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Accessing the Effect of Renewables on the Wholesale Power Market

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The purpose of this paper is to examine how rising wind energy generation (in MWh) impact the wholesale power market's volatility (in SEK) across four bidding regions in Sweden. Prior investigations show that though the increase in electricity production from wind energy lowers the average day-ahead electricity wholesale prices, however, uncertainty and volatility of market price could rise due to wind energy's intermittent nature. This study results show that Swedish power market experiences higher price volatility in long-run frequency when the generation of wind electricity increases. The reason for this high and volatile electricity price might be found from inflexible baseload power generation. The paper further suggests that volatility in the Swedish power market could be increased due to ambitious renewable electricity target by the Swedish government. The analysis concludes by providing the evidence that further adjustment in regard to the energy and regulatory policies might foster the better integration of a higher share of renewables into the power system.

Keywords: Renewable Electricity, Wind Energy, Electricity Market, Price Volatility, Regulatory Policies
JEL classifications: Q470

1. INTRODUCTION

Throughout the last few decades, a stable and unsurpassed industrialization and economic growth have been experienced around the globe. It is predicted that the growth rates will be rising faster in the coming decades and will reach 1-2.8% yearly in the 21st century (Acheampong, 2018). These predictions have made by experts by considering a good number of factors includes technological advancement, efficiency in the production capacity, the elasticity of the output and the performances of capital and labour. This rapid increasing growth will be steadier in the developed world and could grow by 4.1% yearly in the 21st century (Markandya et al., 2014; Wu et al., 2018). At the same time, due to raising population and a higher standard of living, the research found long-run causality in-between the rapid raising income with electricity consumptions.

In this article, these concerns and challenges in regard to the electricity consumption are articulated from the supply and demand side of electricity. Indeed, the most obvious challenge could be how to supply and meet the rapid raising of electricity which is not storable (Wu and Huang, 2014). With the purpose of addressing the rapidly rising energy requirements, it might require installing more power station, raising power station capacities which might require the full 20th century. However, though the supply side in the electricity production efficiency is believed already in peak, it is unlikely able to supply the rapidly raising global energy demand. Therefore, to address this limitation in the supply side imbalance of the traditional power plants the acceptance and the demand of renewable energy like wind power has been raising rapidly (Andreas et al., 2017; Apergis and Apergis, 2017). Although, yearly average wind energy generation raising significantly world-wide considering the lower marginal costs, however, increasing wind penetration has been leading various challenges in regard to the operations and controls as a result of intermittency as well as unpredictability.

The main concern and challenge throughout this development are how generation from wind energy affecting supply-demand electricity function. Generally, supply and demand for electricity are highly uncertain followed by the intermittent and seasonality characteristics; hence, inter-day and day-ahead volatility in the wholesale market is higher compare to any other energy-related commodities. More specifically, the challenge arises how the over fluctuating wind electricity production could affect the volatility of electricity price (Aquila et al., 2017; Clò et al., 2015). From supply-demand equilibrium perspective power market connection, to avoid temporary imbalance, the generated and supplied electricity should be equal as the proportion of electricity demand (Liebensteiner and Wrienz, 2019). However, as a result of lacking real-time data in regard to the electricity prices, it is hard for electricity consumers to access real-time data and work on that accordingly (Spalding-Fecher et al., 2017; Staffell and Pfenninger, 2018). For this reason, determining the equilibrium prices as well as the quantity of electricity is considered one of the difficult and challenging tasks.

In relation to the demand side, suitable weather help to generate large-scale and sufficient wind energy. This weather condition and sensationally put the challenge of matching the demand for electricity. This demand-side imbalance also could cause an unstable power market, and the electricity price could be more volatile as a result of the high level of uncertainty (Kyritsis et al., 2017). On the other hand, from the supply-side perspective, excess supplies of the wind electricity from wind turbines could reduce wholesale electricity price in the power market. In a the similar way, due to the seasonality or extreme weather conditions, wind energy feed-in could not be able to produce enough load, the electricity price could be high in the wholesale electricity market (Polinori, 2019). Due to lower marginal costs and large-scale energy generation, when wind energy replaces the more expensive offers from existing traditional power plants within the energy system, this term is called the merit order effect (Bell et al., 2017; Cludius et al., 2014). Nevertheless, this phenomenon also indicates that little wind electricity generation could result in increases in electricity prices which may start to increase further as a result of losing supply which consequently raises the inter-day electricity price volatility. It appeared and argued in many studies that the significant of the effect could be more prominent among the regions which generate a large scale of electricity from wind compared to the other regions.

In addition, during recent decades, most of the power markets in the European Union (EU) have restructured for the purpose of allowing competitions in regard to the production and distribution of electricity. However, how renewables such as wind energy generation lead to volatility/uncertainty of Swedish power market is inclusive. This is highly important as high electricity price volatility has plagued day-ahead wholesale power markets, lead to the important contribution to formulate a risk-averse market participant as well as system operators in regard to the gird availability as well as the stabilization of electricity market. Moreover, electricity price volatility is considered one of the important primary input for traditional energy pricing model, have significant impacts on the production, distribution and in the retailing activities of electricity.

The overall objective of this paper is quantifying the effect of wind power production on the volatility of the spot electricity prices in Swedish electricity wholesale market. More specifically, this study examines how wind penetration (in MWh) impacts in Sweden wholesale electricity market (measured by SEK also with respect to the standard deviation of SEK on the basis of daily average spot prices). This study will be added important insights to current literature in the field of finance as well as economics who associates with designing power markets, evaluating electricity prices behaviour and stabilization of the power markets. Most significantly, this study generates the first rigorous analysis of the valid and reliable time-series data as well as supplies concrete evidences to the energy and environmental policy makers in regard to the renewables generation externalities, investment decision and portfolios and economic and financial strategies in regard to the wind energy generation and stability of the power market.

2. WIND POWER AND SWEDISH ELECTRICITY MARKET STRUCTURE

The electricity market in Sweden is divided into four important parts includes generating electricity, transmitting electricity, distributing electricity and finally retailing electricity (Ek et al., 2013). Wholesale trade market includes producers or generators, suppliers, and various industrial bodies having a high intensity of electricity demand. In the majority of the cases, few market participants involve in electricity generation as well as transmission of electricity where the vast majority of the players engage with the retailing and distribution section. As a result of de-regulated electricity market production and retails are open to enhancing competition whereas natural monopolistic market can be found in the distribution and transmission section which is subjected to be regulated like electricity price regulation in order to enhance electricity market efficiency. Swedish power market has split into four important bidding areas from SE1 to SE4 (Åberg et al., 2019). It is important to note that most of the electricity produced in the northern part of the country (SE1 and SE2), whereas most of the electricity consumes in the southern part of the country (in SE3 and SE4).

In regard to the structure of the electricity wholesale market in Sweden, the following structure is commonly observed. Actors or market players purchase the electricity (transmission section- from energy companies/generation section – from the day-ahead format) from Swedish energy exchange (Broberg and Persson, 2016). To be ensured that electrical power supply is in a balance, any market players responsible for unbalancing the electricity market have to compensate the require amount of costs to restore the balance which leads to reducing the incentive for driving up the electricity prices through offering a small amount of supply of electricity. In addition, current research, as well as development evidently suggest that electricity market players access limited possibilities for exercising electricity market power (Bustos-Salvagno, 2015; Erdogdu, 2013). It is also important, though power consumers do not have real-time data or information; however, there are exit and entry barriers, a limited number of energy companies serves few electricity consumers, homogeneity characteristic of electricity and the above-mentioned electricity pricing mechanisms makes this market exhibits the perfect competition market (Newbery and Greve, 2017). Therefore, considering these market structure and characteristics of electricity in this article, this market is considered as perfect competition market.

3. FACTORS AFFECTING ELECTRICITY SUPPLY AND DEMAND

A good number of factors that influence the electricity supply. The raising prices of the renewable's energy substitute sources like coal or natural gas-based power stations along with state government regulations and national tax policies have led renewables power production especially the wind energy highly competitive (Sanghvi, 1982). More specifically, renewable energy target (RET), environmental and global warming concern, high taxation on highly emitted power production, integrated resource-planning are some of the most important policy concerning factors that derive the renewable electricity supplies like wind energy. Moreover, fuel price fluctuations like gas or oil influence the electricity supplies which is offered. Similarly, traditional power plants outage due to the maintenance, difficulties in the transmission as well as breakdown are some of the important influential factors affect electricity supply (Rubin et al., 2015; Staffell and Pfenninger, 2018). A major portion of electricity in the Swedish power market is produced by coal as well as the nuclear power station; hence, most influencing factors for affecting electricity supply are the availability of nuclear power as well as coal price level (Fridolfsson and Tangerås, 2013). Worth pointing out that wind electricity generation in Sweden could be divided into two different categories include the onshore as well as off- shore wind electricity production. The availability of load generation of the offshore wind electricity production is another important factor influencing electricity supply as well as pricing.

Another two influential factors that influence electricity supply are installation capacities, also the level of integrations among various electricity markets (Burger and Weinmann, 2015). In the event when base load power plants dominated the installations capacities; this might result in the inflexibilities for the reason that changing output might affect the heat as well as pressure -sensitive parts. In addition, high-cost installation of the power plants with lower variable cost, these power plants needed to be run across the year accompanied by very limited changes of output for covering the costs of investments (Niu and Insley, 2013). The second major factor about the interconnectedness of the electricity market, which illustrates that any short of misalignment could result in the inefficiencies in the electricity market.

Similar to the electricity supply, a good number of factors that affect the electricity demand and this demand for electricity has been deriving by various sources. The production process of electricity is considered the vital factor where electricity demand has been deriving by the vital characteristics of the production process like daytime, seasonality, technological advancement, and the rate of economic growth (Chang et al., 2016). It is evident that stable economic growth, as well as industrial development, are the two most important drivers of rising electricity demand. In addition, the rapidly raising population growth rate is considered another major river of rising energy demand (Sachs et al., 2019; Verhoef et al., 2018). In Sweden, electricity demand is driven by another important factor which is the temperature where extreme low and high temperature increase the use of heating and Colling and affecting the demand of electricity (Cialani and Mortazavi, 2018).

In the short-run, electricity demand can be defined as inelastic. As a product, electricity is a highly necessary object which is substitutable with very few energies which lead the demand for electricity more elastic. One of the leading power market stability factors is mandatory production (must-run production), also known as autonomous power demand and is detached from electricity load (Bernstein and Madlener, 2015). In addition, as electricity consumers cannot access or obtain the real-time information in regard to the electricity prices, hence, short-run consumer's electricity demand is elastic (Betancourt, 1981; Ghosh and Das, 2002). From the perspective of electricity market demand curve, the relationship is outlined along the following lines. Considering the intermittent power availability (such as wind as well as solar energy) shifting the residual demand perspective is considered an influential determinate to determine the equilibrium price (Perez and Real, 2016).

Moreover, in the shorter-term, from electricity market dispatch perspective, it is experienced the supply shocks as a result of intermittent renewable like wind energy (Li and Park, 2018). As described before, wind energy generation cannot predict or controlled due to the seasonality, which poses difficulty in regard to the supply predications. On the other hand, owing to the lower marginal cost of intermittent renewables energy generation, this renewables power exhibits the base of the electricity supply curve (Cialani and Mortazavi, 2018). The amount of residual demand (excess demand cannot cover by renewables), hence need to be supplied by traditional oil, nuclear or gas-fired power stations (Pezzulli et al., 2006).

Estimating power price volatility is dependent on the capability of forecasting of the supply and demand. While difficulties in regard to the predication capabilities of intermittent renewables and limited traditional power plants, therefore, affect significantly on the electricity price volatility (Raviv et al., 2015). For instance, throughout summer when intermittent renewables like solar and wind generate and supply a higher amount of electricity while flexibilities are limited in the traditional power plants, this excess electricity supplies from renewables lead to the downward pressure to the electricity price. The vice versa could happen when due to the seasonality, the limited wind is generated, the price of electricity need to be higher in this case for the purpose of giving incentives to the traditional power generators with the aim of supplying more electricity in the power market (Bennedsen, 2017;

Bessec et al., 2015). Limited forecasting abilities in this scenario could impose instability in the power market; limited forecasting capabilities might result in irregular trading activities in power markets also the majority of the trading might be taking place in spot electricity markets.

In the short-run equilibrium perspective, the above-mentioned relationship might be illustrated in the following way. When wind electricity production come into the electricity supply curve, the lower marginal cost of producing renewables electricity lead to a rightward shift to the short-run electricity supply curve as a result of the comparatively higher marginal cost of traditional power plants. As discussed before, the base power station is unlikely able to changing the level of output as it aims of maintaining the lifetime duration of parts. However, exception could be noticed in the hydro energy which is more flexible in regard to the output deployment and could easily adjust the output for both cases meeting the peat time demand as well as reducing the excess supply. This type of adjustability and flexibility help to reduce the electricity price volatility for long-term.

This analysis leads to the summary of this part is that the lower electricity prices following by increasing supply of renewables is illustrate as the merit order effect. Importantly, the power market has the capability to revert electricity supply shock depending on the availability as well as flexible electricity supply. Throughout this conceptual framework within the demand and supply relations revels that electricity prices could be lower due to the higher renewables penetration; however, electricity price could be more volatile when higher wind energy generation in the power system. In this relation, a deep-dive analysis of these results from previous studies is required.

4. MATERIALS AND METHODS

4.1. Implication of Seasonal Patterns

A vast majority of wind electricity generation have the distinctive features followed by a higher degree of intermittent characteristic which leads by natural climate variability factors includes air density as well as air temperature, the velocity of wind and rivers runoff. To understand and quantify this sensitivity of renewables electricity production to the weather and climate variability and include them in the price model will lead to assess better about how renewables affect electricity price volatility (Wozable et al., 2015). This means that before finalizing the data, it is important to consider that how supply and demand of electricity response in terms of different days and months of the year. In mathematical precision, the seasonal factor can be included in the equation as

$$p = y + s \tag{1}$$

In this equation, p represents the price of electricity, y in this equation is the stochastic part, and finally, s represents the seasonal variable. This seasonal factor s! might be detailed further by dividing into the constant parameter-c, weekdays variables- ξid_j also the monthly variable- $v_i m_j$. More precisely, ξ_i As well as v_i are representing the parameters whereas m_j and d_j represents dummy variables for the weekday (i ranging from 1 to 7, j ranging from 1 to 12). All things are putting together; the following equation effectively represents the seasonal variations component.

$$s = c + \sum_{i=1}^{q}\xi_i(d_j) + \sum_{j=1}^{r}v_i(m_j) \tag{2}$$

Where, s represents seasonal variation factor, c, ξ_I and v_i represents as parameters and d_j as well as m_j represents as the weekdays and monthly dummy variables respectively. For the purpose of full reduction of seasonal variation, an ordinary least square regarrison or OLS regression performed by the help of monthly and weekly dummies. More specifically, dummies created for weekdays (Monday to Sunday) also from January to December where January and Monday used in the equation as the reference variables. Finally, OLS regression for seasonal variation s generates the output of p And this output afterwards utilized to achieve the seasonally adjusted data.

4.2. Modelling Volatility with GARCH

Due to intermittency character of renewables electricity, markets could be more unstable, and electricity prices could be more volatile with the presence of price spikes (Engeland et al., 2017). In order to address this challenge while examining the electricity price volatility over the time, this study utilized a noble approach called Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The major aim of using GARCH modelling in the current study is, this model does perform better in regard to the forecasting and quantifying the price volatility for both in short as well as long run. Likewise, the other methodology like SARMA and ARMAX this GARCH method depends on the autoregressive terms on which this method can successfully incorporates seasonal variation in the model. Compare to the OLS regression analysis, this GARCH model is highly dynamic and have the ability to capture better the past shocks (Escribano et al., 2011). Importantly, compared to the other hybrid methodologies like ARX-EGARCH, GARCH is the simpler model to perform the descriptive analysis.

The GARCH model generally runs to examine the inter-relationships for the economics and financial time series data where volatility could be changed in accordance with the patterns. The GARCH modelling approach could be expressed as follows.

$$Y_t = \mu + \sum_{i=1}^{l}\phi_i(y_{t-1}) + \sum_{j=1}^{m}\theta_j(w_{t-j}) + \in_t \tag{3}$$

$$h_t = \omega + \sum_{i=1}^{q}\alpha_i(\in_{t-i}^2) + \sum_{j=1}^{r}\beta_j(h_{t-j}) + \sum_{k=1}^{s}y_k(w_{t-k}) \tag{4}$$

In equations 4 and 5, the variance equation is expressed by (in *SEK*) where the mean equation is represented by Y_t(*in SEK*) Y_t as well as μ in the equation number 3 is constant whereas autoregressive term φ_i used in this mean equation for the period i. Natural logarithm in regard to the electricity prices is represented by y_{t-1} in the mean equation to cover the period from t to i. θj in the mean equation represents the parameter of wind electricity generation whereas w_{t-j} represents natural logarithm for wind electricity generation. For the purpose of examining the weekday's impact in the mean equation, seven lags have incorporated in equation four. The full form of error term $\in_t$ used in the mean equation can be expressed by $\sqrt{hizi}$, where zi represents normally distributed ranging from N = 0 to 1.

On the other hand, in the equation (4), ω representing the variance value for theconditional variance equation usually for long run basis. α used in conditional variance equation to express on what extend current shocks affect the value whereas β used in this equation to express the past shock's persistent effect and h_{t-j} represents the inclusion of the terms. y_k represents wind energy generation parameter whereas w_{t-k} represents natural logarithm for wind energy production.

The competitive and effective electricity market is characterized by intermittent price spikes which afterwards return again to the mean value because of the demand and supply forces in the electricity market. The parameter β and α used in the conditional variance equation for testing the stabilities of the Swedish electricity market. In case when $\alpha_i + \beta_j < 1 \, also \, when \, \alpha_i \, and \, \beta_j = 0$ means both possess the positive values their sum will be greater than one. In this case, though the mean in the model is reverting, however, shock's effect (both past and current) has a temporal effect on conditional variance equation (h_t).

In the mentioned GARCH model variables are incorporated by stepwise. At the beginning only the electricity price and variance are measured.

$$y_t = \mu + \sum_{i-1}^{l} \phi_i (y_{t-1}) + \in_t \tag{5}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i (\in_{t-i}^2) + \sum_{j=1}^{r} \beta_j (h_{t-j}) \tag{6}$$

Afterwards, wind electricity production representing by w (in MWh) as well as total electricity load representing by ι (in MWh) are incorporated in the equations.

$$y_t = \mu + \sum_{i=1}^{l} \phi_i (y_{t-1}) + \sum_{j=1}^{m} \theta_j (w_{t-j}) + \sum_{k=1}^{n} \psi_k \left(l_{t-k} \right) + \in_t \tag{7}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i (\in_{t-i}^2) + \sum_{j=1}^{r} \beta_j (h_{t-j}) + \sum_{k=1}^{s} y_k (w_{t-k}) + \sum_{g=1}^{u} \Delta \psi_g \left(l_{t-g} \right) \Delta \tag{8}$$

Lastly, wind penetration measured by $wind\ energy\ /\ total\ load$ and represents by p incorporate in the model.

$$y_t = \mu + \sum_{i=1}^{l} \phi_i \left(y_{t-1} \right) + \sum_{j=1}^{m} \theta_j \left(w_{t-j} \right) + \sum_{k=1}^{n} \psi_k \left(l_{t-k} \right) + \sum_{g=1}^{d} \xi_g \left(p_{t-g} \right) + \in_t \tag{9}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i (\in_{t-i}^2) + \sum_{j=1}^{r} \beta_j \left(h_{t-j} \right) + \sum_{k=1}^{s} y_k \left(w_{t-k} \right) + \sum_{g=1}^{u} \psi_g \left(l_{t-g} \right) + \sum_{h=1}^{v} \xi_h \left(p_{t-h} \right) \ldots \tag{10}$$

Along the lines of existing research, the major objective of this time series quantitative analysis is to examine the effect of wind electricity production' effects on electricity price volatility. To run the descriptive analysis and to perform the results, 10% significance level is considered in this study

4.3. Data Sources and Description

This study utilized daily day-ahead electricity price and wind energy generation data for both conditional mean as well as variance equations in the GARCH model for the purpose of better understating about how daily wind electricity production affects the average day-ahead wholesale electricity price in Sweden. This investigation covers the years from January 2017 to January 2018 the most important time period when notable changes took place in the Swedish renewable energy policy. In regard to the manufacturing efficiency of wind turbines and installation capacity of wind energy, Swedish wind stations reached a peak level during this time frame (Clò et al., 2015). The data set for daily day-ahead electricity prices and wind electricity generation are collected from Nord Pool which is the leading power market in the European energy exchange. The data are collected for four bidding areas in Sweden includes SE1, SE2, SE3 and SE4 in order to make better comparison among different regions concerning the renewables and electricity price volatility. The study considers 730 samples from each particular region, thereby, 3650 (four bidding regions and as a whole Sweden) samples data are analyzed in this study to accomplish the result. All four regions are included in the study and regional data are analyzed to examine the fact of whether regional differences could make any difference in terms of the electricity price volatility. Electricity daily price is measured by SEK, whereas the wind energy generation is measured by MWH in this study. The determine that whether the data included the outlier or not, which might cause the skewness of the skewness of the model, the following study is performed, and results can be seen as follows.

Electricity production from wind energy and the day-ahead electricity prices from January 2017 to December 2018 across the Sweden is summarized by the (Figures 1-5). The Figures follow a series axis assignment to make a better comparison in regard to the wind energy production and its subsequent impact of the electricity price. The series axis assignment on the left-hand side of the figure shows wind energy generation in MWh and on the right-hand side day-ahead electricity price measured by SEK.

Figure 1: Daily wind energy Generation (in MWh) and Day-ahead electricity price (in SEK) across Sweden

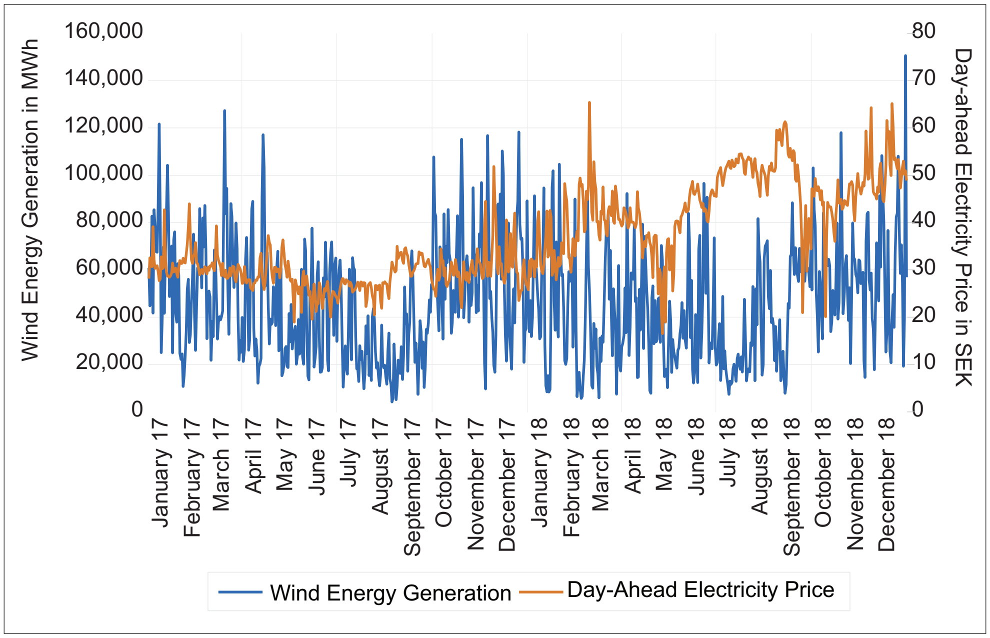
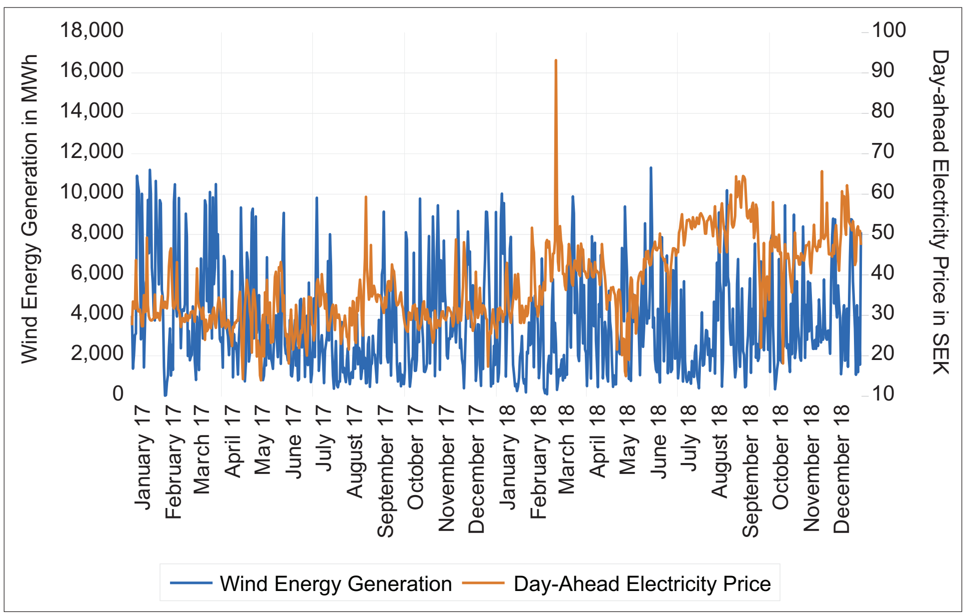


Figure 2: Daily wind Energy Generation (in MWh) and day-ahead electricity price (in SEK) for SE1



The line chart in the figures indicates the price and wind energy generation with a number of distinct outliers which might cause skewness in the applied model. Importantly, the figure show a number of distinct spikes in regard to the day-ahead electricity prices such as in February 2018 across Sweden and March 2018 for all the four regions in Sweden. These distinct series of day-ahead electricity price spikes reflect the existence of volatility of the electricity market in Sweden.

As mentioned earlier, the spot electricity market in Sweden is divided into four regions includes SE1, SE2, SE3 and SE4. Electricity spot markets price of electricity is determined by auction in these bidding areas. However, there is a considerable number of differences among four reasons relating to the renewables power production, seasonality power consumption and installation capacity of wind energy. Therefore, for better understating it is important to examine for all four Swedish bidding areas to make sure that whether zonal differences followed by different characteristics make any differences in the day-ahead electricity prices and wind energy production.

As depicted in the Figures 6-10, the total power load as well as wind energy production in Sweden from January 2017 to December 2018. These Figures clearly illustrate the seasonal variation, total power load and the availability of the wind energy depending on the seasonality. Current research suggests that wind turbines performances varied throughout the different season due to the fact of seasonal wind energy patterns. For example, during wintertime production from wind turbines as well as the tidal source are most prolific and most promising

Figure 3: Daily wind energy production (in MWh) and day-ahead electricity price (in SEK) for SE2

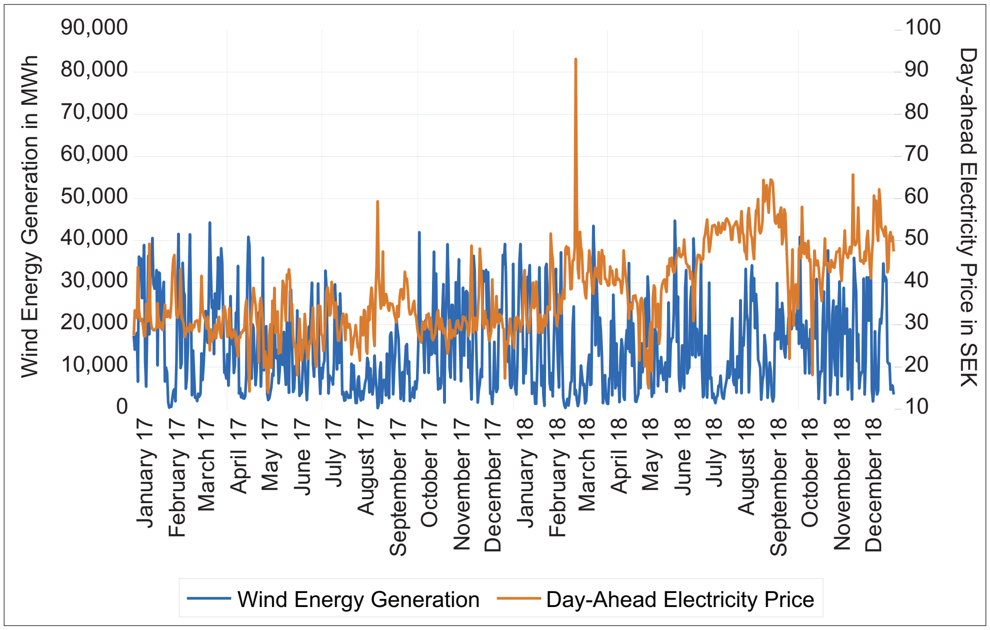
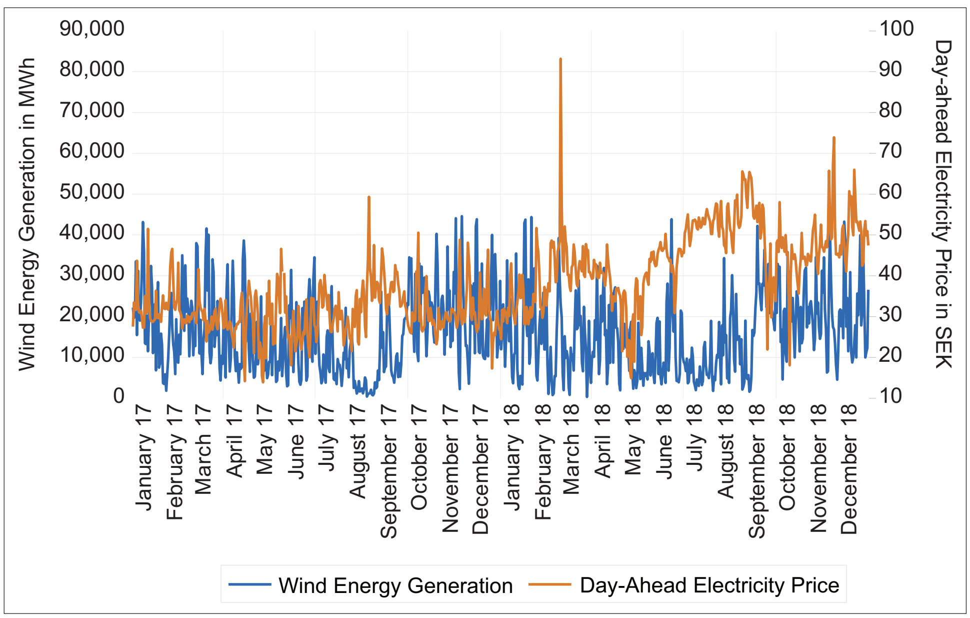


Figure 4: Daily wind energy production (in MWh) and day-ahead electricity price (in SEK) for SE3



sources of energy. This seasonal variation is noticeable in those figures in all bidding areas indicating the highest wind energy generation during the winter season and the low wind energy production during summer.

4.4. Data Analysis: Reliability and Validity

In order to make sure that the used data provide a valid result, the data set has used stepwise in this study for better understanding the explanatory power. In regard to the reliability, all financial time series data used in this investigation are collected from a very reliable source called Nord Pool. For the purpose of consistent reliability of the collected data set to round off actions saved consistently up-until the final step of the calculation. While calculating the result, it is also vital to consider that no certain observations are allowed for influencing the study results.

4.5. Detect and Remove Outliers from Data

Before applying the GARCH model, the study wants to know whether the collected data set and the price model are suitable for the GARCH model or not. To make sure the applicability of the GRACH model, firstly the time series data analyzed and made graphical representations to identify whether there is any volatility clustering in the collected data for all bidding areas. The analysis and graphical representation imply a good number of volatility clustering (such as February 2011 for SE1 and March 2018 for SE2) for all bidding regions and as a whole in Sweden. Finding such types of volatility clustering implies that higher volatility followed by higher volatility and lower volatility followed by lower volatility. More specifically, these volatility clustering indicates simple serial co-relation exists in the square return, which is the variance of the return. Which also indicates that the ARCH effect

Figure 5: Daily wind energy Generation (in MWh) and day-ahead electricity price (in SEK) for SE4

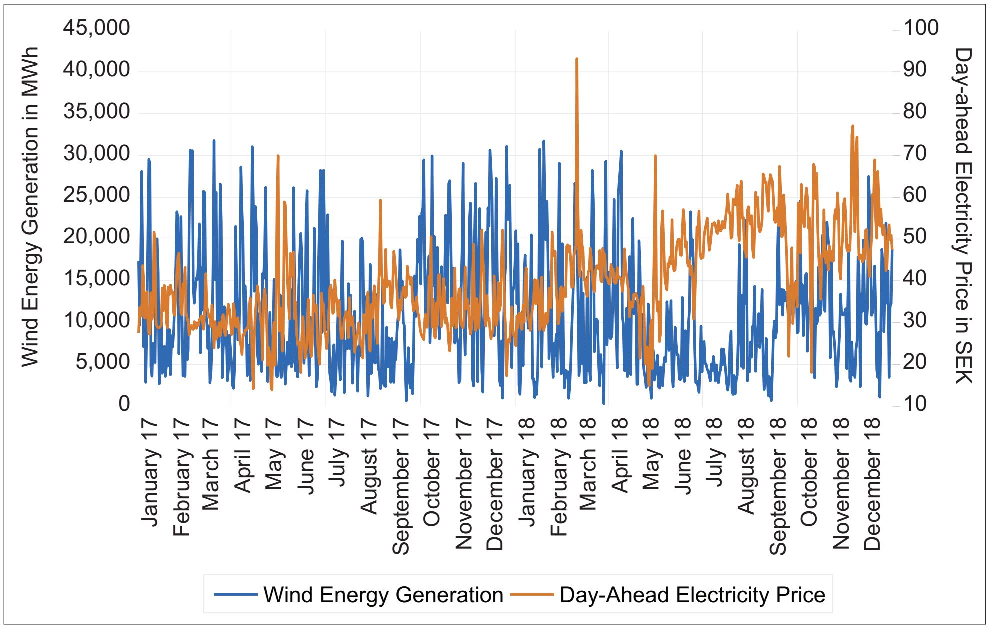
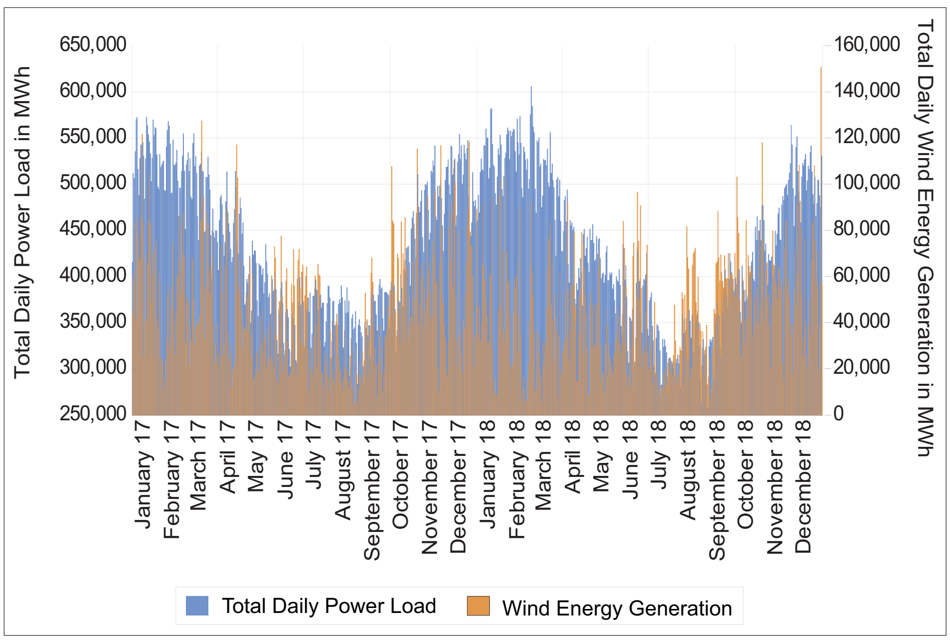


Figure 6: Total Power Load (in MWh) and wind energy contribution (in SEK) across Sweden



exists, and we need to apply the GARCH model to accomplish the study objective. Figures 11-15 represent the volatility clustering for the bidding regions and also as a whole in Sweden.

After the observation and graphical representation of the data, it is clear that price series contains a number of spikes and volatility clustering. Each of the spike stands for outlier and this extreme deviation (or outliers) could result in the higher kurtosis. Therefore, before making further descriptive analysis, it is important to reduce the impacts of the outlier without deleting any current observation. This can be done by applying the threshold value of three standard deviations of the mean. In order to make the price model more accurate, all outliers in the data are detected and scaled accordingly. First of all, the mean value as well as standard deviation along with low and peak electricity prices relating to the three standard deviations from entire samples measured to align with the prior investigation. This calculated values afterwards replaced by the values within three standard deviations of the mean. The Figures 16-20 represents the adjusted data set in regard to the outliers.

5. RESULTS

5.1. Results of Seasonal Climate Variation

In order to perform the descriptive analysis, first of all, this study performs OLS regression analysis in order to address the seasonality and the results of if this analysis can be found from in Table 1. Table 1 indicates overall day-ahead electricity market in

Figure 7: Total power load (in MWh) and Wind energy contribution (in SEK) for SE1

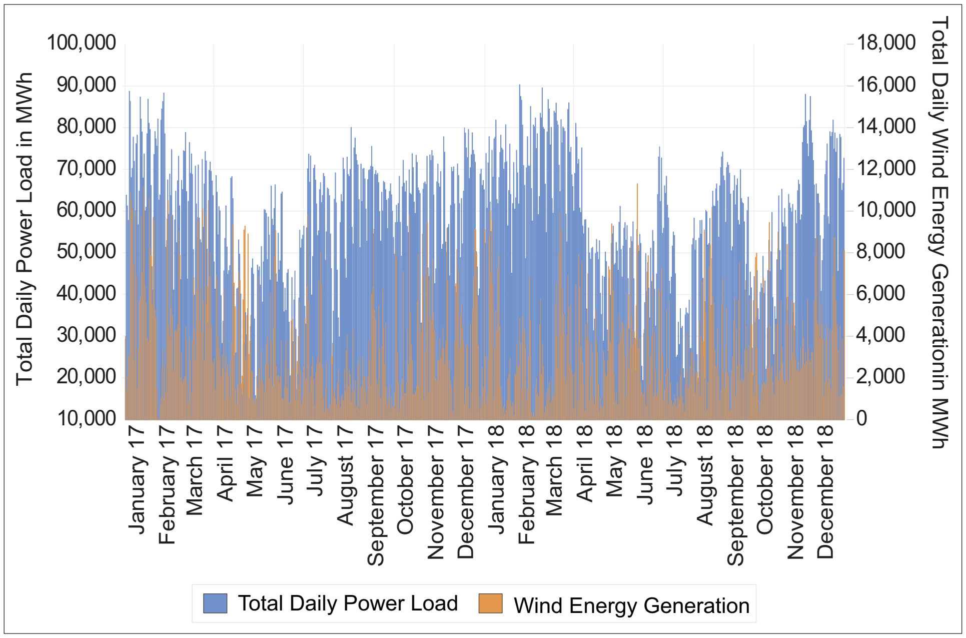
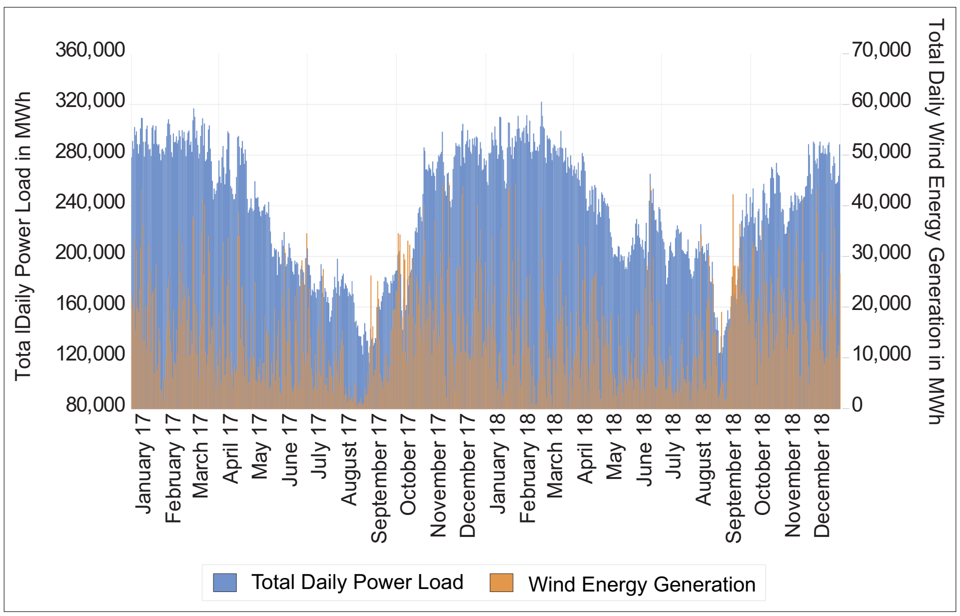


Figure 8: Total power load (In MWh) and Wind energy contribution (in MWh) for SE2.



Sweden also the all four bidding regions include SE1, SE2, SE3, and SE4 in relation to the values of coefficients, dummies as well as p-values respectively.

As it is observed from the regression analysis in Table 1, in regard to the whole Swedish day-ahead electricity market the constant values for weekdays (Saturday as well as Sunday) found negative and significant. This finding implies that the average wholesale prices of electricity are significantly lower at weekends. The regression analysis also confirms that every month of the year (except October) are significant, which indicate that seasonal variation has a higher impact on the formation of electricity prices. The regression analysis also focuses on all four bidding areas and found similar results and price patterns as it is noticed in the whole Sweden. The regression results from all four bidding areas indicate that in region SE1, SE2, SE3 and SE4 the constants values, weekdays and all months (except October) illustrates the seasonality with 10% significance level. In the final stage, before analyzing the GARCH methodology, a natural logarithm of data of all variables have performed. This finding and the comparatives statistical analysis can be found from the Table 2 which indicates the values of mean, median, minimum, maximum, standard-deviation, kurtosis and skewness for both phases before as well as after the adjustments of seasonal variation and outliers' effect.

In Table 2, it can be noted that though the mean as well as median represents a little change in regard to their values, however, the values are now more smoother following the removal of the outliers as well as reduction of the seasonal variation. Which might be observed by a smaller kurtosis as well as skewness.

Figure 9: Total power load (IN MWh) and wind energy contribution (in MWh) for SE3

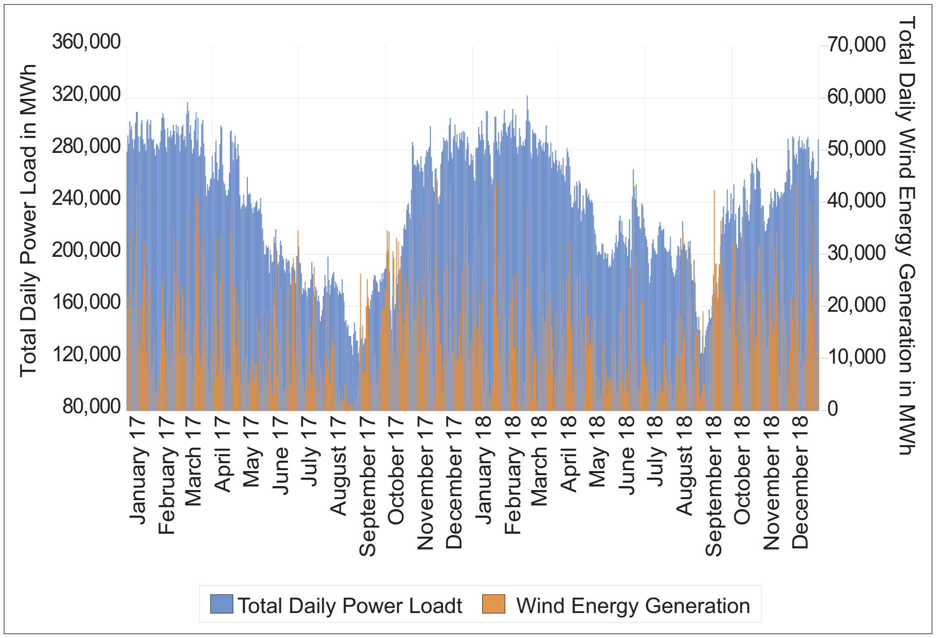
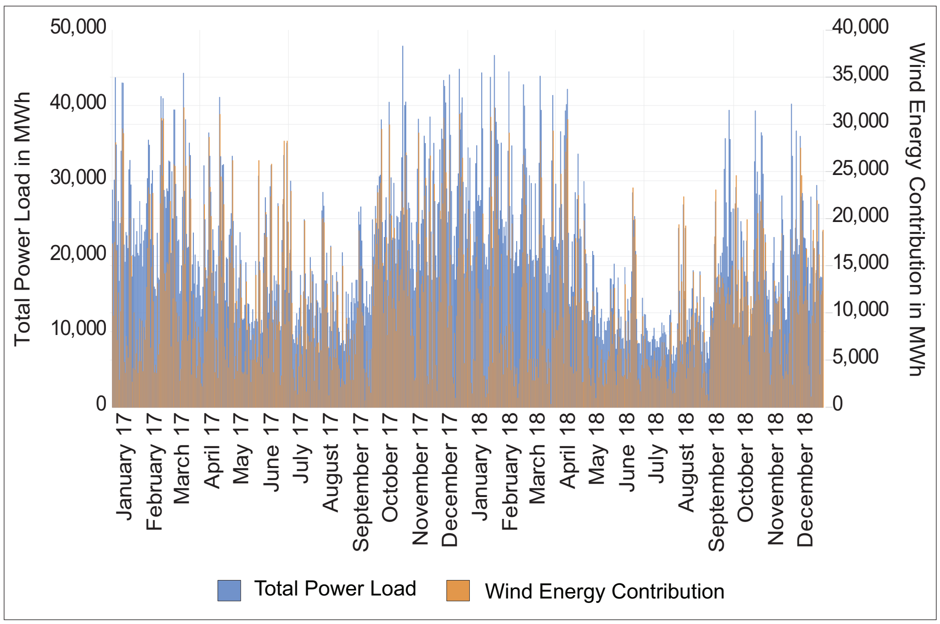


Figure 10: Total power load (in MWh) and wind energy contribution (in SEK) for SE4



5.2. Overall GARCH Model Results with Price

Table 3 represents GARCH model findings estimated from the equations 6 and 7 accompanied by the autoregressive parameters (Φ_1 to Φ_7) for the conditional mean equation also the ω, β and α for the conditional variance equation for all bidding areas in Sweden (from SE1 to SE4). P values in this analysis are represented within parenthesis.

Table 3 clearly indicates a good number of patterns emerge in the price model. For instance, weekly seasonality lag value of Φ_7 is found significant for all bidding areas in Sweden includes SE1, SE2, SE3, SE4 and as a whole for whole Sweden. This finding indicates that weakly seasonal variation effects are observable in the price model. On the other hand, in the conditional variance equation, parameter ω has found significant for the bidding areas SE2, SE3 as well as SE4 and another parameter α has found significant for the bidding areas SE1, SE2 as well as SE4. Importantly, the β value of the conditional variance equation found significant for SE2, SE3 as well as SE4. To clarify, in the variance equations, β represents the past shock's effect, whereas the value of α represents the effects of the current shocks. Analysis of the findings from the above discussion clearly implies that the explanatory variables have very lower effects in regard to the price uncertainty or volatility relations.

5.3. GARCH Results (Price, Log-Wind and Log-Load)

Table 4 in this study represents the GARCH method's results derived from the equations 8 and 9 accompanied by autoregressive

Figure 11: Volatility clustering for electricity prices in Sweden

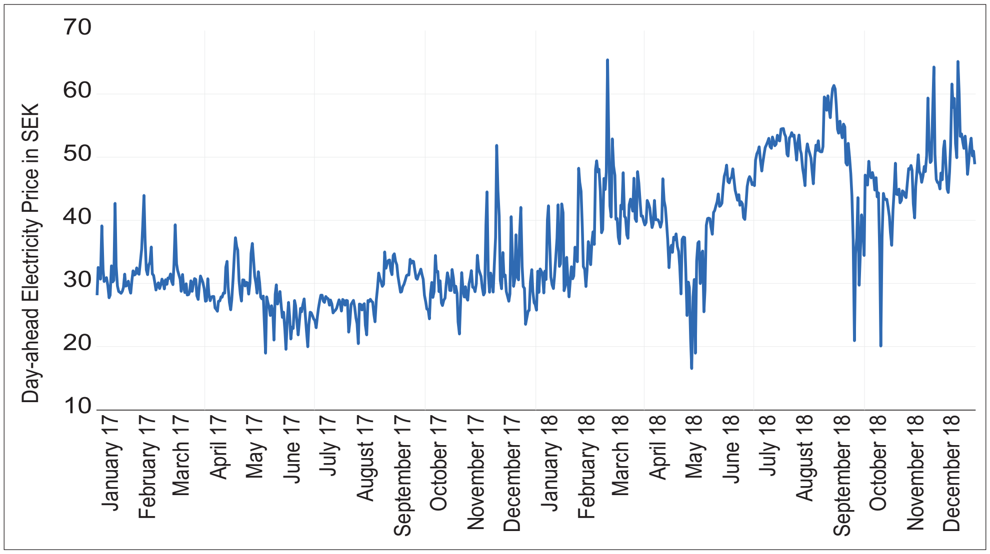
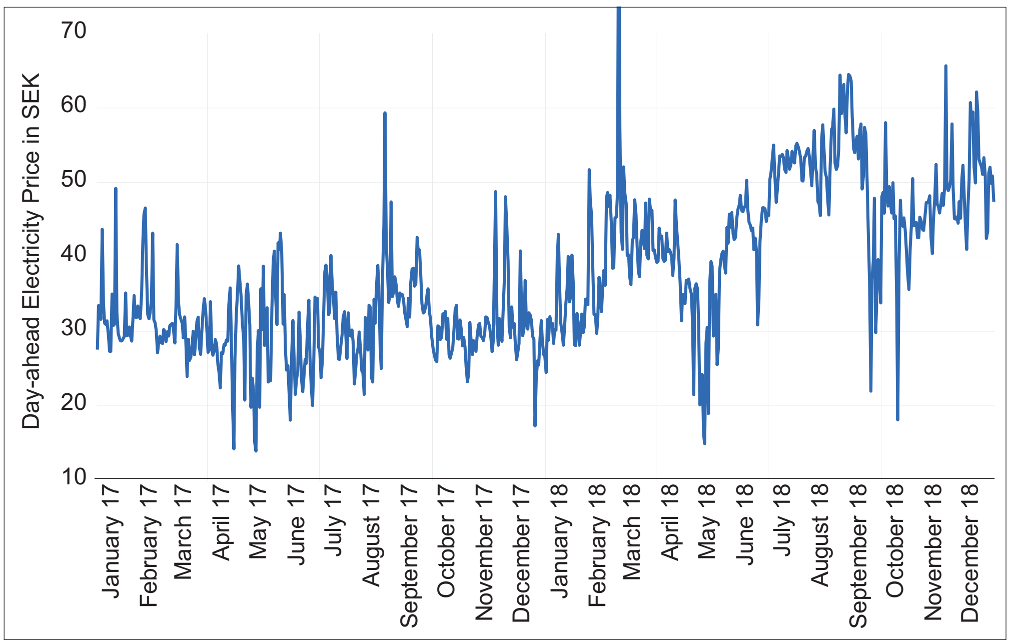


Figure 12: Volatility clustering for electricity prices for SE1



parameters (from Φ_1 to Φ_7), log (wind) represents by w in the equation 8 as well as log (load) represents by l in the similar equation. On the other hand, the values of variance equations include ω, α, β, log(wind) as well as log (load) for all bidding regions of Sweden presented in Table 4. Similar to the previous analysis, the *P* values in the price model represents within the parenthesis.

As it is observed from the Table 4, the mean equation values for SE indicates that the values for φ_i *are* significant. More specifically, the significance term for φ_i represents the Weakley patterns in the model. However, the significance level of log(wind) represents the total amount of wind energy generation influence in the mean equations. On the other hand, in the conditional variance equation for SE, no variables are found to be significant in regard to the 10% level of significance.

Moreover, in the bidding region SE1, the constant as well as parameter φ_i is found significant at the 10% level. Notably, though the level of significant value for φ putting little emphasis on the price model, however, 7th log term of φ_i indicates the weekly seasonal variations in the price model. On other note, in the variance equation, the values for ω, β Log (wind) as well as log (load) are found a significant level of 10% for SE1. The β value for SE1 is 0.9884 represents the consistent impacts of the previous shocks; however, α's indicates insignificant in this border analysis. The sum of these two values $\beta + \alpha = 0.9884+0.0088 = 0.9972 < 1$, which clearly implies that conditional variance in this regard is mean-reverting. More specifically, the analysis reveals that the shocks are temporary and is not permanent. Also, the analysis indicates the positive values for all of the variables.

Figure 13: Volatility clustering for electricity prices for SE2

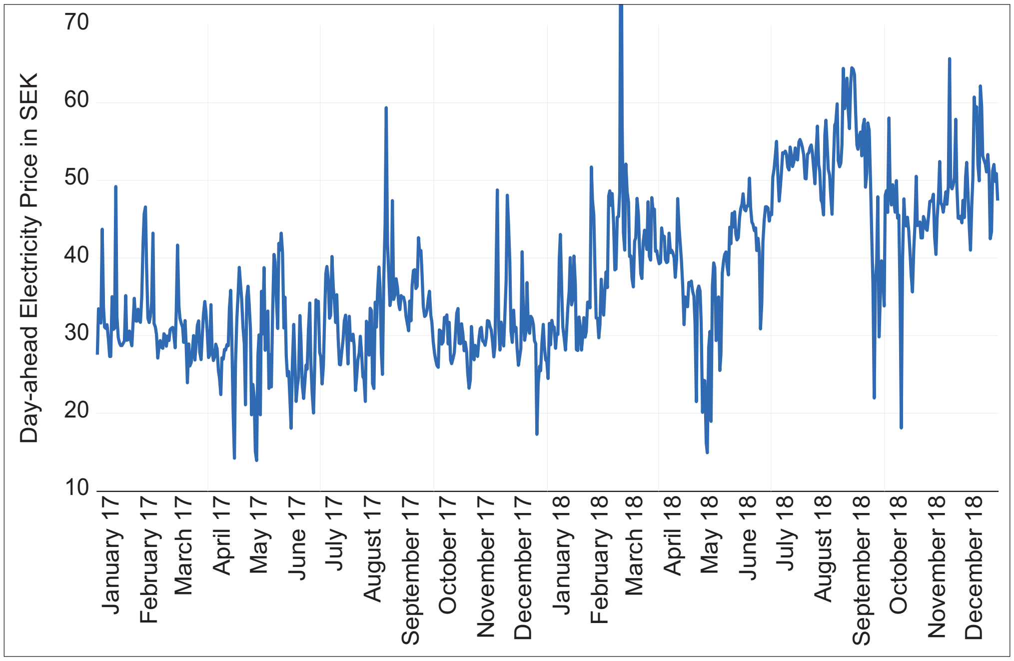
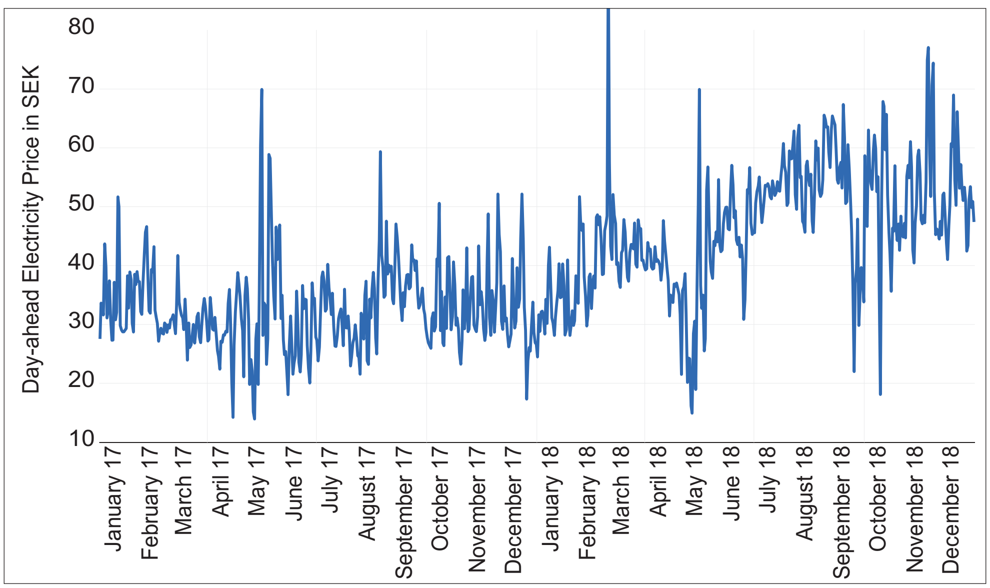


Figure 14: Volatility clustering for electricity prices for SE3



Alike to the bidding region SE1, the constant as well as the parameter in the bidding region SE2 φ_i is found statistically significant at 10% level. In addition to this, in the variance equation, the values of ω, β, α, log(wind) as well as log (load) all are found statistically significant at 10% level. The value of β and α are 0.91569 and 0.13566 and their sum is $\beta+\alpha=0.91569+0.13566=1.05135>1$, which implies that the value of conditional variance, in this case, is not mean-reverting. More specifically, it can be said that the shocks impacts are permanent in this case. In this model, $\alpha, \log(load)\, as\, well\, as$ wind/load are found negative, whereas other variables found positive.

In the bidding region SE3, the constants as well as parameter for the conditional mean equations found statistically significant in 10%. As mentioned before, the parameter here represents weekly seasonal variation. The value of β and α are 1.44340 and 0.00013 and their sum is $\beta+\alpha=1.44340+0.00013=1.44353>1$, which implies that the value of conditional variance, in this case, is not mean-reverting. More specifically, it can be said the shocks impacts are permanent in this case. On the other hand, the values for ω, β, log(wind) as well as log (load) are found statistically significant at 10% level. Though log (wind) in this equation found negative, however, all others variable in this equation are found positive.

Similar to the other four bidding regions, the constant as well as parameter in bidding region 4 also found statistically significant at 10% level. The sum of $\beta+\alpha=9.6876$, which implies conditional mean-variance equation is not mean-reverting. More specifically,

Figure 15: Volatility clustering for electricity prices for SE4

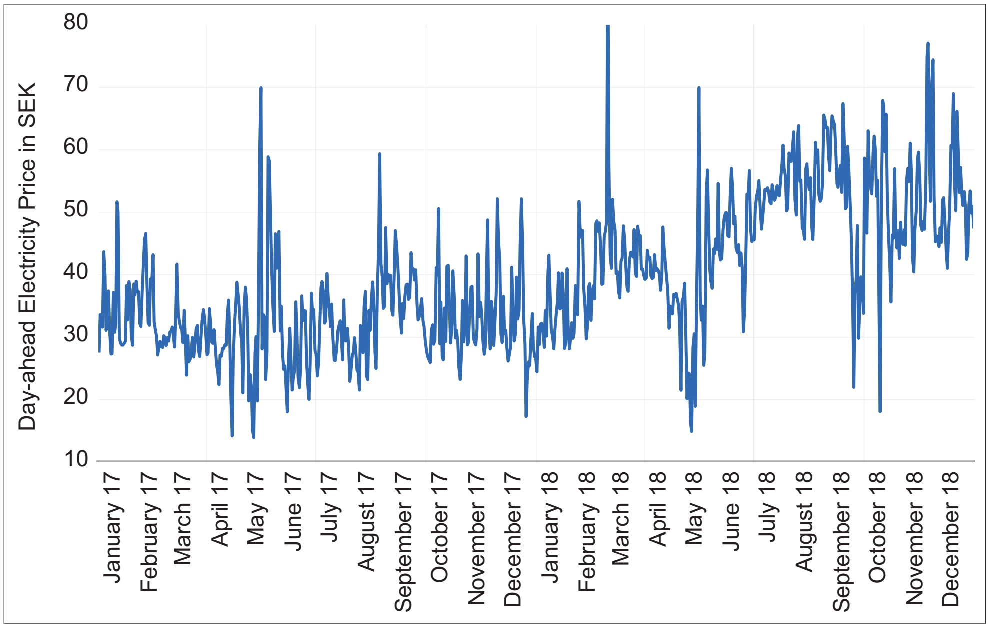
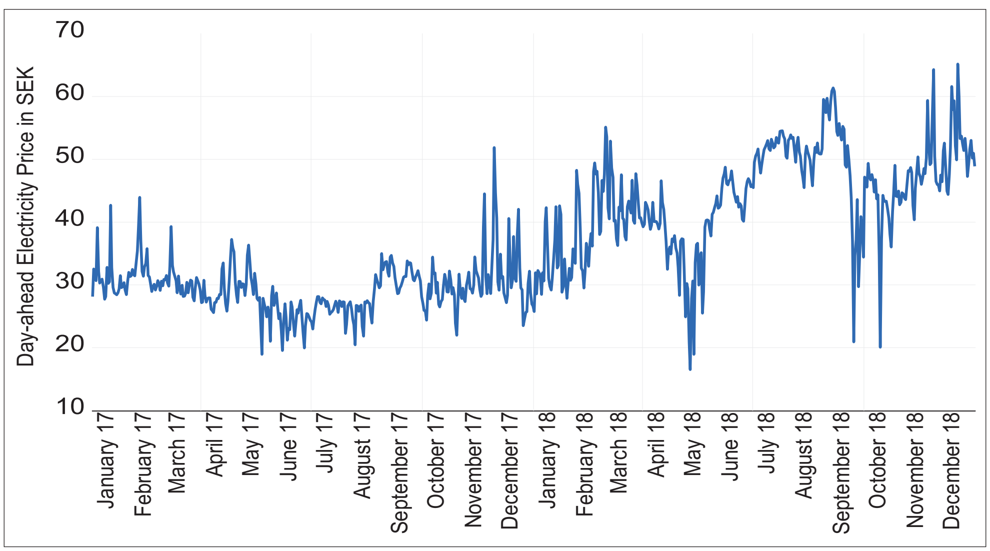


Figure 16: Day-ahead electricity prices across Sweden (adjusted for outliers)



this implies that the effect of the shocks is permanent. β, ω as well as log (load) in this equation found statistically significant at 10% level. Though log (wind in this bidding region found negative and in-significant; however, other variables are found positive. After carefully evaluation of Table 4, there some notable, and emerging patterns noticed. Firstly, conditional mean equations among all bidding areas show weekly variations. Secondly, conditional variance shocks show that past shocks have significant impacts on the daily day-ahead electricity prices. Lastly, explanatory power rises among all bidding regions in the first run; however, the dynamic is very low.

5.4. GARCH Modelling Results (Price, Log-Wind, Log-Load and Wind Generation)

Finally, Table 5 represents the results of the GARCH model formulated from the equation 10 as well as equation 12. Autoregressive parameters (from Φ_1 to Φ_7), Log (wind) Finally, represents by the symbol ω and log(load) represented by l also the wind penetration is representing their values at the conditional mean equation across Sweden as well as all four bidding regions including SE1, SE2, SE3, SE4. Similarly, variables of the conditional variance equation also representing Sweden as well as all four bidding regions in Sweden.

In the conditional mean equation of Table 5, Sweden representing by SE and ϕ_i, and log(wind) as well as wind/load in the mean equation are found statistically significant. This shows weekly patterns also implies that conditional mean equations significantly vary in the variation of wind energy generation. More specifically, higher wind energy generation leads to the lower wholesale electricity prices and vice versa. In regard to the variance equations, β, α *as well as* ω are found statistically significant. As discussed earlier, α (value =0.11780) represents the current

Figure 17: Day-ahead electricity prices for SE1 (adjusted for outliers)

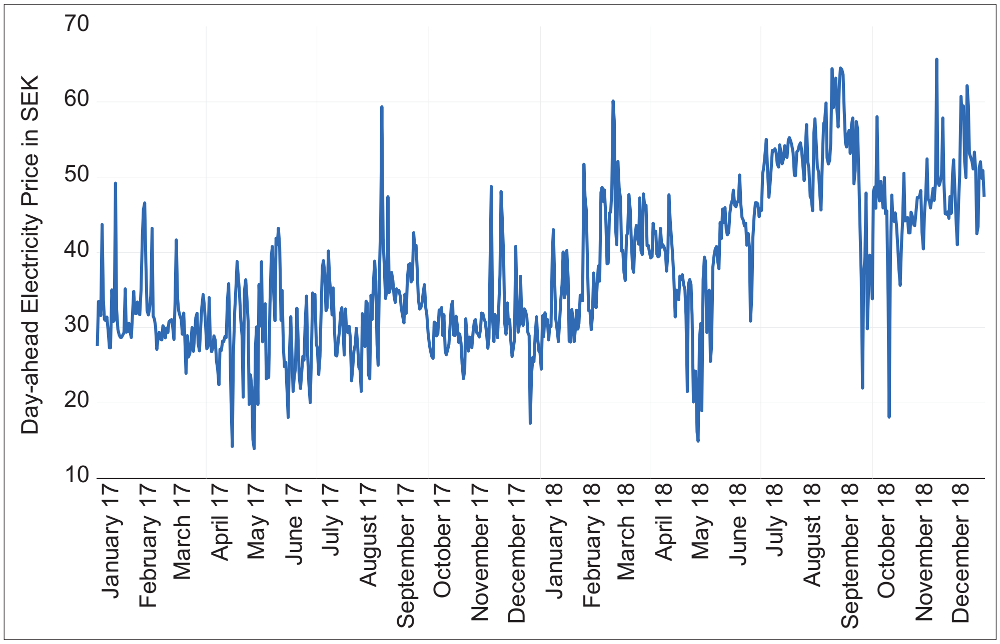
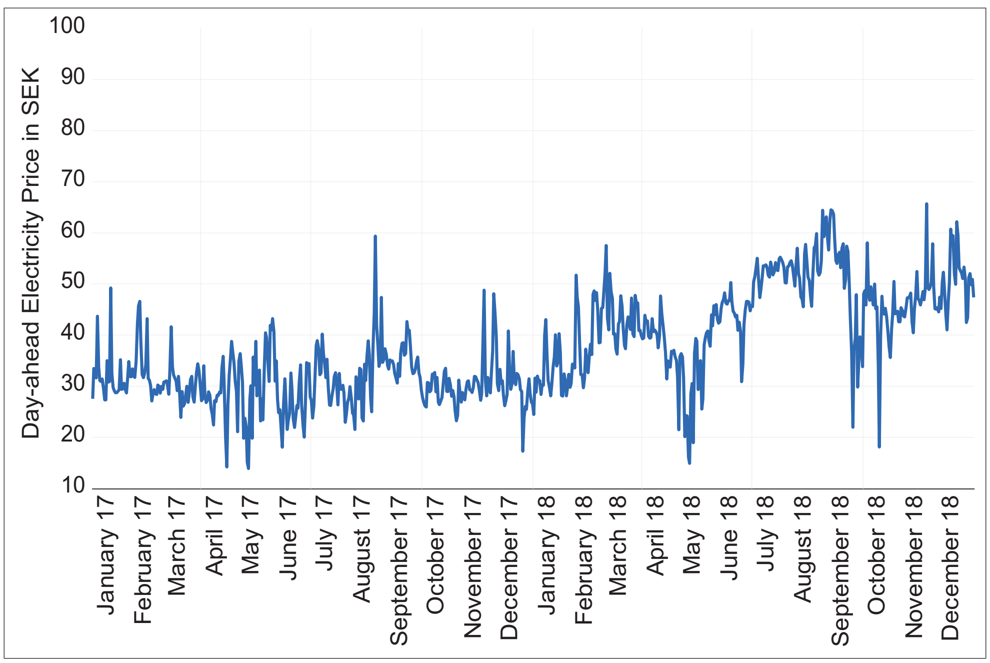


Figure 18: Day-ahead electricity prices for SE2 (adjusted for outliers)



shocks and $\beta\left(Value = 1.34675\right)$ represents the previous shocks and their sum $\alpha + \beta = 1.46455 > 1$ implies that the electricity market is non-mean-reverting. More specifically, this indicates that past shock's effects are permanent.

In the bidding region SE1, parameter and constant representing by ϕ_i, are found statistically significant at the 10% level. Similar results can be found from the variance equation where β, α, ω, log (wind) as well as wind penetration are found statistically significant at 10%. In line with permanent and temporary shocks, the sum of $\alpha + \beta = 0.6854 < 1$, revels that conditional variance equation for region SE1 is mean-reverting. More specifically, shocks effects in this region are temporary. All of the variables (expect α and log-wind) are found positive in this bidding region. In the bidding region SE2, constant and parameters for the conditional mean equation are found statistically significant at 10% level. Similarly, the variance equation for the bidding region SE2 shows that the value of β, α, ω, log (load) as well as wind/load statistically significant at the 10% level. $\alpha + \beta = 1.21197 > 1$ meaning conditional variance, in this case, is not-mean-reverting and shock's effects are permanent. All the variables except α, wind/load and log(load) are found positive in the bidding region SE2.

Along the lines, previous reasoning, the constant as well as parameters for the bidding regions SE3 as well as SE4 found

Figure 19: Day-ahead electricity prices for SE3 (adjusted for outliers)

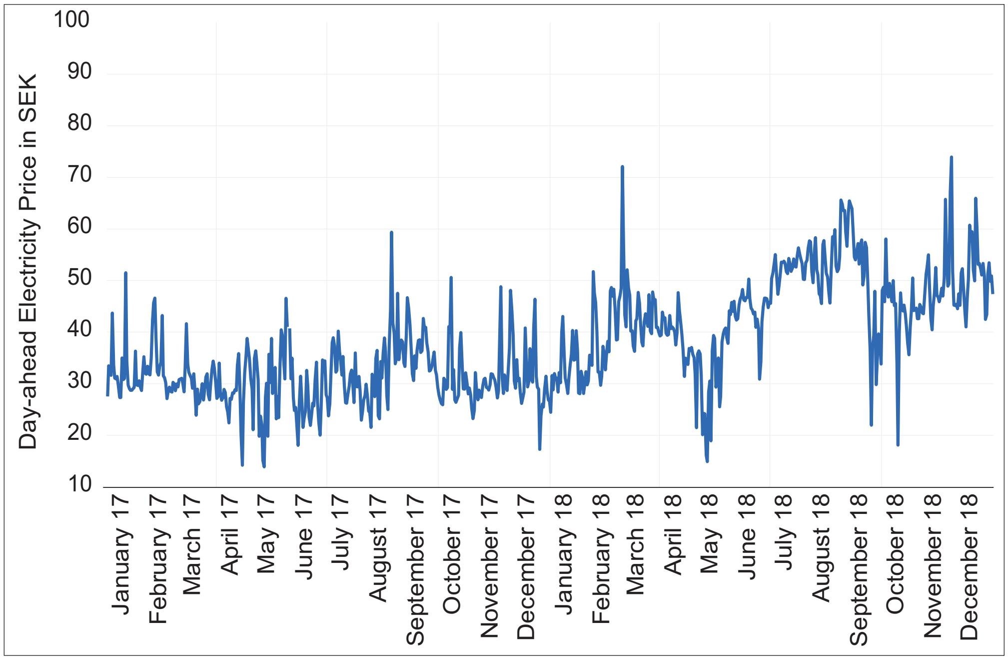
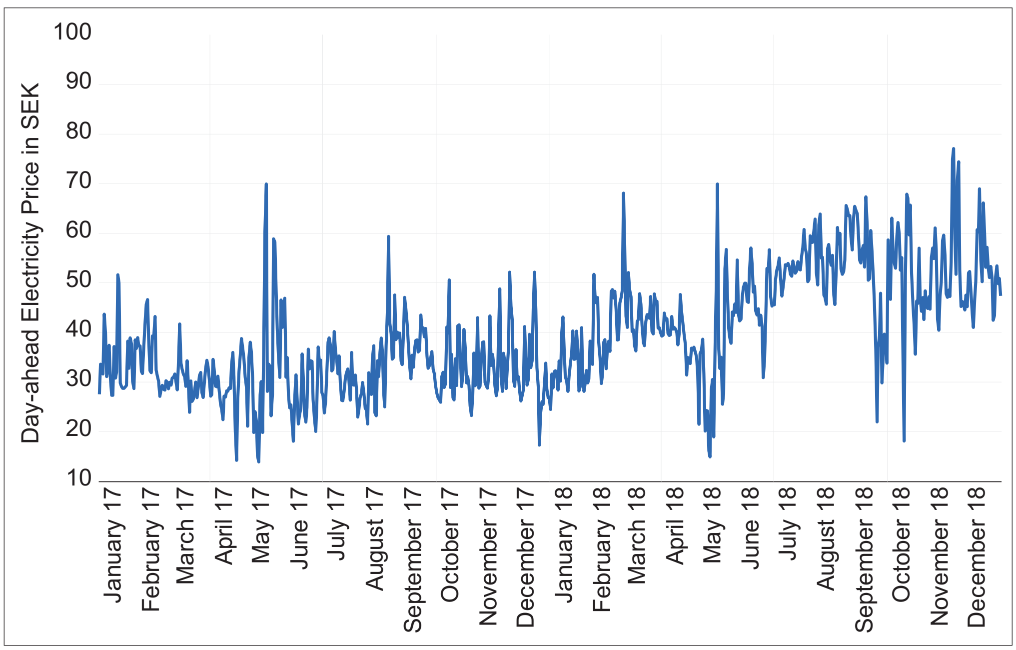


Figure 20: Day-ahead electricity prices for SE4 (adjusted for outliers)



statistically significant at the 10% level in Table 6. Similar to the previous analysis, the parameters for both regions indicate weekly variations. For SE3 the sum of $\alpha + \beta = 10.7655 > 1$ which implies conditional variance for bidding region 3 and also the shock's effects are permanent. On the other hand, the sum of $\alpha + \beta = 1.3452 > 1$ shows that conditional variance for the bidding region SE4 is not-mean-reverting and the shock's effects are permanent. For the conditional variance equation in the bidding region SE3, ω, log-wind, log-load as well as wind/load found statistically significant at the 10% level. On the other hand, in regard to the conditional variance equation for the bidding region SE4, β, ω, log(wind) as well as wind/load (wind generation) are found statistically significant at the 10% level. Log (load) as well as wind/load (wind generation) found negative for the variance equation in the bidding region SE3 whereas all other variables are found positive. On the other hand, except log(wind) other variables seems positive for the bidding region SE4.

From the above reasoning, a number of emerging patterns are noticeable among all four bidding regions and as a whole in Sweden. Firstly, the weekly seasonal pattern from the conditional mean equation is noticeable to all bidding regions and also in

Table 1: Coefficients as well as p values to adjustment seasonal variation in all bidding areas includes SE, SE1, SE2, SE3, SE4

Parameter	SE		SE1		SE2		SE3		SE4	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
C	1.98211	(0.0000)	31.392	(0.0000)	33.981	(0.0000)	30.911	(0.0000)	32.701	(0.0000)
Tuesday	−1.33987	(0.6732)	1.11	(0.8060)	1.11	(0.8060)	0.63	(0.9867)	2.98	(0.7177)
Wednesday	−1.31642	(0.7144)	-1.77	(0.9728)	−1.13	(0.9718)	−3.98	(0.7880)	−4.48	(0.6789)
Thursday	−0.78065	(0.9887)	−0.19	(0.9966)	0.28	(0.9657)	2.98	(0.6986)	−11.81	(0.7123)
Friday	−7.98806	(0.9172)	−13.87	(0.2117)	−13.87	(0.2115)	−13.77	(0.2335)	−47.81	(0.2189)
Saturday	−31.3220	(0.0002)	−32.71	(0.0004)	−32.71	(0.0004)	−41.97	(0.0001)	−56.33	(0.0001)
Sunday	−38.7350	(0.0000)	−39.45	(0.0002)	−38.79	(0.0001)	−44.88	(0.0000)	−56.30	(0.0000)
February	−41.5480	(0.0001)	−53.21	(0.0001)	−53.21	(0.0002)	−53.56	(0.0031)	−53.81	(0.0002)
March	−57.8990	(0.0001)	−59.11	(0.0000)	−59.13	(0.0000)	−65.28	(0.0000)	−65.80	(0.0000)
April	−58.9857	(0.0001)	−63.77	(0.0000)	53.88	(0.0000)	−68.87	(0.0001)	−73.11	(0.0000)
May	−61.5597	(0.0000)	−58.97	(0.0001)	−57.66	(0.0001)	−73.11	(0.0000)	−78.61	(0.0001)
June	−88.9754	(0.0001)	−51.77	(0.0000)	−51.72	(0.0016)	−61.22	(0.0001)	−46.91	(0.0006)
July	−117.991	(0.0000)	−91.88	(0.0000)	−93.13	(0.0000)	−101.9	(0.0000)	− 115.88	(0.0000)
August	−94.569	(0.0000)	−73.98	(0.0000)	−73.98	(0.0000)	−58.99	(0.0000)	−74.77	(0.0000)
September	−79.8765	(0.0000)	−31.78	(0.0000)	−31.78	(0.0000)	−53.33	(0.0002)	−50.33	(0.0001)
October	−133.720	(0.1316)	5.68	(0.5859)	5.68	(0.5863)	−0.98	(0.8976)	0.11	(0.9776)
November	235.450	(0.0201)	33.21	(0.0071)	33.21	(0.0071)	32.18	(0.0345)	28.66	(0.0532)
December	−388.956	(0.0004)	−26.99	(0.2113)	−27.11	(0.0288)	−38.44	(0.0088)	−39.66	(0.0079)

Source: Own calculation based on data collection from Nord Pool

Table 2: Descriptive analysis for all bidding areas (SE1 to SE4) for before as well as after adjustment of seasonal variation

Series	Mean	Median	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis
SE	298.311	39.977	211.754	357.890	78.600	0.398	0.711
SE (Seasonality Adjusted Price)	311.954	167.621	209.411	302.900	49.956	0.397	0.689
L_g SE Price	4.886	4.112	4.876	4.879	0.148	−0.056	−0.358
SE1	289.54	241.780	388.900	38.66	86.11	0.411	0.588
SE1 (Seasonality Adjusted Price)	291.35	241.881	321.800	111.322	41.466	0.408	−0.031
L_g SE1Price	5.311	5.318	5.778	5.058	0.193	−0.051	0.013
SE2	255.90	288.311	467.879	44.97	77.689	0.411	0.581
SE2 (Seasonality Adjusted Price)	258.87	254.455	366.980	188.456	41.667	0.411	−0.032
L_g SE2 Price	5.892	5.370	5.992	5.226	0,165	−0.993	0.011
SE3	299.2	288.358	443.792	39,33	78,11	0.411	0.674
SE3 (Seasonality Adjusted Price)	277.66	277.793	298.662	133.662	52.890	0.271	−0.345
L_g SE3Price	6.890	6.890	5.66	5.680	0.234	−0.234	−0.007
SE4	311.67	233.890	444.890	16.24	66.560	0.061	−0.156
SE4 (Seasonality Adjusted Price)	248.7	277.611	322.970	111.355	33.560	0.076	−0.345
L_g SE4 Price	6.708	4.89	6.981	6.981	0.167	−0.56	0.174

Source: Own calculation based on data collection from Nord Pool

Table 3: GARCH model's results with prices

Mean Equation	SE		SE1		SE2		SE3		SE4	
Constant	0.05850	(0.9760)	0.5650	(0.0003)	4.11676	(0.0001)	0.23489	(0.0000)	0.6874	(0.0001)
Φ_1	0.06357	(0.6777)	0.6112	(0.0000)	−0.11327	(0.0000)	0.03452	(0.0000)	−0.00467	(0.8790)
Φ_2	−0.08568	(0.1342)	−0.581	(0.0000)	−0.17863	(0.0001)	−0.02346	(0.0005)	−0.00322	(0.8945)
Φ_3	0.05342	(0.3589)	0.2870	(0.0000)	−0.12690	(0.0000)	−0.00498	(0.1143)	−0.04346	(0.1236)
Φ_4	−0.03139	(0.5146)	−0.086	(0.0213)	−0.11456	(0.0000)	−0.03478	(0.0000)	0.03156	(0.5432)
Φ_5	0.00436	(0.8760)	−0.1348	(0.0000)	−0.16783	(0.0000)	−0.05341	(0.0000)	−0.04335	(0.2178)
Φ_6	0.03710	(0.6894)	0.4329	(0.0000)	−0.14356	(0.0000)	0.02438	(0.0000)	0.01856	(0.5830)
Φ_7	0.76503	(0.0004)	0.4350	(0.0000)	0.76205	(0.0000)	0.84120	(0.0000)	0.85634	(0.0000)
Variance Equation										
ω	−0.01769	(0.8350)	0.0003	(0.3749)	.28506D-0	(0.0000)	.167321D-05	(0.0000)	0.00021	(0.0578)
α	0.00048	(0.9957)	0.4973	(0.0001)	−0.00231	(0.0000)	.23599D-04	(0.3187)	0.2580	(0.0000)
β	1.48940	(0.8590)	0.3833	(0.1850)	1.88690	(0.0000)	18.8959	(0.0000)	1.78400	(0.0034)
Adj,R2 Adj, Adj, R2	0.43210		0.3890		0.23480		0.27580		0.29311	
Log Likelihood	−411.336		833.911		2033.88		1281.266		1884. 31190	

Source: Own calculation based on data collection from Nord Pool

Sweden. Secondly, the conditional variance equation indicates that the previous shocks have higher impacts on the day-ahead wholesale electricity prices. Lastly, the influences of the explanatory variables rise slightly among all bidding regions, also in Sweden.

Table 4: GARCH model's results with prices log-wind and log-load

Mean Equation	SE		SE1		SE2		SE3		SE4	
Constant	−3.44390	(0.5988)	3.9567	(0.0000)	0.1139	(0.31108)	0,39860	(0.0530)	0.29970	(0.0002)
Φ_1	0.17320	(0.6441)	0.2180	(0.1720)	−0.06940	(0.04110)	−0.02541	(0.5883)	−0.00039	(0.6880)
Φ_2	−0.02330	(0.2441)	−0.0332	(0.7940)	−0.03857	(0.03110)	−0.02448	(0.7443)	−0.00813	(0.0030)
Φ_3	−0.00357	(0.8143)	0.1860	(0.2230)	0.04530	(0.03211)	−0.03956	(0.3322)	−0.03233	(0.0033)
Φ_4	0.03408	(0.0791)	0.0410	(0.8911)	−0.03788	(0.03188)	0.084	(0.0411)	0.04988	(0.0000)
Φ_5	−0.04189	(0.2859)	−0.3457	(0.0004)	−0.02120	(0.03156)	−0.05490	(0.0711)	−0.03180	(0.0041)
Φ_6	0.01339	(0.3144)	0.0311	(0.6133)	0.01892	(0.02892)	0.00588	(0.7892)	0.04789	(0.0002)
Φ_7	0.07188	(0.0000)	0.2881	(0.0311)	0.93081	(0.03377)	0.93299	(0.0000)	−0.03567	(0.0048)
Log (Wind)	0.00689	(0.0432)	0.02450	(0.8466)	0.02119	(0.81700)	0.03450	(0.8130)	−0.02344	(0.7840)
Log (Load)	0.51340	(0.8340)	0.23451	(0.6399)	0.11388	(0.71180)	0.31155	(0.7680)	0.11890	(0.8450)
Variance Equation										
ω	−0.00825	(0.9324)	0.0056	(0.0000)	0.0004	(0.00120)	0.0003	(0.00780)	.32166D-04	(0.0000)
α	0.06530	(0.8897)	0.0088	(0.4630)	0.13566	(0.02711)	0.00013	(0.8762)	.89023D-04	(0.2982)
β	0.61340	(0.8992)	0.9884	(0.0000)	0.91569	(0.11833)	1.44340	(0.0068)	8.88760	(0.0000)
Log (Wind)	0.04229	(0.8670)	0.0059	(0.0087)	−0.00430	(0.00311)	−0.00241	(0.4456)	−0.01321	(0.1334)
Log (Load)	0.53459	(0.8112)	0.2866	(0.0000)	−0.01180	(0.00956)	0.00928	(0.6340)	0.95633	(0.0000)
Adj, R2	0.51190		0.4550		0.33452		0.33211		0.34529	
Log Likelihood	−2314.654		588.95434		1219.6588		1566.7840		1350,88	

Source: Own calculation based on data collection from Nord Pool

Table 5: GARCH model's results (prices log-wind log-load also wind-Penetration). Mean Equation

	SE		SE1		SE2		SE3		SE4	
Constant	0.09237	(0.6911)	1.877	(0.0000)	4.11988	(0.0001)	0.41209	(0.0000)	0.1456	(0.3445)
Φ_1	0.03921	(0.5490)	0.1080	(0.0890)	−0.18766	(0.0000)	−0.00798	(0.1970)	−0.01849	(0.1870)
Φ_2	−0.06678	(0.3951)	−0.0188	(0.2856)	−0.03881	(0.1390)	0.00057	(0.8991)	0.00590	(0.07892)
Φ_3	−0.01892	(0.7110)	0.0327	(0.1290)	−0.1856	(0.0000)	−0.03723	(0.0000)	0.05786	(0.0820)
Φ_4	0.05988	(0.0892)	0.05	(0.2797)	−0.07671	(0.0071)	−0.00063	(0.7882)	0.04988	(0.4120)
Φ_5	−0.04856	(0.2380)	−0.1882	(0.0002)	−0.00431	(0.08310)	−0.00750	(0.0792)	−0.01756	(0.08201)
Φ_6	0.04178	(0.2890)	−0.0188	(0.6345)	−0.19853	(0.0000)	0.00511	(0.1992)	0.00782	(0.8982)
Φ_7	0. 93883	(0.0000)	0.0711	(0.0047)	1.00811	(0.0000)	1.01356	(0.0001)	0.02217	(0.0048)
Log (Wind)	0.01879	(0.0412)	−0.0188	(0.7930)	−0.00138	(0.9933)	0.01897	(0.8995)	0.5664	(0.6371)
Log (Load)	0.00059	(0.9860)	0.27560	(0.6872)	0.14560	(0.8911)	0.24450	(0.8355)	0.03674	(0.7890)
Wind/Load	−0.33560	(0.0071)	0.6371	(0.7866)	0.22378	(0.8560)	0.17564	(0.8359)	−0.2344	(0.7331)
Variance Equation										
ω	−0.00022	(0.0488D−04)	0.0049	(0.0000)	0.0034	(0.0001)	.84548D−05	(0.0002)	0.00066	(0.0066)
α	0.11780	(0.07167)	−0.0468	(0.0000)	−0.0004	(0.0000)	.71167D-04	(0.2678)	0.011	(0.1897)
β	1.34675	(0.01239)	0.7322	(0.0000)	1.21237	(0.0000)	10.0655	(0.0000)	1.3342	(0.0366)
Log (Wind)	0.02966	(0.8960)	−0.0067	(0.5459)	−0.01678	(0.0000)	0.0077	(0.0000)	−0.04332	(0.0911)
Log (Load)	0.52766	(0.8972)	0.3447	(0.0000)	−0.03988	(0.0000)	− 0.3356	(0.0000)	0.03782	(0.3992)
Wind/Load	0. 02134	(0.9332)	0.3566	(0.0098)	−0.14688	(0.0000)	−0.14487	(0.0000)	0.88782	(0.0000)
Adj, R2	0.58893		0.488		0.32344		0.38910		0.31890	
Log Likelihood	1427.672		611.560		911 22890		1423.5667		1324, 450	

Source: Own calculation based on data collection from Nord Pool

Table 6: Average daily electricity prices, price volatility also Wind energy generation from SE1 TO SE4

Region	Daily average electricity price (SEK)	Daily average electricity price volatility (SEK)	Daily average wind energy penetration (Wind/Load)
SE	258.89	33.30	0.1132
SE1	263.11	31.31	0.0561
SE2	232.42	39.68	0.1874
SE3	261.23	31.03	0.0739
SE4	367.48	49.76	0.2875

Source: Own calculation based on data collection from Nord Pool

6. SUMMARIZING RESULTS

This study led to some important findings after summarizing the descriptive statistics for the data set those consequently provides a number of patterns emerge. Firstly, in regard to the mean equation, P values are found high across all the regions to reject the null hypothesis influence. One of the valid results derived from the study is that the mean equations are constant as well as seasonal variations parameter are found significant in Sweden and across all bidding regions in Sweden. This indicates that no equilibrium prices in the day-ahead markets due to the highly uncertain wind energy penetration derived by seasonality variation.

More specifically, the uncertainty and volatility pattern of the electricity price can be noticed from the variance equations. On the whole in Sweden and in the bidding regions SE1, SE2 and SE3 all of the variables in this study have added values to the explanatory power and found significant. In regard to the conditional variance, overall in Sweden and the biding areas SE2, SE3 as well as SE4 it is not-mean-reverting, indicate that shock's effects are permanent. This could be explained by the erratic behaviors to the mean equations. These summarizations of the statistical analysis increase the necessity to compare the studies outcome with similar investigations which is the discussion topics in the next chapter.

7. DISCUSSION

In comparison the study findings with the existing studies as a whole, a number of patterns emerge. Firstly, adding the electricity load as well as wind energy generation or wind penetration in the equation the explanatory power increases in the equation. This finding is aligned and similar with the findings of Polinori (2019) who agree that increasing wind energy generation decreases wholesale electricity price, however, rises the price volatility of electricity due to the wind power's intermittent nature. Similarly, adding wind/load (wind generation) implies that higher wind energy generation implies higher-order merit order effect, that denotes rising wind penetration will lead to the disincentive in regard to the expensive offers from traditional power plants.

This finding implies that more wind energy will push traditional power plants from the merit order curve and replace them via the higher merit order effect. These findings are similar to the findings of Pereira and Rodrigues (2015) who found higher merit order effect of wind energy. The possible reason could be, lower marginal cost of renewables which consequently increase merit order effect and which subsequently, reduce day-ahead average wholesale electricity prices.

7.1. Long-Run Effect of Wind Energy on Electricity Price

In regard to the comparison of the mean equation of this study with the existing research, few similar and distinctive patterns are followed. Firstly, negative sing in the log-wind found in the conditional mean equations meaning that increasing the wind energy generation leads to decreases the day-ahead electricity prices and inverse happens if little wind is in the total power load. Align with the previous studies; this study reveals that log-wind (mean equations) is positive across the Sweden as well as bidding regions SE1, SE2 also in SE3 in Table 6, however, an exception is noticed in the bidding region SE4 where wind load found negative. On the other hand, this sing found negative in the bidding regions SE1 as well SE2 in the Table 5 but positive for across the Sweden and bidding regions SE3 as well as SE4. The reasons for this in Table 4 can be explained in the way that in the region SE4 wind energy contributes vastly for the total power load and the wind contribution highest, which may lead to this result.

Hence, from the preceding analysis, it could be said significant wind penetration required to have its impact on lowering the electricity prices. The distinctive nature of Tables 4 and 5 can be explained in the way that adding wind penetration dummy in the mean equation indicates that significantly higher wind penetration led to reduce of day-ahead electricity prices for the bidding regions SE1 and compare to the other bidding regions. In all the previous studies, the wind (load) found negative and significant meaning increasing wind energy generation decreases the day-ahead electricity prices; however, mixed results found in this study.

7.2. Price Volatility in the Swedish Electricity Market

In regard to the comparison of the variance equations with existing studies, there is a number of patterns emerged from this study. Firstly, this investigation is closely matched with the study findings of whom themselves explain that variances in the conditional variance equations changes over time due to the seasonal variations, which consequently increase the uncertainties and price volatilities. The similar pattern can be found in all bidding regions and as a whole in Sweden where variances found varies over the time due to the seasonal patterns. In addition, previous studies found that past shocks have an important role concerning the uncertainties, price variances as well as overall volatilities. In this study, past shocks found higher impact on the Sweden as well as in the bidding regions SE1, SE3 and SE4. These indicates that similar to the other study grater past shocks are noticeable in Sweden.

In the theoretical framework, stronger effects of past shocks (meaning permanent impacts) could be illustrated by the theoretical foundation of the merit-order effect. More specifically, in the four bidding areas, non-mean-reverting characteristic of the variance equations could be explained by the merit order effect. To illustrate this firstly, mean-non-reverting nature found in the descriptive analysis indicates that demand is inelastic as well as inflexible whereas supply is also inflexible as a result of the limited capability for forecasting the supply mix and limited capability of changing the power output or supply. Existing research suggests that flexible power load such as hydropower reduces the uncertainties and volatilities, however, because of the nature of the wind power, it is found in the study that wind power is inflexible and inelastic which consequently increase the electricity price volatility.

One more important finding can be derived from comparing the regional findings. In region 4, the influences and power of the explanatory variables are found lower compare to the overall Sweden and the bidding regions SE1, SE2, SE3. To understand this difference, a closer observation required in terms of the wind contribution listed in the Table 6. Table 6 represents day-ahead average wholesale electricity prices (in SEK) daily average electricity price volatilities (in standard deviation) as well as daily wind energy generation (as load) across Sweden (SE) and all bidding areas.

Expect the bidding region SE4 (evidently distinct from all bidding regions), all bidding regions in the Table 6 indicate that in the long run, higher wind energy generation help for reducing electricity prices in the wholesale market, however, increase the price volatility. This finding is similar to the study to the prior studies concentered on the long-term impacts of renewables on electricity price where these investigations found a positive relation concerning wind energy and price volatility. However, increasing the uncertainties or the electricity price volatility of day-ahead electricity prices can be explained by the intermittent nature, seasonal variation and the availability of real-time information of wind energy generation.

8. CONCLUSION AND RECOMMENDATIONS

The purpose of this paper was to examine how increasing wind energy generation effects day-ahead electricity price volatility across the Sweden as well as the four bidding regions includes SE1, SE2, SE3, SE4. Using the time-series data set, this study analyzed day-ahead electricity prices in and wind penetration data from January 2017 to December 2018. The study identifies higher merit order effects and seasonal variation in regard to the wind electricity production in Sweden. From the mean equation, the study concludes that rising wind penetrations lead to reduce the whole-sale electricity prices. On the variance equations, the study found higher effects of the past shocks, which are permanent in the longer time frame. Moreover, wind contribution, seasonality variation and total load are other some important sources of uncertainties found in four bidding regions having greater influences on daily electricity price volatility in Sweden.

However, this paper further confirms that the dynamic of the influences is varied in some of the cases among different regions. In general, the theoretical framework suggests that more flexible renewable sources such as hydropower help to reduce the electricity price volatility. However, from descriptive analysis and from the GARCH model, it is found, wind energy generation and supply in all regions are inelastic as well as highly inflexible. From this finding, the major conclusion of this study can be drawn that electricity price volatility raises to these regions in Sweden because of higher inflexible supply of wind energy generation in the long run. No clear conclusion could be derived for the short run wind energy generation, its flexibility and subsequent relationship with the electricity price volatility. After all these descriptive analyses, it may be said that wind energy production rises long-term electricity price volatility in Sweden; however, short-time price volatility found inconclusive.

8.1. Implication of Policy and Practices

Increasing demand for electricity and higher carbon emission derived from raising energy demand increases the necessity of the renewables power production such as wind energy. However, this study reveals that a number of power markets reformations and changes required to address the wholesale electricity price volatility. Firstly, due to the unreliable and seasonal characteristics of wind energy and higher dependency on the wind energy requires to have a flexible and reliable baseload power system to address the uncertainties. For instance, reserves flexible baseload system like hydropower more might have a higher impact in regard to the reduction of the electricity price volatility resulting from merit-order effects. Policies need to be developed so that a more flexible electricity supply system will be developed which will help to reduce to the price volatility.

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