820	0.603	0.705	0.768	0.829	0.920	1			
9	Nordrhein–Westfalen	0.711	0.919	0.654	0.705	0.710	0.813	0.835	0.924	1		
10	Rheinland–Pfalz and Saarland	0.515	0.723	0.500	0.585	0.646	0.700	0.804	0.953	0.885	1	
11	Baden–Württemberg	0.407	0.586	0.426	0.533	0.627	0.634	0.765	0.857	0.710	0.891	1
12	Freistaat Bayern	0.493	0.666	0.538	0.678	0.798	0.776	0.900	0.861	0.720	0.792	0.874

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