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Impact of renewable energy on electricity prices - comparative analysis of Denmark and Germany

Bachelor’s thesis
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Tuomas Rintamäki

AALTO UNIVERSITY
SCHOOL OF SCIENCE
PO Box 11000, FI-00076 AALTO
http://www.aalto.fi

ABSTRACT OF THE BACHELOR'S THESIS

Author: Tuomas Rintamäki

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Instructor: PhD Afzal Siddiqui, University College London

Abstract:

In Denmark and Germany, renewable energy makes up over 20 % of electricity production. This thesis focuses on the short and long-term price impacts of Danish wind power, and German wind and solar power. Due to their negligible short-run marginal costs and intermittent output, these renewable energy sources displace conventional electricity production and disrupt the otherwise more predictable supply and demand balance. Although renewable energy is already a major player in the electricity market, extensive quantitative research on their price impacts has been scarce so far. As the European Union energy policies require new investments in renewable electricity production, a clear understanding of the price impacts is needed.

To estimate the impacts of wind and solar power, I model electricity price volatility as a SARMA process along with an exogenous variable for wind or solar power production. The model is appropriate because short-term electricity prices can be adequately forecasted by looking at the past values and by utilizing the information on repetitive weekly demand patterns. Based on the coefficients for wind and solar power, the model provides a clear interpretation for their price impacts. The robustness of the model is confirmed by numerous regressions that pass diagnostic tests.

All the statistically significant results are economically significant. First, both Denmark east and west daily wind power decrease the daily area price levels and volatility. In Denmark, the maximum wind output occurs during the peak hours, thereby cutting the high peak hour prices. Second, Denmark west wind power increases the weekly volatility of Denmark west prices due to the volatile production. For Denmark east, the long-term impact is not statistically significant.

In Germany, daily solar and wind power have a decreasing impact on daily electricity price levels. Compared to wind power, solar power is more stable and it causes the volatility to decrease. Contrary to the result for Denmark, daily German wind power increases the daily volatility. This contradiction is explained by a relatively flat wind output curve that has a substantial price-decreasing effect on first off-peak hour (00-07) prices. In addition, wind power increases the weekly volatility due to the intermittent nature of production.

With a low and volatile wholesale electricity price, the profitability of electricity plants is endangered. Combined with the challenges that intermittent supply from renewables pose for the transmission grid and security of supply, adjustments to production capacity and regulations are required to stabilise the market.

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Contents

1 Introduction

On May 26, 2012, Germany set the new world record for renewable energy by producing nearly half of its electricity demand with solar power [1]. Both European and global adoption is progressing, as investments in renewable energy saw a 17% increase from 2010 to 2011 [2]. At the same time, the efficiency of the renewable technologies is improving, and manufacturers are achieving economies of scale that is driving component prices down. The general political slant towards renewable energy is positive.

The increasing popularity is also driven by the fact that many countries are subsidising investment in renewable energy such as wind and solar power by offering generous fees for the producers. Because of their weather-driven nature, and their out-of-merit dispatch, large-scale installations of wind and solar power are playing an increasingly important role in the supply and demand balance of electricity. Ultimately, that balance determines electricity prices in market-based systems. Therefore, a clear understanding of the price effects of renewable energy in market-based electricity systems such as Nord Pool and EEX is needed. Even now, wind and solar power are displacing traditional combustion plants that form the huge asset base of utility companies.

Several articles have estimated the effects of wind power production on the price levels, and the common conclusion is that wind power production decreases prices. Holttinen et al. [3] use the popular EFI (now a part of a Norwegian research organisation, Sintef) Multi-Area Power Market Simulation model, EMPS, that focuses on optimising weekly hydro power production. Wind power production is modelled as a run-off-river supply that decreases the spot prices due to zero marginal costs. However, the weekly resolution in EMPS loses the information on the intermittent nature of wind power.

In turn, Jonsson et al. [4] use hourly data and a non-parametric regression model to provide more detailed results not only price on levels but also on the distribution of the prices and volatility of the western Denmark area prices. In addition, they have access to day-ahead wind power forecast data that is actually used when the market players try to optimise their profits. Their conclusion is that wind power production has a substantial decreasing effect on prices and volatility. Instead of being a passive component in the market, wind power is seen as a price maker. The estimated prices are a complex function of the hour and wind power production. Therefore, prices do not behave linearly as a function of wind power.

The renewable energy reformation in Germany has required a lot of feasibility studies on the profitability of new energy investments. However, only recently have there been studies on the effects of the new investments on electricity prices. Ketterer [5] models the influence of intermittent wind power production on the level and volatility of the electricity prices in Germany by using a generalized autoregressive conditional heteroskedasticity (GARCH) model with logarithmic prices. GARCH models are a widely employed methodology in volatility modeling in financial markets as they capture well the spikiness and clustering of volatility. Ketterer finds that wind power decreases the price level but increases daily volatility. However, she notes that after the regulatory change in 2010 to force the German transmission operators to publish day-ahead forecasts for their renewable generation, the volatility-increasing effect of wind power has decreased but not enough to turn the effect negative. Therefore, Ketterer's results conflict with Jonsson's when it comes to the effect of wind power on price volatility.

Green and Vasilakos have published several wind power-related studies. First, they [6] study how the British electricity markets would adjust to a growth in wind power generation in the long run. Given the UK targets for the share of wind power production of total generation in 2020, optimal electricity production mix is modeled as a social welfare maximization problem where the production levels of each type of capacity are decision variables. They find that to reach a long-term equilibrium, the mix of generating capacity needs to change to adapt to the volatile wind output. This is achieved with a substantial amount of high-cost capacity running for short periods. The average price is similar with or without wind power but in the former case the effect comes from higher and more volatile peak prices.

Second, they [7] try to predict the short-term price and revenue volatility in the UK given the same wind power targets for 2020. In a competitive market, their conclusion is that hourly prices are greatly affected by wind power speeds: maximum evening peak hour prices can be more than two times larger than minimum. Furthermore, exceptionally high wind power output in the early morning hours can drop the prices to zero. These variations imply that producers are likely to see wide variations in their profitability. The earning potential of thermal generators disappear because they are needed rarely. Being ready-to-run when needed is important as the previous paper suggested.

Conversely, solar power has not inspired so much devoted research on the effects on the price levels and volatility. In an evaluation report of the impacts of the renewable energy subsidies [8], German Federal Network Agency, Bundesnetzagentur, notes that the price spread between high consumption peak hours and low consumption off-peak hours has decreased substantially. In addition, the report graphically shows that the spread has been lowest when the solar power production has been highest, and vice-versa. The obvious drawback of the methodology is that the evidence can be purely coincidental. Along with Bundesnetzagentur, another significant publisher of research is the Fraunhofer Institute for Systems and Innovation Research (ISI). For instance, Sensfuß [9] has developed a complete market model to estimate the effects of renewable electricity on the whole electricity sector.

Originally, this thesis was initiated by a bearish investment report on European utility companies entitled "Renewables to wipe out 50% of profits" by the Swiss bank UBS [11]. The investment report claims that the renewables boom in Germany is cutting the high and profitable peak-hour prices and crashing the prices in low consumption off-peak hours, thereby causing substantial losses for the utility companies. The report highlights the economic importance of the solar and wind power production patterns to the electric utility companies, although the patterns have not been investigated much. Hence, I pay attention to output peaks, and overall shape of the wind and solar power production curves, for example. Similar to the investment report, I expand my thesis by laying out what-if scenarios that explore the outcomes with a larger share of renewables.

The methodology of this paper is largely based on the ideas of Johannes Mauritzen's paper [10]. The main result of the paper is that Danish wind power decreases daily volatility of the Danish area prices whereas weekly volatility increases. Variation of prices is modeled as a seasonal autoregressive moving average model with wind power production as an exogenous regressor. The benefits of this approach are its simplicity and the intuition that the electricity prices on the following day can be forecasted by looking at previous days and using the information on regular consumption patterns. Moreover, the approach gives a straightforward interpretation to the impact of renewable energy on the price volatility. I have extended Mauritzen's analysis to study how wind power affects the price variations by dividing the data set into peak and off-peak hours and running similar regressions on the components.

I focus on the effects of Danish wind power on Danish area price volatility in Nord Pool and the implications of German solar and wind power on Phelix, i.e., German area price volatility. Hence, I am able to explain the contradiction between the results of Ketterer and Jonsson. I put emphasis on exploring how renewable energy causes changes in volatility by looking at the production patterns. I have picked these two countries because they are the most pertinent cases due to early and substantial investment in renewables. Based on Mauritzen's results, my hypothesis for both countries is that renewable generation decreases intraday volatility but increases volatility over larger time windows. The former statement results from renewable generation cutting peak hour prices, and the latter is explained by the intermittent nature of wind and solar energy production.

First, my paper gives a short introduction on Nord Pool and EEX, and the renewable energy policies in the European Union. Second, I start the quantitative analysis by dealing with Danish area price and wind power data, and thereafter by moving to Phelix price data, and German wind and solar power data. Section 4 is again divided to Denmark and Germany. In both subsections I present my model for the effects of renewable generation on daily and weekly volatility, and explore the underlying causes for the impacts. Finally, I provide my conclusions based on the data and models, and lay out what-if scenarios for future market prices in different cases of renewable energy development.

2 Overview of the European energy exchanges and renewables policy

2.1 Nord Pool

At the moment, the Nordic electricity exchange Nord Pool is the most important electricity market in the Nordics with 77% market share. In 2012, the traded volume was 432 TWh, a 37% increase from 2011 [12]. Nord Pool was established in 1993 when the Norwegian parliament decided to deregulate the market for power trading. Since Eastern Denmark joined Nord Pool in 2000, all Nordic power markets have been deregulated. At the moment, Nord Pool is expanding to the Baltics. Nord Pool consists of three markets: the day-ahead physical spot market Elspot, intraday balancing market Elbas, and the financial market. The primary market is Elspot.

Each day, electricity producers and consumers submit their bids for every hour of the following day to the Elspot auction by 12 PM CET. Those bids specify the volume each player is willing to buy or sell at a specific price. Aggregated supply and demand bids of all Nord Pool participants are then used to calculate the system price, i.e., the equilibrium price without considering any internal transmission constraints. Furthermore, the players can have bilateral contracts that are not related to Nord Pool. Naturally, it is important to estimate the supply and demand balance for price forecasting purposes.

In addition to the system level spot price, Nord Pool calculates area prices. At the moment, there are fourteen bidding areas that are divided according to power balance or the geographical areas of different transmission operators. Figure 1 shows the different Nord Pool bidding areas. The area prices are calculated to maximize social welfare by taking into account transmission constraints between different areas. In a deficit area, the supply curve is shifted to right as imports increase supply. At the same time, the demand curve of a surplus area is shifted to right as exports increase. However, when the demand for imported electricity at the system-level price exceeds the area's transmission capacity, the area price is higher than the system price, and vice versa, in an area, where the export demand is higher than the physical limit, the area price is lower than the system price. Consequently, area prices are actually more relevant to different areas than the system price. Figure 2 depicts the area price calculation graphically.

Later, the balancing market, Elbas, is used to secure supply and demand balance in unexpected scenarios such as sudden plant outages. Elbas is a continuous market where highest buy price and lowest sell prices get served first. As also Nord Pool acknowledges, the role of the balancing market strengthens when the share of intermittent renewable electricity production increases.

The system and area prices are used as reference prices for financial contracts such as futures, forwards, options and so-called CfDs, i.e., contracts for differences in system and area prices. Futures and forwards are available both in base and peak load, i.e., for different hours of the day. The market clearing is done by Nasdaq OMX Commodities Europe. The financial market involves no physical delivery of electricity so the contracts are settled in cash. Therefore, the financial contracts can be used for hedging, risk management, or proprietary trading purposes, for instance. As all relatively big players are active in the financial market, the liquidity of the market is consired to be good, excluding holidays.

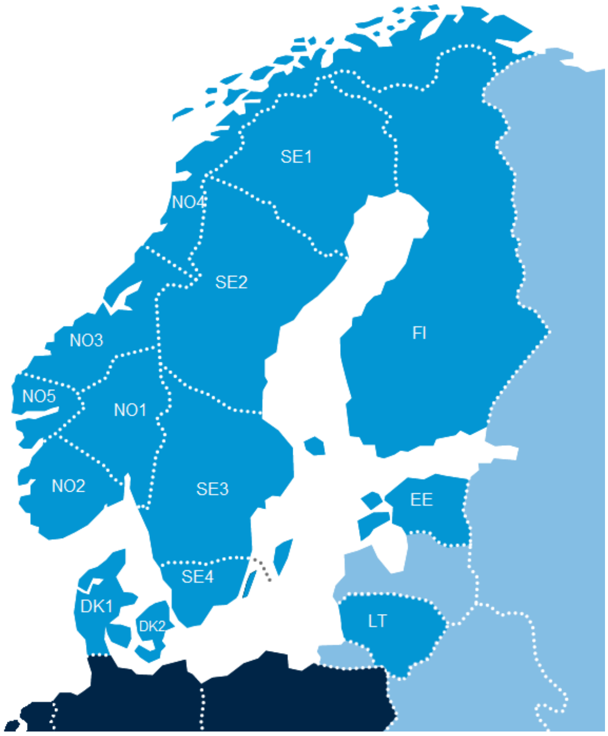


Figure 1: The turquoise-coloured countries with country codes belong to Nord Pool as of January 2013. Source for image: Nord Pool website.

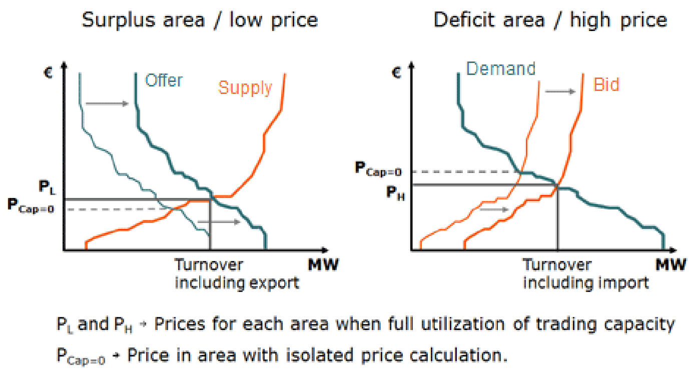


Figure 2: Area price calculation optimizes social welfare compared to two disconnected areas. Also, the prices converge when the area price of a deficit area decreases and the area price of a surplus area increases. Source for image: Nord Pool website.

2.2 European Energy Exchange

At present, the European Energy Exchange (EEX) is the leading energy exchange in three market areas: Germany and Austria, France, and Switzerland. EEX was founded in 2002 when two German energy exchanges merged. After, the volume traded has been growing at fast pace [13].

The political incentive behind EEX has been European market liberalization and the progress towards EU-wide single energy market. Since October 2010 EEX has been publishing European electricity price index (ELIX) that is calculated on the basis of aggregated and uncongested bid and offer curves of all EEX market areas. Therefore, the index corresponds to the market price in a perfectly integrated European market, and is analogious to the system price in Nord Pool.

Similar to Nord Pool, the trading for electricity takes place in day-ahead spot market (EPEX day-ahead), intraday market (EPEX intraday), and financial market (EEX power derivatives) in each of the three areas. The spot markets in Germany/Austria and Switzerland are called Phelix and Swissix, respectively. The financial products for these markets have been further divided to base, peak and off-peak hours. In addition to the three electricity markets, EEX has both spot and derivatives market for NetConnect Germany (NCG) natural gas and EU emission allowances (EUA) as well as Certified Emission Reductions (CER). Moreover, EEX offers trading of Amsterdam-Rotterdam-Antwerp (ARA) and Richards Bay (RB) coal futures that refer to the API2 and API4 indices that are set by the dominant price information provider Argus. The structure of EEX is visible in Figure 3.

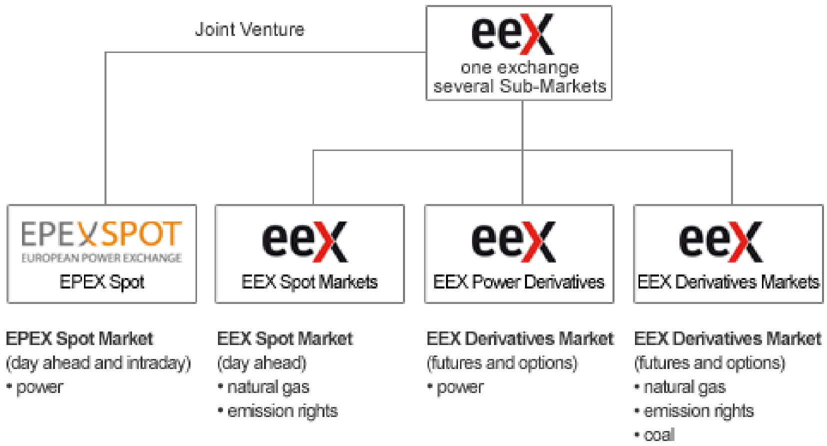


Figure 3: The structure of EEX. EPEX Spot is a joint exchange with the French energy exchange Powernext.

The price calculation in the EEX electricity spot markets is similar to Nord Pool as the price is determined as an equilibrium price [14]. The area prices are calculated so that exports are seen as an increase in demand in a surplus area and as an increase in supply in a deficit area. This is described in Figure 2. This thesis focuses on Germany and Austria area prices, i.e., Phelix prices because I study the effects of German renewable generation. Both physical and financial settlement of EEX has been transferred to European Commodity Clearing (ECC). Thus, ECC is responsible for the physical delivery of the contracts and guaranteeing financial fulfilment.

2.3 Renewable energy and climate targets in Europe

Currently, energy production in Europe is undergoing a significant transition when renewable energy sources are becoming increasingly prominent. Arguably, the most drastic example of this is Germany. After the Fukushima nuclear disaster in March 2011, Germany decided to phase out nuclear energy by 2022 [15]. At the same time, the share of renewable energy needs to increase to 35% to meet the targets set by the government [16].

This trend is followed also in the Nord Pool countries. The Nordic countries that belong to the European Union share the same energy and climate policy as Germany. According to the

Energy Policy of the European Union, each member state needs to cut greenhouse gas emissions at least 20% compared to 1990 level, and renewables should have a 20% share of the total energy consumption in the EU by 2020 [17]. Since the majority of possible hydropower production is already in place and no new nuclear plants are commissioned, the main solution to achieve the targets besides improving efficiency is to promote renewables other such as biomass, wind, and solar power.

The EU member states situated in the Nord Pool area have not stuck with the general level of the EU. Denmark, for instance, has an ambitious aim to supply 35% of its total energy from renewables by 2020 [18], and at the same time, cut greenhouse gas emissions by 34%. Although having already plenty of hydropower and biofuels in the energy system, Sweden has set a target to increase the share of renewables to 50% by 2020 [19]. What is common to all these countries is that the governments have subsidised renewable electricity production generously by giving guaranteed prices, for example. In Germany, electricity producers find the subsidies so attractive that the costs of financing them and the rapidly expanding power grid are skyrocketing. As a result, an environmental surcharge known as Erneuerbare Energien Gesetz (Renewable Energy Law) contribution is increasing the electricity bill for households [20].

As Norway produced approximately 95% of its electricity from hydropower [21] in 2008-2010, there is very little room for renewables in electricity generation anymore. In years with heavy rainfall, Norway tends to have surplus of electricity, which is exported to neighbouring countries. During these years, Norway has had renewable electricity shares of over 100 %. More detailed figures of the renewables share of total energy production are presented in Table 1.

Table 1: The share of renewable electricity production of total electricity consumption. As a whole, the EU should reach 20% share by the end of 2020. The projected figures for 2020 are significantly higher than the current levels. There is no future estimate for Norway, because their share is dependent on rainfalls. Source for data: EUROSTAT and European Environment Agency.

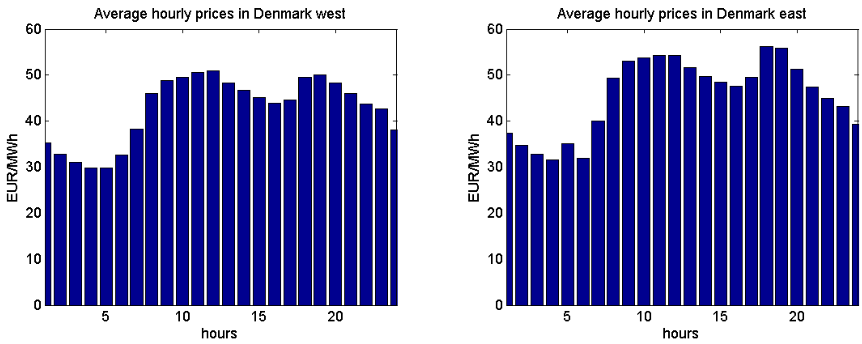
Country	2007 (%)	2008 (%)	2009 (%)	2010 (%)	2011 (%)	2020 (%)
Finland	25.92	30.78	25.77	26.52	27.65	33.0
Denmark	27.04	26.7	27.49	33.11	38.81	51.9
Germany	14.11	14.63	16.2	16.9	20.35	38.6
Norway	106.12	109.42	103.01	89.96	97.92	N/A
Sweden	51.54	54.98	56.44	54.48	58.72	62.9

3 Data

3.1 Nord Pool price data

Nord Pool provided price data for this thesis [22]. The reliability of the data set is high, as the figures are regularly reported and the prices are officially set by Nord Pool. Figures 4(a) and 4(b) show the average intraday profile for the wholesale electricity price in Denmark. Basically, the profile follows consumption patterns. The first peak is observed from 8 to 12 am when people are at work, and the second peak follows from 5 to 8 pm, when people return home. Naturally, prices are higher in daytime than nighttime.

Similarly, there is a weekly pattern that reflects the difference in consumption between working days and weekends. In general, the price level of working days is higher than in weekends. In this study, I do not delete the data for weekends but try to account for seasonality in the models.



(a) Denmark west (b) Denmark east

Figure 4: Average electricity price for Denmark east and west from the beginning of 2007 to the end of 2012. Denmark west prices are a bit lower than Denmark east prices because the high consumption capital area is in the eastern part.

In the long term, the prices are much spikier as Figure 5 shows. The logarithmic scale in the figure expresses percentage changes in prices. Most of the high peaks occur in winter when consumption is highest due to cold weather. On the other hand, most of the sharp falls occur in summer when competition of few consumers between hydro producers can lead to a crash in prices as experienced in summer 2012. In fact, temperature is the most important independent variable in load-forecasting models [23]. However, no consistent yearly pattern is visible in the figure.

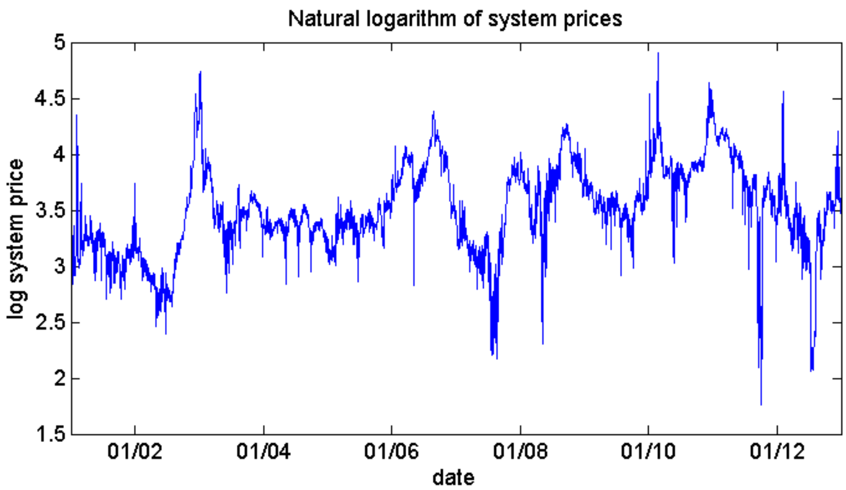


Figure 5: Natural logarithm of Nord Pool system prices from 2001 to 2012. The signicant drop in prices in summer 2012 was caused by exceptionally wet weather conditions. Afterwards, prices have been recovering steadily.

The dependent variable in the model is the volatility of the prices, and the independent variable is wind power production. Based on Mauritzen's results, my hypothesis is that renewable electricity production decreases volatility in the short term and increases it in longer time windows. The daily volatility is simply defined as a standard deviation of hourly prices as Equation 1 shows. Hourly prices for the following day are all announced by Nord Pool at 12:30 PM CET, so I have used the population standard deviation. Similarly, the weekly volatility is the standard deviation of daily prices [Eq. 2]. The daily price is defined as the average of the hourly prices that day. I have taken into account that in the Nordic calendar system the first day of week 1 is not always on 1 January but can be on 31 December, for example. Furthermore, there can be 53 weeks in a year. As single daily volatilities can be very high compared to normal levels, Figure 6(a) shows the logarithmic daily price volatility of system and Denmark east prices, i.e., percentage change in daily volatilities.

$$V_D = \sqrt{\frac{1}{24}\sum_{h=1}^{24}(P_h - \bar{P})^2} \text{ , where} \tag{1}$$

V_D is daily volatility, P_h price in hour h, and $\bar{P}$ average daily price $\frac{1}{24}\sum_{h=1}^{24} P_h$.

$$V_W = \sqrt{\frac{1}{7}\sum_{d=1}^{7}(P_d - \bar{P})^2} \text{ , where} \tag{2}$$

V_W is weekly volatility, P_d price on day d $\frac{1}{24}\sum_{h=1}^{24} P_h$ and

$\bar{P}$ average of the daily prices $\frac{1}{7}\sum_{d=1}^{7} P_d$.

Clearly, Denmark east has greater volatility compared to Nord Pool system prices that are calculated without transmission constraints. This is reasonable because hydropower production in Norway, Sweden, and Finland stabilizes the system price, whereas Denmark is dependent on wind power, exports, and expensive electricity generated from oil and gas. In addition, area prices can exhibit sharp price peaks when the transmission constraints are hit. To control the noisiness in the data and to identify changes, I have added Figure 6(b) where the natural logarithm of the daily volatility is exponentially smoothed with the coefficient $\alpha = 0.5$. Figure shows that there is a slightly increasing trend in daily volatilities both in system and Denmark east prices. In addition, the volatilities have started to diverge in recent years. The recursive formulae for exponential smoothing is given in the following Equations 3 and 4.

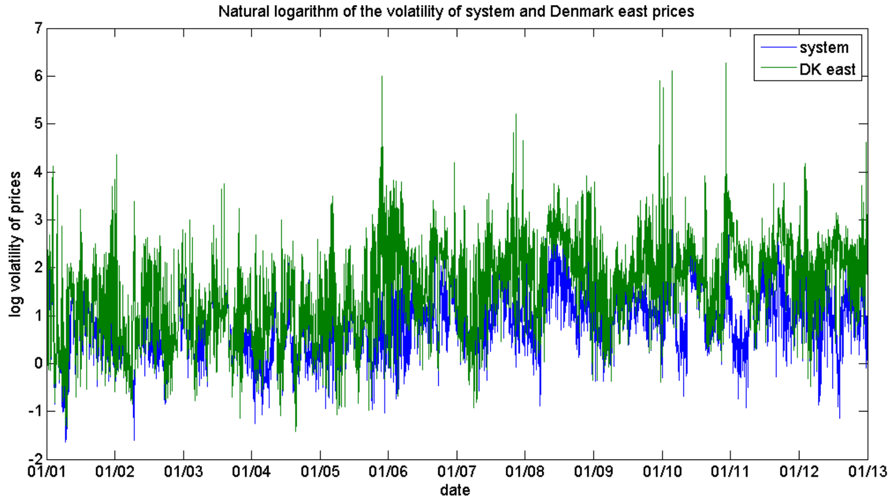
$$s_1 = x_0 \tag{3}$$

$$s_t = s_{t-1} + \alpha(x_{t-1} - s_{t-1}), t > 1 \text{ , where} \tag{4}$$

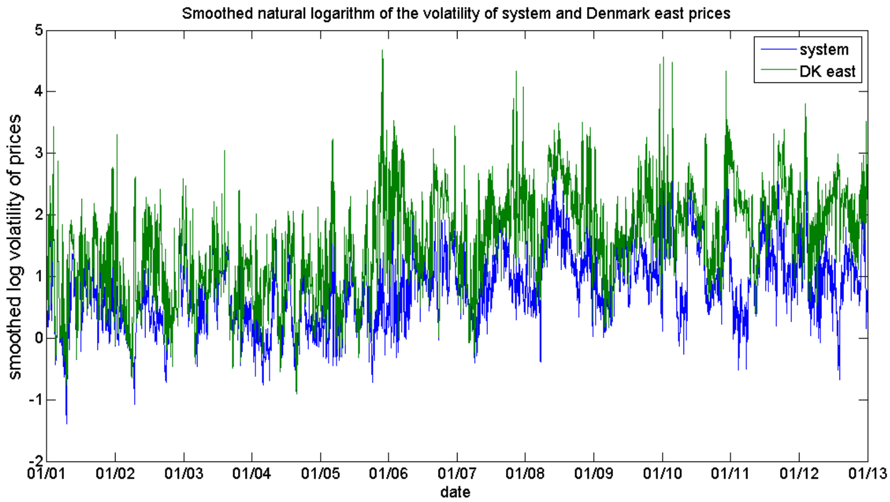
x are actual values and s are smoothed values.

In order to find the best fit of the volatility time series, I use the Box-Jenkins methodology. First, all the price volatility time series need to be stationary so that the regressions are valid. A visual examination of the daily time series in Figure 6(a) suggests that they are stationary. This hypothesis can be formally tested with an augmented Dickey-Fuller test when the intraday and weekly price volatility series for Danish area prices are modeled as an autoregressive model with five lags (AR(5)). This process was selected because it provides an adequate fit for the data. The augmented Dickey-Fuller tests confirm that all the series are stationary as the null hypothesis of at least one unit root is rejected at the 1% significance level.

The second step in the model identification is to plot the autocorrelation functions in Figures 7(a) and 7(b), the partial autocorrelation functions in Figures 7(c) and 7(d), and the spectral density functions in Figures 7(e) and 7(f) of Denmark areawise price volatility. However, these figures do not explictly point to a single valid model. Both the autocorrelation and the partial autocorrelation functions have spikes at lag 1 and near the multiples of 7. The lags at one suggest the short-term

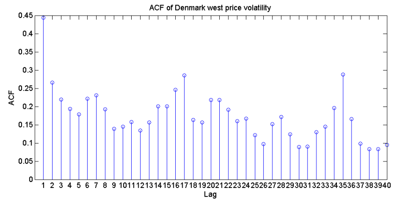


(a) Natural logarithm of the volatility of system and Denmark east prices

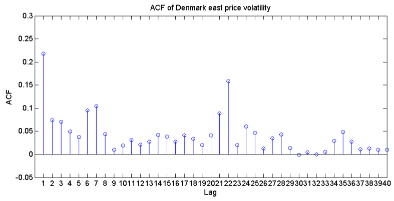


(b) Exponentially smoothed natural logarithm of the volatility of system and Denmark east prices

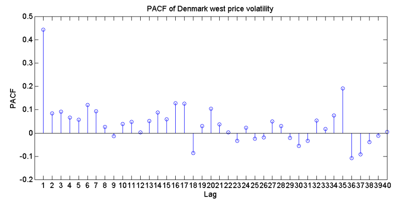
Figure 6: Log volatility and exponentially smoothed log volatility of system and Denmark east prices in 2001-2012. As well, Denmark west prices exhibit greater volatility than system prices on average.



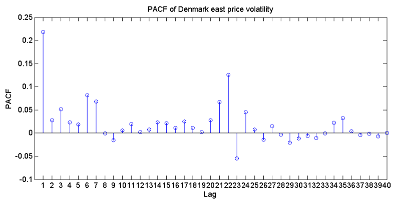
(a) Autocorrelation function of Denmark west area price volatility



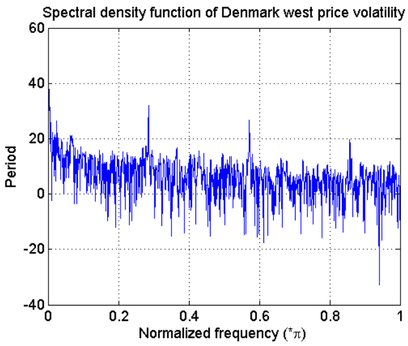
(b) Autocorrelation function of Denmark east area price volatility



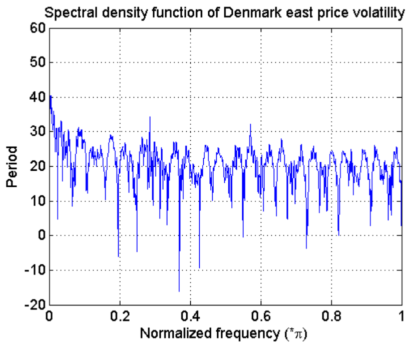
(c) Partial autocorrelation function of Denmark west area price volatility



(d) Partial autocorrelation function of Denmark east area price volatility



(e) Spectral density function of Denmark west area price volatility



(f) Spectral density function of Denmark east area price volatility

Figure 7: Autocorrelation, partial autocorrelation and spectral density functions of Denmark area price volatility in 2007-2012. Generally, Denmark east has less autocorrelation, which signals that Denmark east prices are not as stable as Denmark west prices.

autocorrelation structure can be modeled as an ARMA(p,q) process where p and q are 1 or 2. In addition, the spectral density function for Denmark west has peaks at about 0.29π, 0.57π, and 0.86π, which correspond to $\frac{1}{7}$, $\frac{2}{7}$, and $\frac{3}{7}$ at natural frequencies. This can be calculated using the formula $f = \lambda/2\pi$ where λ is the position of a peak in the figures [24]. Similarly, the spectral density function of Denmark east has the first two peaks, but they are not so pronounced. This confirms the presence of weekly seasonality that can be modeled with a combination of SAR_7 and SMA_7 terms. Apart from the spikes, the partial autocorrelation functions die out quite quickly, but especially the autocorrelation function for Denmark west only dampens slowly. This suggests that a model limited to AR and seasonal AR terms is not sufficient, as the autocorrelation functions should die out exponentially in that case. Thus, I include both MA and seasonal MA terms to my intraday model.

I test the residuals of different combinations of SARMA terms with a Ljung-Box test. The best alternative is SARMA(2,1,1,2) with the model for Denmark west passing the test at all lags in the range of 5 to 30, and the model for Denmark east passing many but not all. This model is later used as a basis for my intraday model.

3.2 Danish wind power

The variable in the models explaining the variations in prices is wind power production in Denmark. Historically, Denmark had a high share of fossil fuel-fired power plants and, therefore, it was badly hit by the oil embargoes during the 1970s [25]. Being mostly surrounded by sea, Denmark chose to invest into research and development of wind turbines and to provide generous subsidies to build capacity. In addition, the Danish parliament passed a law in 1985 that prohibits the production of nuclear energy in Denmark. Consequently, wind power capacity growth has been strong in the last twenty years as Figure 8 shows.

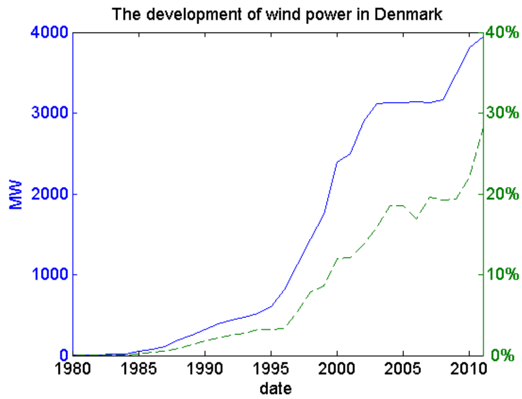


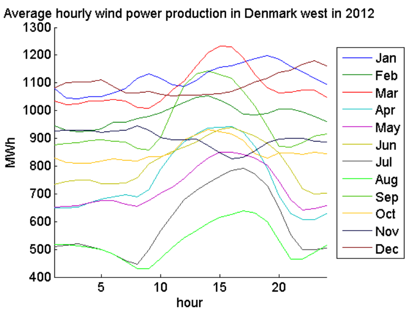
Figure 8: Installed wind capacity in Denmark (left hand side) and the share of wind production of total electricity supply (right hand side). Data source: Danish Energy Agency

At present, Denmark has two separate bidding areas, Denmark east and west, which were not physically connected before "the Great Belt Power Link" which was inaugurated in 2010 [26]. In addition, both parts are now connected to both Nord Pool and EEX. Detailed data of the Danish electricity system are publicly available from the website of the Danish transmission system operator [27]. For this paper, I obtained data for Danish wind power production. The data set is complete in that there are no gaps, but there is some uncertainty over the measurement of the wind power production because the electricity meters used are not perfectly exact. However, the possible errors are assumed to be constant and unbiased.

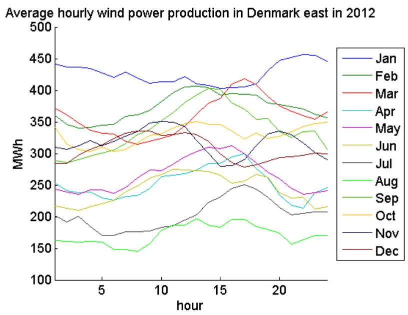
In fact, the best measure for wind power production would have been the forecasted production for the following day because all players set their bids for the following day. However, it is not clear which forecasts the players are using, and Nord Pool has been publishing their forecast only from 2010. However, the errors caused by the discrepancy in actual values and forecasts are assumed to be unbiased.

The intermittency of wind power production is visible in Figures 9(a) and 9(b). Winter months are considerably windier than summer months. Furthermore, there is a significant increase in production levels in the afternoon. That is why it is important to explore the effect wind power has on intraday blocks, such as off-peak and peak hours, to understand the underlying reasons for changes in price volatility. Additional study of daily production levels in Figure 9(c) points out that wind power is not usually very efficient because most of the time daily production is quite low at 0-30 GWh per day. Finally, Figure 10 shows the spiky nature of daily wind production during one year.

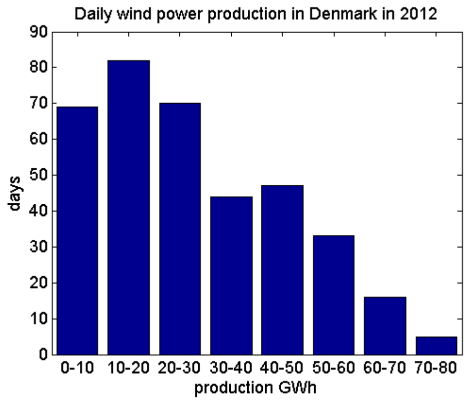
As in the previous section, I try to find the appropriate model for wind power production in both areas. Visual examination of the Figure 10 suggests that the time series are stationary. Moreover, an augmented Dickey-Fuller test confirms that the wind power time series are stationary at 1 % significance level The partial autocorrelation functions in Figures 11(c) and 11(d) suggest that the wind can be adequately modeled as an AR(1) process as the lags die out after lag one, and the



(a) Denmark west



(b) Denmark east



(c) Denmark daily variation

Figure 9: Upper row: Danish average intraday wind power production in each month in 2012, lower row: daily variations in production levels in 2012.

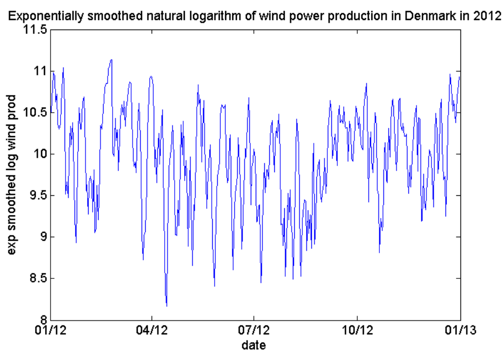
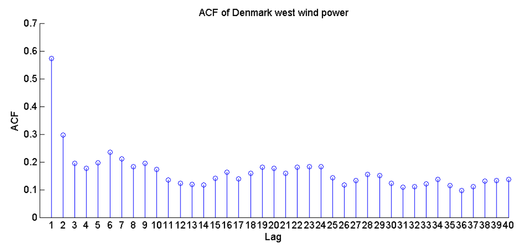


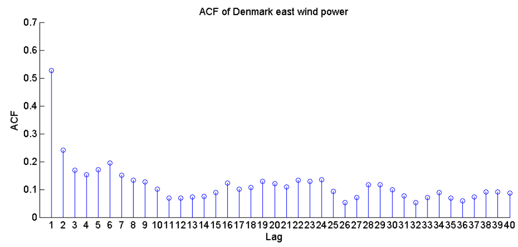
Figure 10: Exponentially smoothed natural logarithm of daily wind power production.

autocorrelation functions in Figures 11(a) and 11(b) dampen exponentially before stabilising to a nearly constant level. Therefore, I include an AR(1) term in the intraday model to account for wind power.

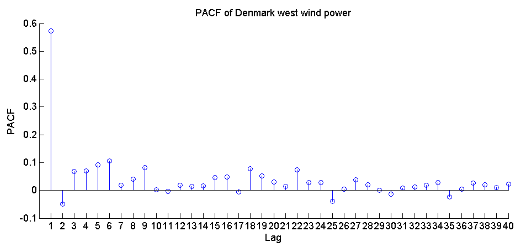
This is a reasonable result because wind conditions can change quite rapidly. Therefore, it is natural that wind power does not have the same weekly seasonality experienced in prices, for example. Also, Mauritzen uses an AR(1) process for wind power in his paper.



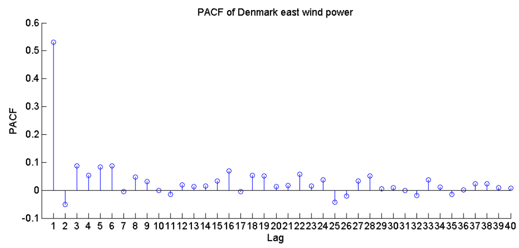
(a) Autocorrelation function of Denmark west daily wind power production



(b) Autocorrelation function of Denmark east daily wind power production



(c) Partial autocorrelation function of Denmark west daily wind power production



(d) Partial autocorrelation function of Denmark east daily wind power production

Figure 11: Autocorrelation and partial autocorrelation functions of wind production for Danish areas in 2007-2012.

3.3 PHELIX price data

Phelix price data were downloaded from Energinet.dk [27] because EEX charges for the data. The data set I use starts from 28 October 2009 because since then the four German transmission system operators (50 Hertz, Amprion, TenneT, and TransnetBW) have been obliged to report their production data publicly. As with the Nord Pool price data, the reliability of the data is high as the figures are officially set by Epex Spot. As Figure 12 shows, the average hourly prices are close to Denmark East prices shown in Figure 4(b) but a bit higher. The shape of the intraday price curve is explained by the same factors as in Nord Pool.

Figure 13 shows the daily volatility of Phelix prices starting from 2002. The daily volatility has been calculated as a standard deviation of hourly prices as in the Equation 1. The figure does not show any yearly pattern, but the volatility has increased slightly from 2002 to 2009. In addition, most of the high peaks have occurred in this period. After 2009, the volatility has been decreasing, and sudden peaks and drops have been rare. A possible reason for this change might be that Germany and Austria produce plenty of electricity from coal, gas, and oil, which became more expensive and turbulent before the economic crisis in 2008-2009. In addition, the purpose of this paper is to estimate if renewable energy, which has gained substantial share in the production mix in the recent years, has decreased daily volatility levels.

I use the same methodology as in the Nord Pool prices section. First, the stationarity of the daily volatility time series starting from 28 October 2009 is tested with an augmented Dickey-

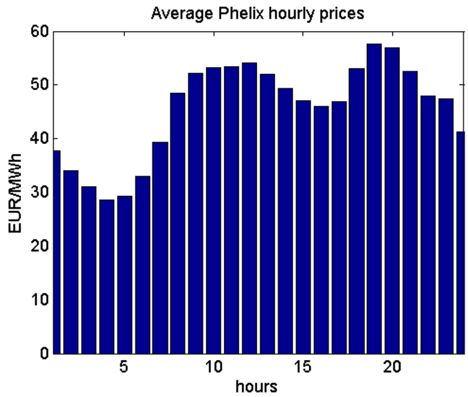


Figure 12: Phelix average hourly prices in 2012.

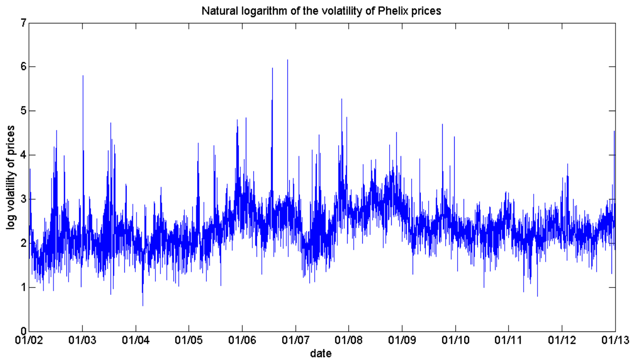


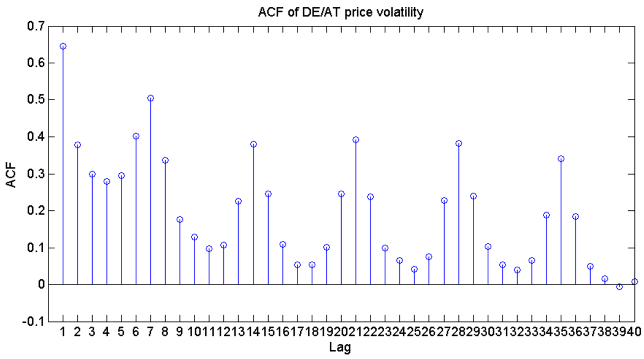
Figure 13: Natural logarithm of the daily volatilities.

Fuller test. The test confirms that the time series is stationary at 1 % significance level when it is modeled as an AR(5) process. A visual inspection of Figure 13 supports the result.

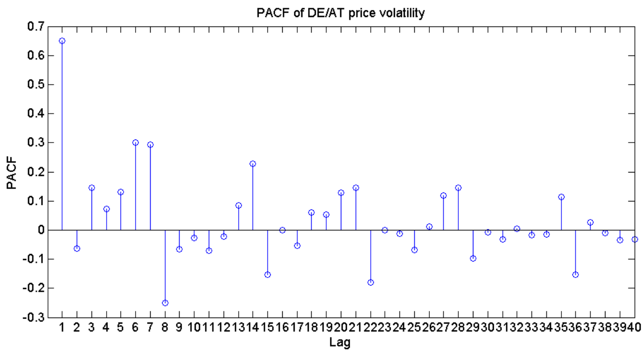
Second, I plot autocorrelation in Figure 14(a), partial autocorrelation in Figure 14(b) and spectral density function in Figure 14(c) to identify the specification of the intraday SARMA model. The autocorrelation and partial autocorrelation functions show similar weekly seasonality as Danish price data because the figures have peaks near lags 7 and 14. Graphically, the functions are close to Denmark east in Figures 7(b) and 7(d). The autocorrelation function does not die out completely but the partial autocorrelation function ends after lag one apart from the multiples of seven. Moreover, the spectral density function has peaks nearly at same spots as Denmark west 7(e) which draw to $\frac{1}{7}$, $\frac{2}{7}$ and $\frac{3}{7}$ at natural frequencies.

As with the Danish data, these findings do not determine the best model directly and several combinations need to be tested. However, the findings do limit the possible model specifications. High peaks at lags one and two restrict the order of the AR and MA terms to two. Moreover, I test with one to three SAR_7 and SMA_7 terms to control for the weekly seasonality. As the time series was proven to be stationary, there is no need to integrate it.

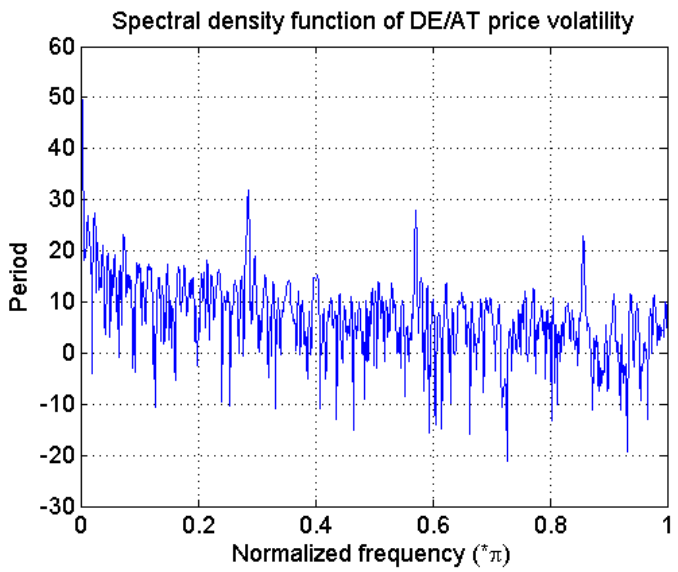
Eventually, the best model for Phelix daily volatility time series is SARMA(2,1,1,1) and it is very close to the model for Denmark. The criterion I use is again the Ljung-Box test which the model residuals pass with all lags ranging from 5 to 30.



(a) Autocorrelation function of Phelix daily volatility



(b) Partial autocorrelation function of Phelix daily volatility



(c) Spectral density function of Phelix daily volatility

Figure 14: Autocorrelation, partial autocorrelation, and spectral density functions of Phelix daily volatility from 28 October 2009 to 31 December 2012.

3.4 German solar and wind power

The effects of German solar and wind power on Phelix prices are estimated by including an exogenous terms for total daily solar, wind, and combined power production from these two sources. There is no need to take Austrian renewable generation into account because it is non-existent. As Figure 15 shows, the share of solar power of the total renewable capacity has increased at fast pace in the recent years. The relative share of wind power rose at the end of the 1990s, but it has lost its share to solar power lately. At the same time, the total installed renewable capacity has increased about 10 GW per year when the capacity of a modern nuclear plant is from 1 to 1.8 GW. This reformation was initiated by the political pressure set by the EU climate targets and the Fukushima nuclear disaster, and it is now driven by the generous subsidies and ever cheapening technologies.

The renewable generation poses heavy requirements for the transmission grid due to the scattering and geographical concentration of the production. In particular, the most popular solar technology is photovoltaic (PV) panels that are made of advanced materials that exhibit the photovoltaic effect. These panels are installed in huge solar power parks and on the house roofs. This causes the production to scatter to small units as many households feed their surplus production into the system and get paid for it with feed-in-tariffs. On the other hand, wind power production takes places mostly in northern Germany, near the Baltic sea [28]. The German government is focusing on off-shore wind farms although the project is facing technical difficulties and financial risks [29]. Connecting these large farms to mainland is tricky and expensive, and additional investments are required to transmit the electricity to Bavaria in southern Germany, for example. With these distances, power transmission losses become substantial.

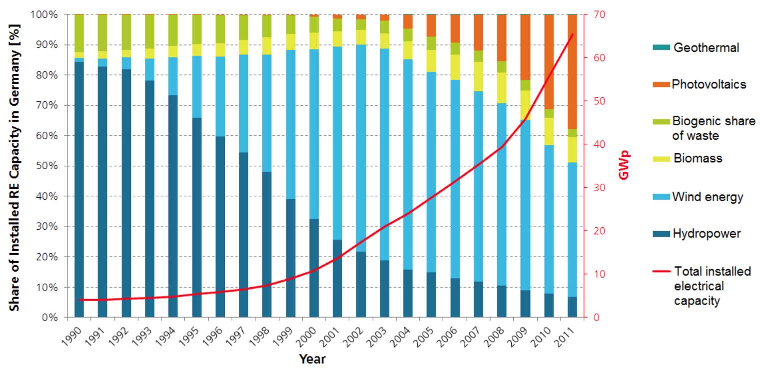
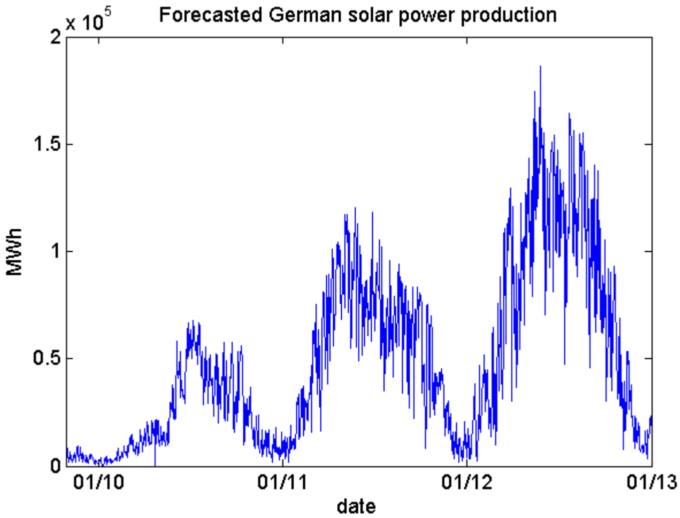


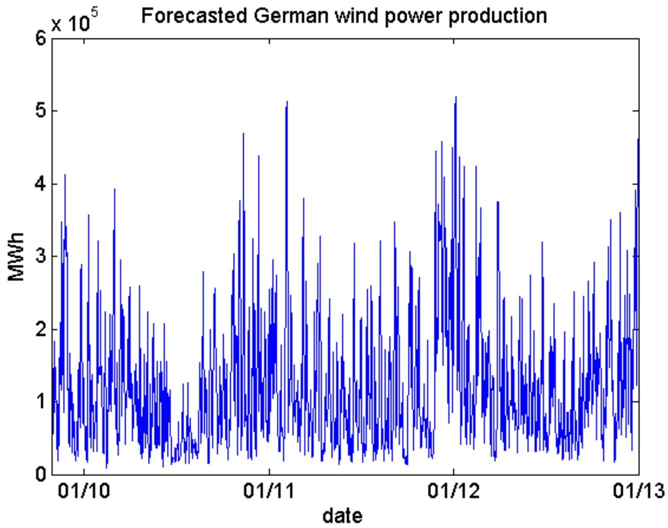
Figure 15: The development of renewable energy in Germany. Image source: Fraunhofer ISI.

The data for daily solar and wind power production were downloaded from EEX's website [30] using a script. Both expected and actual production data are available from 28 October 2009. I choose to use the expected production data for the regressions because all market participants make their decisions for the day-ahead market based on that data, not the actual generation. Therefore, it is more accurate choice for volatility-modeling purposes, but decisions to invest in renewable generation, for example, are made based on actual prouduction data. Hence, the actual generation data are used to compare the solar production patterns to wind power. The data set is complete, and there are no gaps, which makes it reliable. However, it is uncertain what forecasts the market participants are using. There are differences between the different forecasts but these errors are assumed to be unbiased. The forecasted daily solar power production is presented in Figure 16(a) and the forecasted daily wind power production in Figure 16(b).

Figure 17(a) shows that the actual solar power production is almost normally distributed with the output peak occurring during the peak hours and zero output during the night. Hence, solar



(a) Forecasted German solar power production from 28/10/2009 to 31/12/2012.



(b) Forecasted German wind power production from 28/10/2009 to 31/12/2012.

Figure 16: The solar and wind production in 2009-2012. The solar power levels have increased substantially.

power is affecting only peak hours. In the summer months, the output is considerably higher than in winter months. Moreover, increasing production levels from the early summer towards the late summer is caused by the fact that cumulative installed capacity increases. The width of the distribution reflects the temporal differences in sunrises and sunsets throughout the year. In comparison, Figure 17(b) shows that on average there is always some wind power production in Germany. Similar to solar power, the output peak is experienced during the peak hours, but the output curve is rather flat. Thus, wind power is affecting all hourly prices. Compared to Danish wind power in Figures 9(a) and 9(b), the German wind power is more aligned but the difference between winter and summer months is higher.

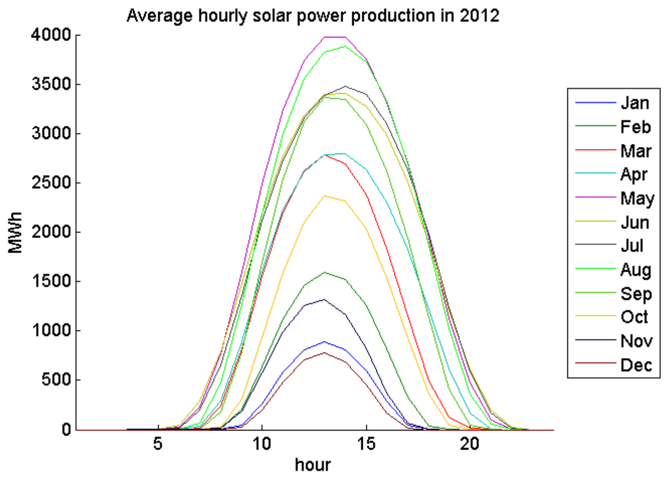
The daily German solar power has been more stable than the German wind power as the average ratio of minimum daily output and maximum daily output in each month in 2012 was 24.7% for solar and only 5.4% for wind power. In addition, the standard deviation of normalized daily wind power output in each month in 2012 was 4% higher than the standard deviation for solar output. The implication for this difference is that solar power is more predictable than wind power, and the effect on daily and weekly volatility should be decreasing compared to wind power.

When these two power sources are combined, the highest output of renewable energy occurs during the peak hours, which can lead to a significant price drop as the price of the production is negligible. In all other hours, the output is lower but so is consumption. However, as the standard deviations for both are over 20%, and wind power output can exhibit sharp dives, the price levels can vary greatly during the week when the weather conditions go from favourable to bad, productionwise. The observation that winter months tend to be the most windiest offsets the lack of solar output to some extent during winters, and vice-versa for summers. Therefore, the average monthly production level does not vary dramatically as Figure 17(c) shows. As the production levels of solar and wind power change significantly from month to month, the effect renewable generation has on price volatility is different in each month. Further research is required to explore these effects.

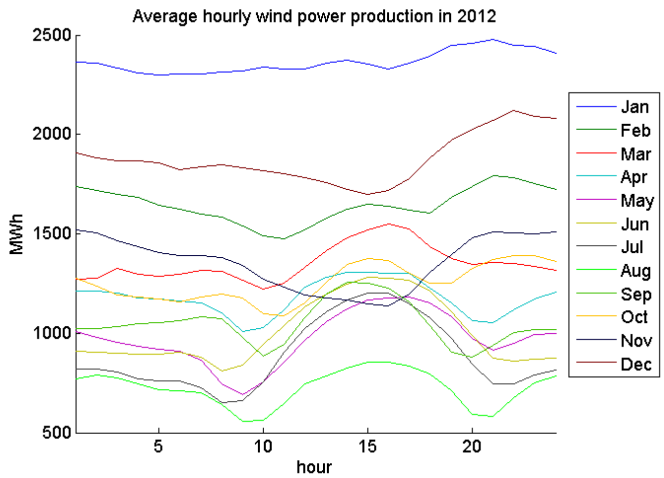
As with the Danish wind power, I model the forecasted German wind and solar power as an lagged process. First, I deal with the solar power. As I am using daily production data, not hourly, I do not need to worry about the possible non-stationary intraday curve shown in Figure 17(a). However, as Figure 16(a) shows, there is a corresponding yearly pattern that might require differencing. Moreover, the production values have been increasing steadily so there can be a trend. Nevertheless, the augmented Dickey-Fuller test confirms that the time series is stationary if it is modeled as an AR(1) process. A yearly differencing slightly decreases the autocorrelation but that would limit my data set for a year, so I accept the result of the augmented Dickey-Fuller test.

The partial autocorrelation function in Figure 18(b) has a peak at lag one. After that the function dies out exponentially or completely. Therefore, the AR(1) process used in the Dickey-Fuller test could be sufficient. The autocorrelation function in Figure 18(a) declines slowly, which means that the observations are similar. This confirms the earlier analysis that solar power is more stable than wind power. Based on this remark, it is not certain if the AR(1) model is sufficient. Therefore, I run tests with an ARMA(1,1) process that is virtually the same as adding one MA term to the price process. Even if the data are differenced monthly, half-yearly, or yearly, the autocorrelation does not die out quickly enough to be clearly better.

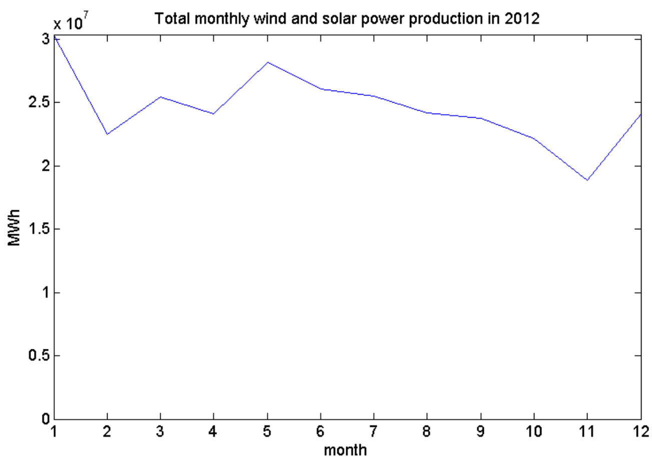
Second, I explore the German wind power data. An augmented Dickey-Fuller test confirms that the time series is stationary, allowing me to model the time series as a lagged process. The autocorrelation and partial autocorrelation functions of the forecasted wind power production are presented in Figures 18(c) and 18(d), respectively. Similar to Danish wind power data, the partial autocorrelation function dies out right after the lag one. The autocorrelation function evens out rather fast to a steady level. Therefore, German wind power can be modeled as an AR(1) process, too.



(a) Hourly solar power production in Germany in each month in 2012.

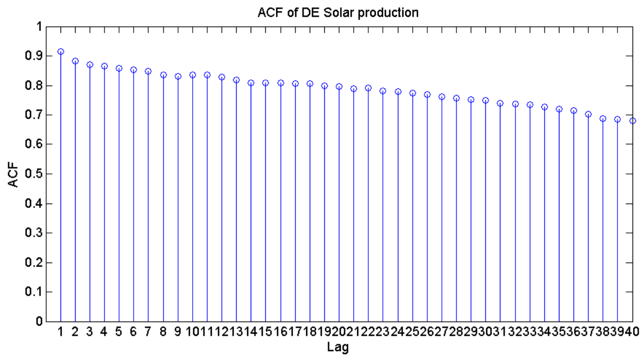


(b) Hourly wind power production in Germany in each month in 2012.

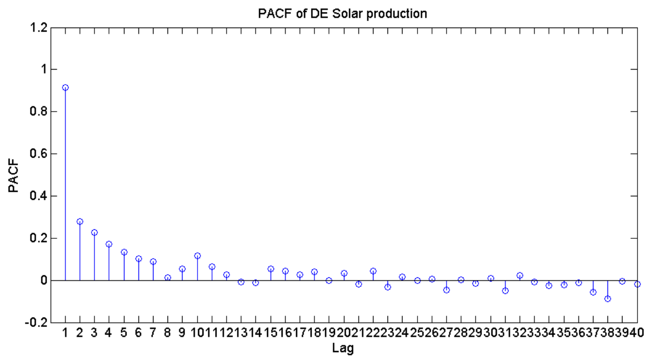


(c) Total wind and solar production in each month in 2012.

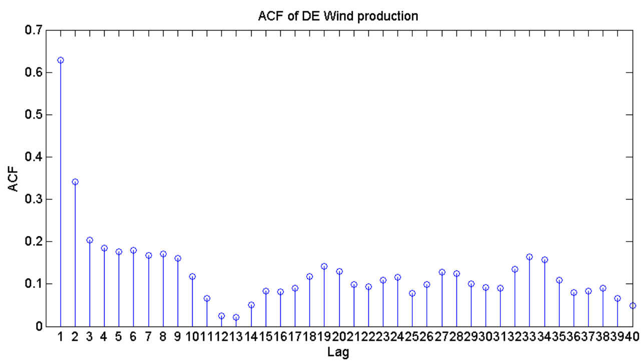
Figure 17: Solar and wind power production and the total production from these two sources in Germany in 2012.



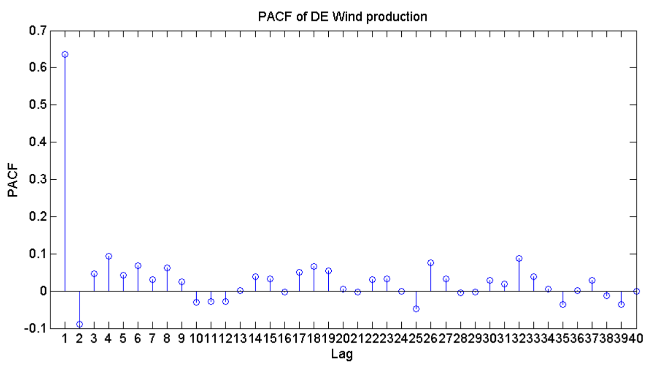
(a) Autocorrelation function of daily German solar power production



(b) Partial autocorrelation function of daily German solar power production



(c) Autocorrelation function of daily German wind power production



(d) Partial autocorrelation function of daily German wind power production

Figure 18: Autocorrelation and partial autocorrelation of the undifferenced daily German solar and wind power production time series from 28 October 2009 to 31 December 2012.

4 Results

4.1 Denmark

4.1.1 Intraday model

Similar to Mauritzen's article [10] and as described in earlier sections, I estimate the effects of wind power on daily price volatility using an SARMAX process, where the standard deviation of electricity prices is modeled as a SARMA process along with the exogenous wind power term. There is no need to integrate the process because the time series do not have a trend. Formally, the model can be written as

$$v_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i v_{t-i} + \sigma_0 w_t + \sigma_1 w_{t-1} + \sum_{i=1}^{q} \beta_i \epsilon_{t-i}, \tag{5}$$

where v_t is the natural logarithm of daily price volatility with p autoregressive (AR) terms v_{t-i}, and q moving average (MA) terms ϵ_{t-i}. Terms α_i and β_i are the coefficients that are estimated for the AR and MA terms, respectively. Wind power production is limited to the terms w_t and w_{t-1} and the corresponding coefficients σ_0 and σ_1 because wind power is modeled as an AR(1) process as noted earlier.

Both areawise intraday models are based on Equation 5. The most important requirement for finding the best fitting model is that all the coefficients are significant at the 1% significance level. To choose the best model among feasible candidates, I go through a process of using Wald tests, comparing the Akaiki Information Criterion (AIC) as well as looking at the autocorrelation and partial autocorrelation functions of the model residuals, and carrying out Ljung-Box test for the residuals. All feasible model candidates were close to each other in terms of the ARMA specification and the actual results. The final model is a combination of the SARMA(2,1,1,2) model for the price process and an AR(1) model for the wind power process both of which I found statistically adequate in the previous sections.

In the end, I model the intraday areawise price volatilities using the same model as Mauritzen [10] excluding the term $\beta_2 \epsilon_{t-2}$, which was not statistically significant. The same model is applied to both Denmark east and west data, and the model is a compromise between parsimony and goodness of fit. Contrary to Mauritzen, I have not used both wind power from Denmark west and Denmark east as an exogenous term because the systems were separate until September 2010. It would be unrealistic to assume that before the integration all or much of the wind power produced in Denmark west is first exported to Germany or Sweden and then imported back to Denmark east, and vice-versa. In addition, there is not yet enough data since September 2010 to measure the effects of exchange between the two Danish areas.

The final model used in my regressions is in Equation 6. The AR terms deal with the short-term price process and the weekly seasonality. These terms are also indicated by the peaks in the partial autocorrelation functions in Figures 7(d) and 7(c). A simple MA(1) term increases the fit further. Finally, adding the MA terms for lags 7 and 14 controls for the seasonal autocorrelation in the residuals. Wind power from Denmark east or west is restricted to an AR(1) process as indicated by the partial autocorrelation functions. All variables are transformed into natural logarithm form so they can be interpreted as elasticities.

$$v_t = \alpha_0 + \alpha_1 v_{t-1} + \alpha_2 v_{t-2} + \alpha_7 v_{t-7} + \beta_1 \epsilon_{t-1} + \beta_7 \epsilon_{t-7} + \beta_{14} \epsilon_{t-14} + \sigma_0 w_t + \sigma_1 w_{t-1} \tag{6}$$

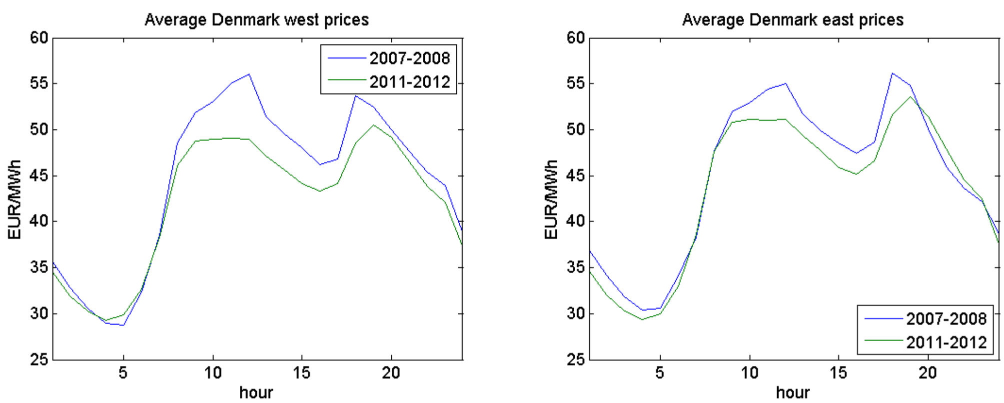
Figures 20(a), 20(b), 20(c), and 20(d) show the autocorrelation and partial autocorrelation functions of the model residuals for Denmark west and east. The autocorrelations of the residuals of the model for Denmark west look flatter than the residuals of the model for Denmark east. There are spikes close to the multiples of 7, which means that the weekly seasonality could be dealt with better. There are spikes also near the lag 30, which points to monthly seasonality. Yet, the model for Denmark west passes the Ljung-Box test with lags from 5 to 30. However, the model for Denmark east does not pass the test with all lags greater than fifteen, but this is not a critical reason to reject the model. Figures 20(e) and 20(f) compare the models against the actual price volatility time series. In general, the model performs rather well with both Denmark east and west data, but it has problems with the extremely spiky and volatile nature of the data.

Table 2 shows the results for areawise regressions for intraday price volatility. The coefficients for wind power from Denmark east and west are labeled $de - wind_t$ and $dw - wind_t$, respectively. For Denmark east, the estimated coefficient for wind generated in eastern Denmark is about -0.076, which can be interpreted to mean that a 1% increase in daily wind power production leads to a 0.076% decrease in intraday price volatility. Therefore, an 100% increase, i.e., doubling the total daily wind power production would mean a 7.6% decrease in intraday price volatility. From the beginning of 2007 to the end of 2012 the average daily wind power production in Denmark east was about 5553 MWh, which means that a 100% change would result to an increase of 11106 MWh wind power per day. During this period, there have been 331 days with over 11106 MWh of wind power production. However, the daily volatilities cannot be compared directly as the daily price levels, which are dependent on several other factors, are different.

For Denmark west, the estimated coefficient for wind generated in western Denmark is about -0.074. Using the same interpretation of elasticity, a 100% increase in daily wind power production leads to a 7.4% decrease in intraday price volatility. In this time scale, the average daily wind power production in Denmark west has been 16647 MWh, so a 100% increase would be about 33294 MWh (282 days in total).

In addition, the lagged terms for Denmark east and west wind power production are significant at 1% level. These terms were included to control for the autocorrelation in the wind power time series. Therefore, they should not be given any economic interpretation. Wind power production on one day does not affect the volatility of prices the following day.

My hypothesis is that the volatility-reducing effect of wind power is caused by wind power cutting the peak hour prices. Figures 19(a) and 19(b) show that the average peak hour prices have come down and notably the two high peaks have dampened or even cut out. The effect is stronger for Denmark west and it is explained by the larger amount of wind power production. Otherwise the prices are overlapping.



(a) Average hourly price in Denmark west in 2007-2008 and 2011-2012.

(b) Average hourly price in Denmark east in 2007-2008 and 2011-2012.

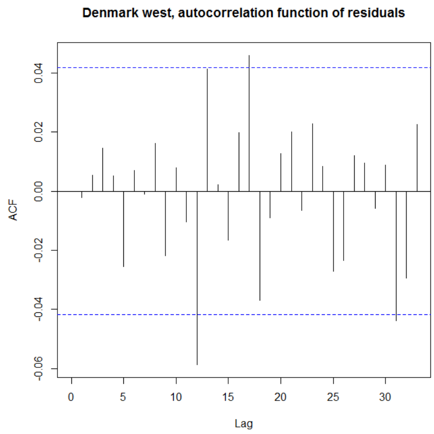
Figure 19: The development of the average Denmark area prices. I have averaged two years of price data to eliminate the effect of possible outliers.

In the regression for Denmark west, Mauritzen's coefficient for wind power from Denmark west is -0.103. For Denmark east, the coefficient for wind power from Denmark east is -0.011 (not statistically significant) and from Denmark west -0.072. Therefore, the final results of my Denmark west intraday model are close to Mauritzen's, although the model is different. This adds credibility also to Mauritzen's initial model although he does not acknowledge the effect of lacking transmission capacity between the two Danish areas. Basically, the coefficients are different because the data set and the variables are different, but most importantly the significant coefficients for wind power are of the same magnitude. However, I do not find as strong of an effect as Mauritzen, but it is still economically significant.

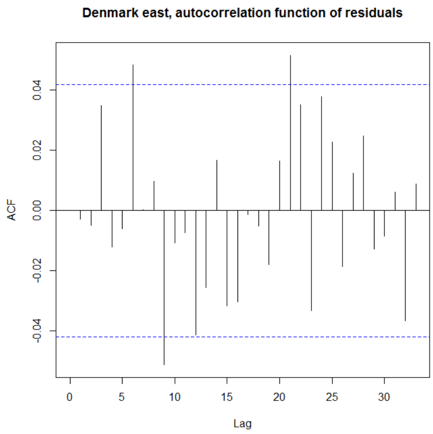
Table 2: The effect of Danish wind power production on intraday Danish area price volatility. All coefficients are statistically significant at 1% level unless otherwise noted.

	DE Area	DW Area
$de - wind_t$	-0.0759	N/A
	[0.0128]	N/A
$de - wind_{t-1}$	0.0470	N/A
	[0.0128]	N/A
$dw - wind_t$	N/A	-0.0751
	N/A	[0.0132]
$dw - wind_{t-1}$	N/A	0.0509
	N/A	[0.0132]
$constant$	2.2005^a	2.1777
	[0.8732]	[0.6963]
α_1	1.3408	1.2343
α_2	-0.3546	-0.2466
α_7	0.9996	0.9998
β_1	-0.8961	-0.8926
β_7	-0.9042	-0.9235
β_{14}	-0.0805	-0.0694

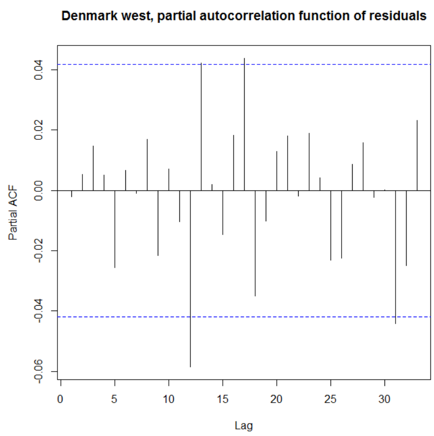
[a] significant at 5% level



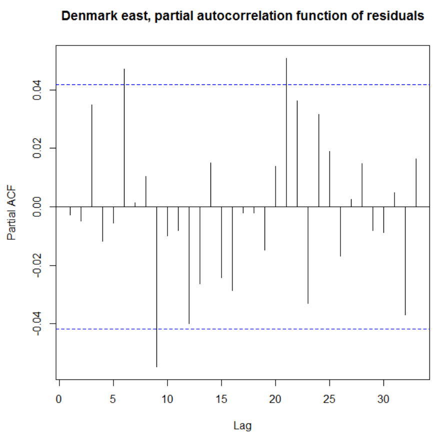
(a) Autocorrelation function of Denmark west intraday model residuals



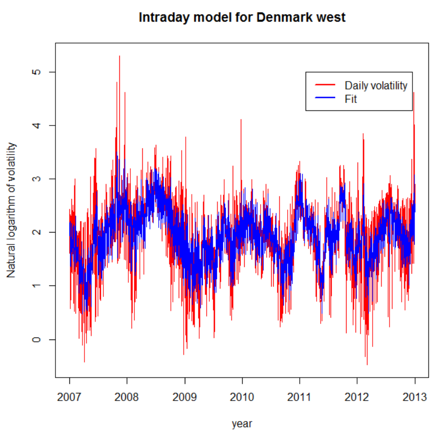
(b) Autocorrelation function of Denmark east intraday model residuals



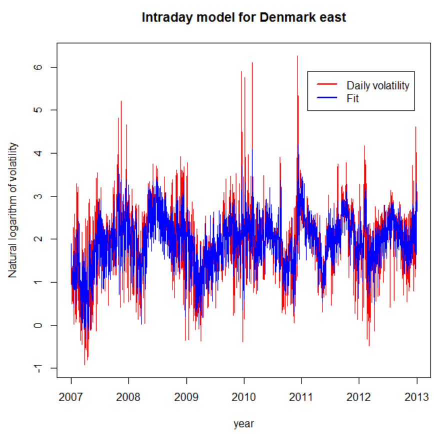
(c) Partial autocorrelation function of Denmark west intraday model residuals



(d) Partial autocorrelation function of Denmark east intraday model residuals



(e) Denmark west model vs. actual time series



(f) Denmark east model vs. actual time series

Figure 20: First and second row: Autocorrelation and partial autocorrelation functions of the model residuals with 95% confidence intervals. Third row: The actual daily volatility time series and model fits.

4.1.2 Division into peak, off-peak 1, and off-peak 2 hours

As noted in the introduction, my hypothesis is that intraday volatility is reduced due to the flattening of the intraday price curve. I further hypothesise that this results from renewable generation cutting the peak prices. Thus, I divided the data set into peak, off-peak 1, and off-peak 2 hours to explore the effects on different blocks. By Nord Pool's definition, peak hours are hours 08-19, off-peak 1 hours are 00-07 and off-peak 2 are 20-23. So, the total durations are 12, 8, and 4 hours, respectively. These blocks fit very well into the general price levels of Figures 4(a) and 4(b), where hours 08-19 have the highest prices.

For these three data sets, I run regressions in the same fashion as in the previous section, but with the dependent variable being the natural logarithm of average prices in each block instead of the natural logarithm of daily volatility. Furthermore, the daily wind power data was averaged instead of summing up the hourly productions because the blocks have different durations. Hence, I can study the differences between the price levels of the blocks, which ultimately causes the daily volatility. If the regressions were done using the daily volatility as the dependent variable, then the result would have been similar as in the previous section: volatility has decreased in each block. This would tell that the prices have converged in each of the blocks. However, as the supply and demand curves move from hour to hour in Figure 21, any extra wind power will have different effects in each hour because the elasticities of the curves vary. Therefore, it is possible that wind power causes the price levels of the blocks diverge if the impacts on each block are not close to each other in magnitude. The situation is presented in Figure 22 with imaginary prices that are constant in each block. In the figure, the prices have diverged due to wind power having greater effect on off-peak 1 hours than peak and off-peak 2 hours. The effect of wind power for each block is calculated using the coefficients that are estimated later in this section by applying a 100% increase in wind power production.

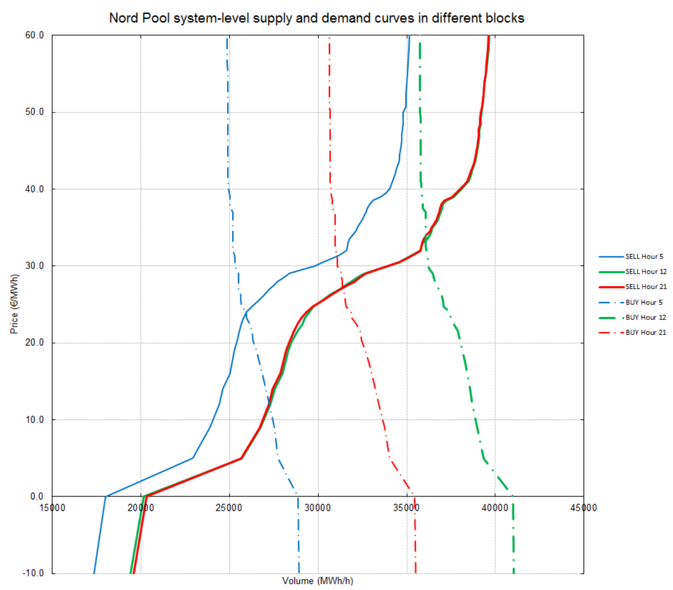


Figure 21: Nord Pool system-level supply and demand curves in three different blocks on 11 May 2012. Hour 5 belongs to off-peak 1, hour 12 to peak, and hour 21 to off-peak 2. Note that supply curves for hours 12 and 21 are overlapping.

I expect these changes only to scale the different coefficients. The same model, which is presented in Equation 6, turned out to be the best also for these data sets. This is reasonable because there is no fundamental difference in the data compared to previous section. However, some ARMA specifications with minor modifications would have been feasible, too.

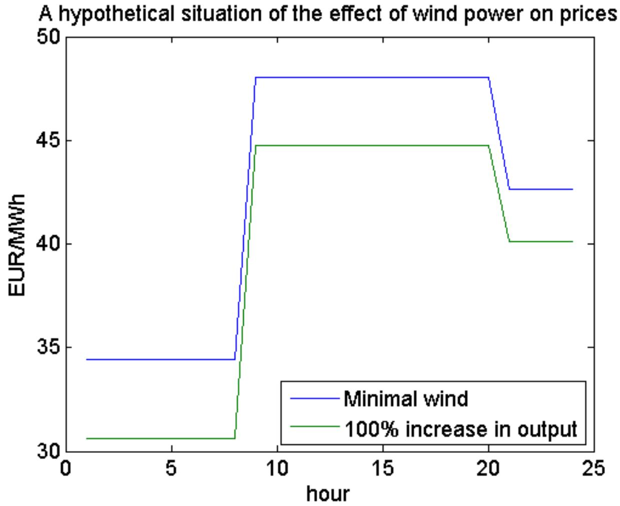


Figure 22: The blue line represents a situation with minimal wind power output. The green line is the prices after a 100% increase in wind power output. The daily volatility has increased 4.3% contrary to the result in the previous section.

Similar to the previous section, I have only used an area's own wind power production in the regressions because the two Danish areas were different systems until September 2010. The results are presented in the Table 3, where I have omitted the coefficients for different SARMA terms for clarity, but they are available in Appendix A. Each row represents the coefficient for wind power term in different blocks in an area.

For Denmark east, the coefficients for peak, off-peak 1, and off-peak 2 are about -0.041, -0.056, and -0.029, respectively. As all the coefficients are negative, all blocks have come down in prices. Surprisingly, the largest effect is in the off-peak 1 hours when consumption is at its lowest level. Apparently, any excess wind power leads to an over-supply situation that brings the price level of this block down effectively. On the other hand, the coefficients for peak and off-peak 2 hours imply that these have become closer to each other as the peak hours have generally higher price levels.

However, the wind power output is not evenly distributed during the day. From 2007 to 2012 the relative hourly output has increased more in off-peak hours than peak hours. Recall that the wind power term is in logarithmic form so relative changes matter instead of absolute values. Despite the less negative coefficient, off-peak 2 hours might come down more in prices than peak hours if the relative wind power production in off-peak 2 hours has increased more. The highest increase in wind power output has been in off-peak 1 hours, which also have the most negative coefficient.

To summarise, there are two components that make up the drop in prices in off-peak hours. First, the relative wind power output has increased more in off-peak hours than peak hours, and secondly, the coefficients for off-peak hours are slightly more negative. To some extent, these effects are offset by the higher price level of peak hours. Therefore, it is possible that the intraday volatility has actually increased in Denmark East, contrary to the results in the previous section. However, the increased volatility requires rather flat wind power output curve where peak and off-peak hours are exposed in equal amounts.

One explanation for the small coefficient for peak hours could be that Denmark East has great export transmission capacity to Sweden, which had slightly greater prices during 2007-2012, although Sweden was not divided into four areas until November 2011. Nowadays, the highest priced area SE4 is directly linked to Denmark east. Therefore, it can be profitable to export excess wind power to Sweden when it is windy in Denmark east. This may reduce the effect of eastern

Denmark wind power generation on its own area price especially in peak hours when consumption is highest.

For Denmark west, the coefficient for off-peak 1 hours, -0.11, is significantly larger than the coefficient for peak hours, -0.068, and off-peak 2 hours, -0.060. All coefficients are negative which means that the prices have come down in each block. Again, the coefficients for peak and off-peak 2 hours would imply that these two blocks have come closer to each other in prices, but wind power ouput has generally been increasing more in off-peak hours than in peak hours. The very negative coefficient for off-peak 1 hours could be explained by the fact that Denmark west has less demand than Denmark east. Moreover, Denmark west is connected to Norway 2 and Sweden 3 both of which had lower prices than Denmark west on average in 2012, causing the domestic wind power production to stay in Denmark west. Compared to Denmark east, the transmission situation is opposite when it comes to prices of the neighbouring areas. Therefore, Denmark west prices are more sensitive to any excess wind power supply during the low consumption hours. In conclusion, it is again possible that the daily volatility increases contrary to the result in the previous section if the wind power is distributed so that off-peak hours are subject to great wind power production.

Another approach to the coefficients for both areas are the supply curves and merit-order effect. At the low end of the Danish supply curves are wind power production and inexpensive imports from the neighbouring countries. The low priced part is followed by a jump to a higher price level with CHP and conventional production using mostly coal as a fuel. For Denmark, most of this production is large-scale and stable, making the supply curve low-pitched. Only in high volumes when expensive backup generation is brought online, the supply curve becomes steep. Hence, it seems that the demand curve is hitting the stable part of the curve in each block, but as off-peak 1 is near the high jump, the effect of wind power is greater then.

Table 3: The effect of Danish wind power production on intraday Danish area prices in different blocks. All coefficients are statistically significant at 1% level unless otherwise noted.

	Peak	Off-peak 1	Off-peak 2
$de - wind_t$	-0.0413	-0.0557	-0.0287
	[0.0034]	[0.0048]	[0.0021]
$de - wind_{t-1}$	0.0006^c	-0.0131	-0.0035^c
	[0.0034]	[0.0048]	[0.0021]
$dw - wind_t$	-0.0681	-0.1112	-0.0597
	[0.0035]	[0.0074]	[0.0036]
$dw - wind_{t-1}$	-0.0066^b	-0.0202	-0.0046^c
	[0.0035]	[0.0074]	[0.0036]

^{b} significant at 10% level

^{c} not different from zero

4.1.3 Weekly model

From the beginning of 2007 to the end of 2012, the correlation between the difference in consecutive daily Denmark west prices and the difference in consecutive daily wind power produced in Denmark west is rather high at -0.37. The windier it is, the lower the daily price level is. For Denmark east, the same correlation drops to -0.17, which may reflect the smaller amount of wind power. My hypothesis is that the weekly volatility increases because of the intermittent nature of wind power shown in Figure 9(c).

Mauritzen's [10] idea to model the effects of wind power on weekly volatility is to use the standard deviation of daily prices given in Equation 2 as a dependent variable, and the total wind power production as an external regressor. Contrary to Mauritzen, I did not find any of his weekly models feasible with the data set from 2007 to 2012. Nor did I find a statistically significant model using different ARMA specifications. It is worth noticing that Mauritzen's results are not that robust either as the general significance level of his wind power coefficients is only 10%. In addition, the standard errors for Denmark west are higher than the actual coefficients - for Denmark east they are two to six times larger.

At a weekly level, the total wind power production can distribute in numerous ways. First, the wind power output could be relatively constant during the week. Second, there can be a couple of days with high wind power output, and the rest of the week close to zero output. Both of these cases could result into an even weekly wind power output. However, the weekly volatility is likely to be considerably higher in the latter case. As there is a clear correlation between daily price and wind power levels, the standard deviation of daily wind power output (Equation 7) is a better explanatory variable for the weekly volatility. The intuition is that if there is no wind power production, then Denmark needs to resort to imports and high-cost backup production, but in case of windy weather conditions, the prices drop as the marginal costs of the production are negligible.

$$V_W = \sqrt{\frac{1}{7}\sum_{d=1}^{7}(W_d - \bar{W})^2} \text{ ,where} \tag{7}$$

V_W is weekly volatility, W_d total wind power output on day d, i.e, $\sum_{h=1}^{24} W_h$ and

$\bar{W}$ average of the daily wind outputs, i.e., $\frac{1}{7}\sum_{d=1}^{7} W_d$.

To increase the validity of my model, I have extended the data set to start from the beginning of 2002. With this data set I was able to find a statistically satisfactory model for Denmark west using both the total production and the standard deviation of weekly wind power production from Denmark west. Unlike Mauritzen, I have only used an area's own wind power production as an external regressor for the same reason as earlier. The best model was an ARIMA(1,1,0) model, which is presented in Equation 8, where v_t is volatility in week t and w_t is a wind power term for the week t. Differencing greatly increased the fit of the model, which questions the stationarity of the weekly volatility series. However, integration is justified by the zig-zag shape and the mean-reverting nature of the weekly volatility time series. The result is presented in Table 4 where $dw - wind_t$ denotes total weekly wind power output in Denmark west and $dw - wind_t - std$ the standard deviation of daily outputs.

$$v_t = v_{t-1} + \alpha_1(v_{t-1} - v_{t-2}) + \sigma_0 w_t \tag{8}$$

The coefficient for total wind power from Denmark west is 0.11. When the coefficient is interpreted as earlier, doubling of wind power in western Denmark leads to an 11% increase in the weekly volatility in Denmark west prices. In addition, the coefficient for the standard deviation of weekly wind power production from Denmark west is 0.10. Similarly, doubling of the standard deviation of production results into a 10% increase in weekly volatility. This not only tells us that wind power has increased the weekly volatility but also the long-term volatility depends on the standard deviation, i.e., intermittency of the production. As Figure 23 shows, the standard deviation of weekly production has been increasing both in Denmark east and west in 2002-2012. The trend has been stable and so strong that it cannot be caused by natural differences in weather conditions. This development is driven by the fastly increasing total wind power production as Figure 8 shows. Thefore, the producers have not been able or willing to tackle with the intermittency. The future weekly volatility could either decrease or increase depending on the actions taken to deal with the difference between low and high output peaks.

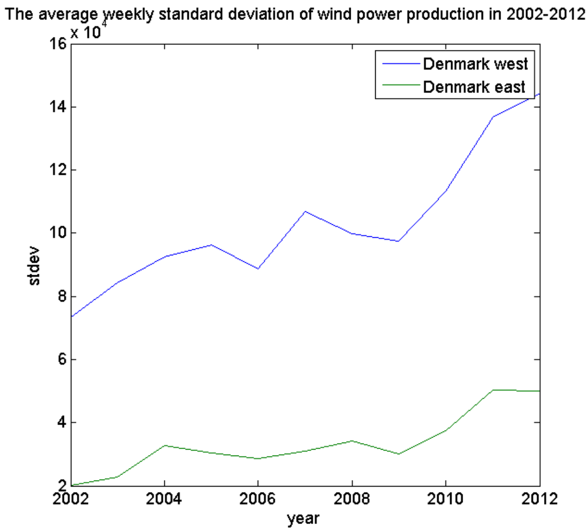


Figure 23: The development of the average standard deviation of weekly wind power output in Denmark from 2002 to 2012.

For Denmark east, I was not able to establish a satisfactory model with either of the explanatory variables ($de - wind_t$ and $de - wind_t - std$), which may reflect the fact that there is not as much wind power available in eastern Denmark as in western Denmark. Moreover, Figure 23 shows that the standard deviation of wind power production has increased but not as much as in Denmark west. Denmark east could also be exporting its wind power production to Sweden 4 to larger extent than Denmark west to Norway 3 and Sweden 3, thereby the effect on its own area prices to be ambiguous. However, both of the wind power coefficients for Denmark east are positive, and the coefficients for AR(1) terms are close to corresponding Denmark west coefficients. Therefore, increasing wind power capacity in future could show similar effect as now can be observed in Denmark west.

Despite the sensible results, neither of the models is validated by diagnostic tests. The residuals of the models do not conform to the assumptions of generalized linear model. The fit is worse but the assumptions are met to larger extent if the weekly model is a high-order AR model such as AR(4). In either case the coefficient for wind power does not change dramatically. The weekly volatility time series is likely a completely random process that cannot be modeled perfectly with ARIMA models that require structured data. Therefore, the coefficient are not reliable. In fact, quantifying the effect of wind power on weekly volatility can be an extremely hard task, and only qualitative guidelines can be given.

The positive coefficients for total weekly wind power output and the standard deviation are supported by the merit-order effect, i.e., the ascending ranking of electricity generation types by their short-run marginal costs (SRMC). Figure 25 shows how applying wind power shifts the supply curve to right. The SRMC of wind power is zero so it is among the first to be brought online. When the demand is assumed to be fairly constant, the price decreases in the case of windy conditions. The correlation between daily wind power and price levels refers to this shift in supply curve.

Table 4: The effect of the standard deviation of the weekly Denmark wind power production on weekly Denmark prices volatility. All coefficients are statistically significant at 1% level unless otherwise noted.

	DE Area	DE Area	DW Area	DW Area
$de-wind_t$	0.0521^c	NA	NA	NA
	[0.0491]	NA	NA	NA
$de-wind_t-std$	NA	0.0647^c	NA	NA
	NA	[0.0525]	NA	NA
$dw-wind_t$	NA	NA	0.1123^a	NA
	NA	NA	[0.0438]	NA
$dw-wind_t-std$	NA	NA	NA	0.1001^a
	NA	NA	NA	[0.0452]
α_1	-0.4179	-0.4216	-0.4885	-0.4916

[a] significant at 5% level

[c] not significant

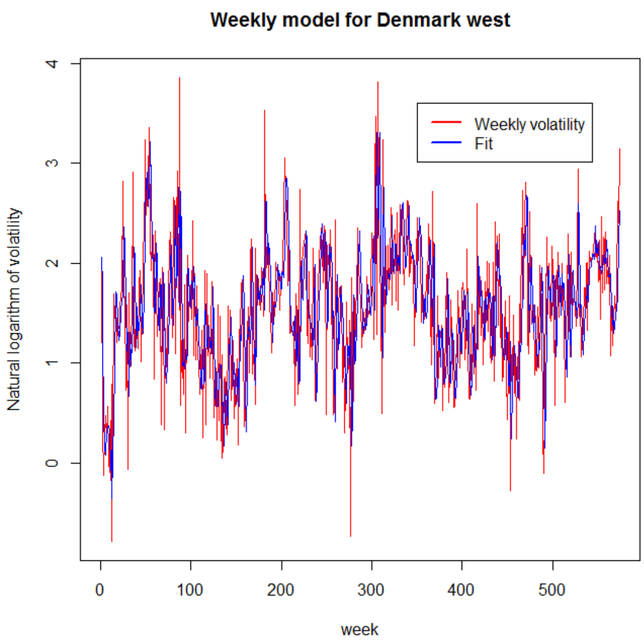


Figure 24: The fit of the weekly model for Denmark west with total wind power production as an exogenous variable

While the intraday wind power output curves in Figures 9(a) and 9(b) have rather persistent shape regardless of the total amount of wind power during the day, the long-term wind power output curve 10 is unpredictable. Having great effect on peak hours, wind power decreases the peak hour prices most as Figures 19(a) and 19(b) suggest, causing the daily volatility to decrease. However, the total daily output is purely stochastic process which leads the supply curve to oscillate horizontally. The oscillation is strengthened by more stochastic production or higher capacity, resulting into increased long-term volatility. Hence, the positive coefficients for the standard deviation and the total weekly wind power output. In a system without intermittent renewable production, the supply curves would be more invariable. In case of Denmark, there is no inexpensive hydro or nuclear production buffering the changes in wind power.

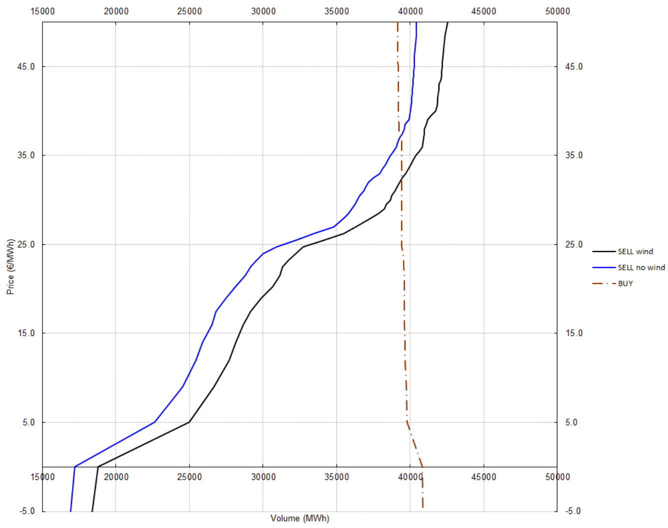


Figure 25: A hypothetical situation of two days with different wind conditions, but identical demand.

4.2 Germany

4.2.1 Intraday model

From section 3.3, Phelix prices have similar intraday and weekly pattern as the Denmark prices. In addition, the autocorrelation structure of the daily volatility is similar. The daily volatility is calculated using Equation 1. Compared to wind power, solar power has a persistent autocorrelation structure because the ratio of outputs on the cloudiest and sunniest day was approximately 25% on average. Despite this, I estimate the effects of both solar and wind power on daily Phelix price volatility using the same methodology as earlier: prices are modeled as an SARMA process along with the exogenous forecasted renewable generation term. I ran three regressions where the exogenous term is solely total solar power output, total wind power output, or the two added together. As a basis, I use the same model as I used for Danish intraday data in Equation 6. All variables are transformed into natural logarithm form so that I can give a clear interpretation to the results. Moreover, the same requirements apply. The best model is validated using Wald tests, Akaiki Information Criterion (AIC), and by looking at different properties of the model residuals such as ACF, PACF, and testing the null hypothesis of white noise.

After testing different combinations, I end up with the model in Equation 9, which is basically the same Denmark intraday model, but the term $\beta_{14}\epsilon_{t-14}$ has been dropped. The model is a combination of the SARMA(2,1,1,1) process for price volatility and AR(1) for renewable generation both of which I found appropriate in the previous sections. This modification improves the model residuals. It is no surprise that there is not much difference between the two models as the two countries have similar electricity systems and are geographically close to each other. The current and lagged terms for forecasted wind, solar and combined output are denoted with w_t and w_{t-1}, s_t and s_{t-1}, and r_t and r_{t-1} (short for RES), respectively. As the wind power production is usually a lot higher than solar power production, the combined output r_t time series behaves like wind power time series, and therefore, can be modeled as an AR(1) process, too. In the model, the AR(2) terms and the MA(1) term handle the short-term price process, and the $\text{SAR}(1)_7$ and $\text{SMA}(1)_7$ terms restrain the weekly autocorrelation of the model residuals. Intuitively, the volatility can be expressed in terms of the volatility of two previous days and previous week's value.

$$v_t = \alpha_0 + \alpha_1 v_{t-1} + \alpha_2 v_{t-2} + \alpha_7 v_{t-7} + \beta_1 \epsilon_{t-1} + \beta_7 \epsilon_{t-7} + \sigma_0 s_t + \sigma_1 s_{t-1} \tag{9}$$

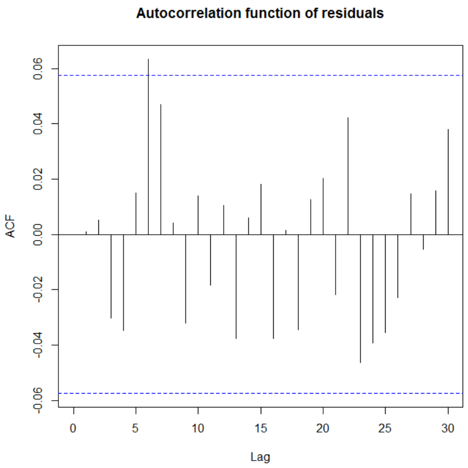
Figures 26(a), 26(b), and 26(c) show the autocorrelation function, partial autocorrelation function and the model fit, respectively, when the exogenous term is forecasted solar power output. Figures for other exogenous variables are given in the Appendices B and C because they are alike. The autocorrelation and partial autocorrelation functions remain between the 95% confidence intervals apart from the spikes near lag 7 caused by the weekly seasonality. Despite this, the residuals pass the Ljung-Box test with all of the exogenous variables. Also, the model for Denmark west passed the Ljung-Box test, and Denmark east was performing well apart from a few lags. The fit of the model shows that the model performs rather well in general, but it is not capable of dealing with the spikiness and sudden changes in volatility. This is a general drawback of regression models.

Table 5 shows the results of the regression where $de-solar_t$ and $de-solar_{t-1}$, $de-wind_t$ and $de-wind_{t-1}$, and $de-res_t$ and $de-res_{t-1}$ are the forecasted solar, wind, and combined outputs for the current and previous day. Note that all the SARMA coefficients are very close to the corresponding coefficients of the Danish model regardless of the chosen exogenous variable. Therefore, the price processes remain similar, letting each exogenous variable explain the process.

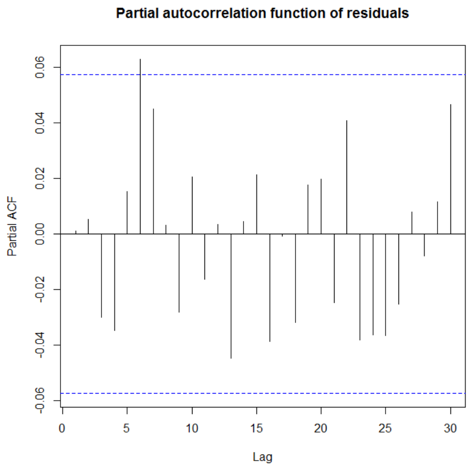
The estimated coefficient for solar output is -0.0369 which can be interpreted to mean that a doubling of the solar power output leads to a 3.7% decrease in daily volatility. This coefficient is less than half of the coefficients for wind in Denmark. The difference is explained by the differences in the systems because the total solar power produced in Germany in this period is nearly two times the total wind power produced in Denmark. Despite the large production figures, solar power generated only 5.2% of total electricity consumption in Germany in 2012 whereas wind power generated 30.3% in Denmark. Yet, most of the solar power production affects only the peak hours with the highest prices. This has a decreasing effect on daily volality. In fact, the high peak prices has been cut as the Figure 27 shows.

In addition, the coefficient for the lagged solar power is negative at -0.0287. The heavy autocorrelation of solar power indicated that the values are similar. In fact, if the lagged solar power term is dropped out, the coefficient for the current solar power decreases even further from -0.0369. With two solar power terms, that coefficient is distributed as the two values are likely to be rather close to each other. The lagged term was only added to control for the autocorrelation in the solar power time series and should not be given any economic interpretation. Recall that I am using the forecasted solar output so market players have always more recent information available than the lagged value.

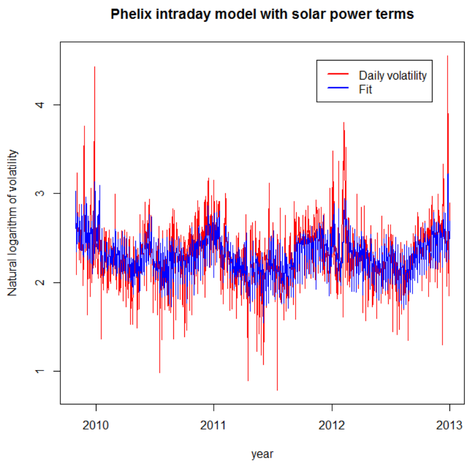
For wind power output, the estimated coefficient is 0.0426, i.e., doubling of total forecasted wind power generation increases the daily volatility by 4.3%. Also the lagged term is positive with a coefficient of 0.1030 but it should not be given an economic interpretation for the same reason as above. The result is in line with Ketterer [5] but conflicts with the results from Denmark. The wind power generation in Germany was almost five times larger in 2012 compared to Denmark, but the share of total consumption was still only 8.1%. The reason for these contradicting results could



(a) Autocorrelation function of Phelix intraday model residuals



(b) Partial autocorrelation function of Phelix intraday model residuals



(c) Phelix model vs. actual time series

Figure 26: First and second row: Autocorrelation and partial autocorrelation functions of the model residuals with 95% confidence intervals. Third row: The actual daily volatility time series and model fit.

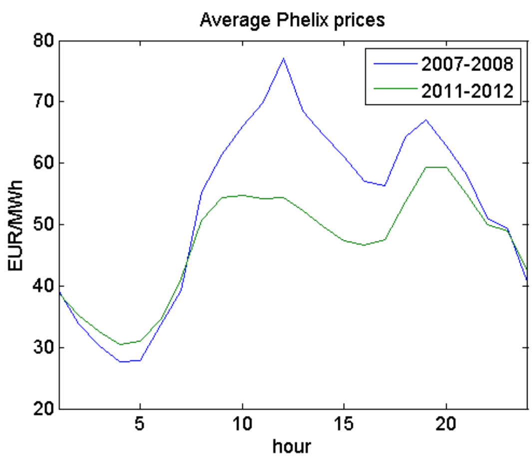


Figure 27: The development of the average Phelix prices. I have averaged two years of price data to eliminate the effect of possible outliers.

be the flatness of the German wind power curve shown in Figure 17(b). As I noted in the section where I divided the Danish data to off-peak and peak hours, excess renewable generation has highest effect on off-peak hours. Hence, high wind output in off-peak hours can crash the prices causing the volatility to increase. This hypothesis is tested for Germany in the following section to find out why wind power has positive coefficient. To start with, figure 28 shows that the largest drop in prices from 2011 to 2012 occurred when the price is near the local minima, i.e., in off-peak 1 hours and in the peak solar output hours 12-17. The average daily standard deviation increased 5.6% from 2011 to 2012 as a result of these changes although the hourly prices decreased as much as -8.5 EUR/MWh on average.

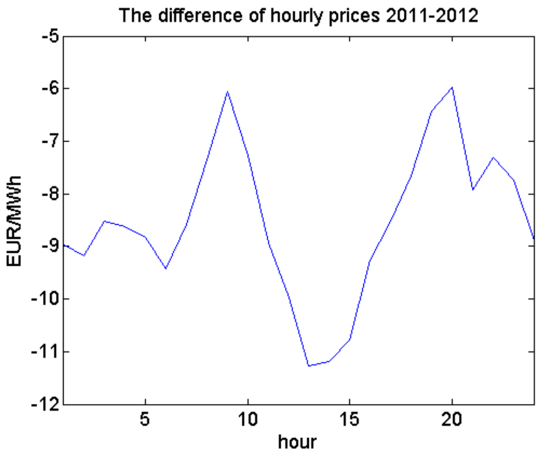


Figure 28: The difference between average hourly prices in 2011 and 2012. The prices were much lower in 2012.

The combined output is driven by wind power because the German wind power output is nearly two times larger than the solar power output. That is why also the coefficient for the combined output $de - res_t$ is positive at 0.0468. Hence, doubling the total combined output results into a 4.7% increase in daily volatility. When mere solar power decreases the daily volatility by cutting the peak prices, the combined effect of wind and solar power decreases heavily off-peak prices through excess supply and the solar power output peak prices (hours 12-17). The coefficient for combined output is a bit larger than for wind power. This could stem from the aforementioned effects on the price curve but this would again need closer studying of the different blocks.

Table 5: The effect of German solar, wind and combined output on daily Phelix price volatility. All coefficients are statistically significant at 1% level unless otherwise noted.

	Phelix (solar)	Phelix (wind)	Phelix (res)
$de - solar_t$	-0.0369	NA	NA
	[0.0135]	NA	NA
$de - solar_{t-1}$	-0.0287^a	NA	NA
	[0.0136]	NA	NA
$de - wind_t$	NA	0.0426	NA
	NA	[0.0132]	NA
$de - wind_{t-1}$	NA	0.1031	NA
	NA	[0.0133]	NA
$de - res_t$	NA	NA	0.0468^a
	NA	NA	[0.0190]
$de - res_{t-1}$	NA	NA	0.1633
	NA	NA	[0.0190]
$constant$	3.0154	0.6972^a	-0.1429^c
	[0.2466]	[0.2776]	[0.4016]
α_1	1.2198	1.1750	1.1937
α_2	-0.2543	-0.2109	-0.2167
α_7	0.9952	0.9938	0.9936
β_1	-0.8845	-0.8639	-0.8778
β_7	-0.9418	-0.9282	-0.9262

[a] significant at 5% level

[b] significant at 10% level

[c] not significant

4.2.2 Wind power and division into peak, off-peak1, and off-peak 2 hours

In the previous section, I hypothesised that the positive coefficient for German wind power is caused by the price crashing excess supply in the off-peak hours. To explore the effects of wind power on different blocks, I divide the data into peak, off-peak 1, and off-peak 2 hours. I use the same definition for these blocks as in the section for Denmark because the German intraday price curve is alike. Hence, peak hours are 08-19, off-peak 1 00-07, and off-peak 2 20-23. Moreover, I pay attention to the dip in the intraday curve in hours 13-18 in Figure 12 to assess the effect of the slight peak experienced in wind output in these hours as Figure 17(b) shows. The effect of these hours is compared to all peak hours.

I average the hourly wind power output data instead of summing up because the lengths of the blocks are different. Furthermore, the dependent variables are the average hourly prices in each block because I want to focus on the changes in price levels rather than estimating the standard deviation of the blocks. A graphical presentation of the situation with hypothetical prices is given in Figure 22. However, I run one regression with the peak hours using the standard deviation of prices, and the sum of hourly wind power production to investigate whether wind power or possibly some other factor such as solar power is causing volatility in peak hours. If there is no statistically significant effect, the volatility increasing effect of wind power observed in the previous section should be explained solely by the difference in price levels of peak and off-peak hours. No important information about wind power is lost due to the changes in the way I deal with the data because the time frame is so short that averaging or summing the wind power does not distort the data. I expect the changes to be reflected in the scaling of the parameters.

Therefore, the form of the regression model is exactly the same as in the previous section, and it is given by Equation 9 where daily volatility is changed to the average price level in each block. The price and wind power processes maintain the same autocorrelation and weekly structure regardless of the changes made. Although other specifications would be feasible too, I choose this model for consistency, and simply because it shows the best perfomance with the different exogenous variables along the line. All variables have been transformed into natural logarithm form to make the interpretation more convenient.

The results are presented in Table 6. To summarise, all prices and wind power terms ($de - wind_t - avg$) are averaged over hourly values expect for "Peak stdev" that denotes the regression where I have used the standard deviation of peak prices and the sum of hourly wind power production during these hours ($de - wind_t - sum$). Label "Dip" corresponds to hours 13-18. The conclusion is that wind power has a decreasing effect on prices in each block because the coefficients are -0.098, -0.25, and -0.11 for peak, off-peak 1, and off-peak 2 hours, respectively. For instance, the interpretation for the coefficient for peak hours is that if wind power increases 100% in peak hours, the prices come down 9.8%. The coefficients for peak and off-peak 2 hours are rather close to each other so wind power has almost an equal effect on these hours. Hourly prices in these two block are rather close to each other but wind power production is slightly higher in peak hours apart from the winter months. When these facts are taken into account, the final effect wind power has on these two blocks should be fairly equal. Hence, the price levels of the blocks should not converge at least to a significant extent.

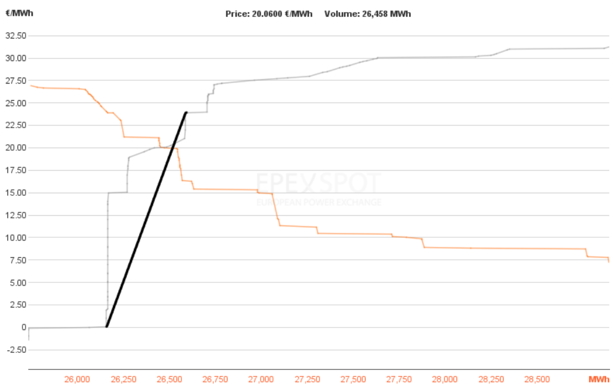
However, the coefficient for off-peak 1 hours is remarkably negative at -0.25 which is approximately 1.5 times more negative than the two other coefficients. Similar to Denmark, the most intense effect on prices is found in off-peak 1 hours but in Germany, the effect is more pronounced. Although the wind power output is lowest during the off-peak 1 hours as Figure 17(b) shows, the output curve is so flat that the difference between the highest and lowest output is not very large. Therefore, if it is windy, the greatest effect on prices is observed in off-peak 1 hours while peak and off-peak 2 hours remain at the same level. This results into a intraday price curve profile depicted in Figure 27 (line 2011-2012) where the low price level in off-peak 1 hours is followed by a sharp ascent to the peak hour level. The observed profile is caused supply and demand dynamics. There is a lot of excess wind power output in the off-peak 1 hours that crashes the prices, and cannot be exported completely to the neighbouring countries. Then, as the people get up, the demand picks up and the prices increase. Such a threshold in intraday prices increases the daily volatility compared to a electricity system without renewable generation.

The additional regression for hours 13-18 labeled "Dip" shows that wind power is partly causing the observed dip during the peak hours. The coefficient for the dip is -0.11 which is a bit more negative than the coefficient for all peak hours -0.098. Therefore, wind power should increase the volatility in peak hours through a "bumpy" price curve. The regression labeled "Peak stdev" confirms this because the coefficient for wind power is positive at 0.0343, i.e., doubling the total wind power output in peak hours increases the volatility of the peak prices by 3.4%. The corresponding coefficient for the whole day is 25% larger at 0.043 according to the regression in the previous section.

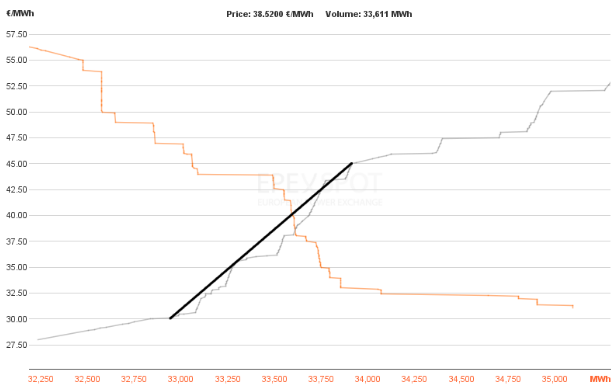
Therefore, the fact that wind power increases daily volatility in Germany is explained by the threshold behaviour, and the dip in peak hours. For Denmark, the extent of the threshold behaviour is nowhere near Germany, and the intraday price profiles do not show such a large dip. There is a clear difference in average hourly wind power curves in Germany and Denmark west as the Figures 17(b), and 9(a) show. The output curve for Germany tends to be flatter and especially off-peak 1 hours are almost on the same level as peak hours. The difference in the curves could be explained by geographical reasons: wind power production in Denmark west takes places near the coast with harsh weather conditions whereas the German wind power production is distributed more in the northern mainland. Further research on wind turbine production patterns on different sites, and on the differences in turbine types in these two countries could explain the output curves better.

Further research could also be conducted on supply curves. I do not have access to raw Phelix bid data but Epex Spot publishes aggregated Phelix bid curves. Figures 29(a), 29(b), and 29(c) show examples of these curves in one hour in off-peak 1, peak and off-peak 2, respectively. The strong effect wind power has on off-peak 1 hours implies a steep supply curve at the low end. In Figure 29(a), a parallel shift to right in the supply curve would result into a large price decrease as the average slope near the intersection is $\frac{23.75\,\text{EUR}}{433\,\text{MWh}} = 0.05484$ EUR/MWh ≈ 0.055 EUR/MWh. I do the measures using a ruler in an image processing software. The effect is usually even larger because the supply curve makes jumps. On the other hand, if the same amount of wind power is applied in hour 9 (peak) or 22 (off-peak 2), the price effect is not as great because the average slopes, $\frac{15\,\text{EUR}}{970\,\text{MWh}} \approx 0.015$ EUR/MWh and $\frac{11\,\text{EUR}}{400\,\text{MWh}} \approx 0.0275$ EUR/MWh, respectively, are low-pitched around the intersection. The assumption of the same amount of wind power is justified by the flat intraday output curve. Hence, the results of the regressions in this and the previous section seem to be in line with these slopes.

According to [31] gross electricity production from nuclear and renewable energy made 42% of total electricity consumption in Germany in 2012. The share of net production is a bit lower. Consequently, the Phelix supply curve consist of inexpensive nuclear and renewable energy at the low end. These sources do not meet the demand so they are followed by a jump to a higher price level with conventional production from coal. When also price-lowering imports from e.g. French and Nord Pool are taken into account, the intersection point falls near the jump in low-demand off-peak 1 hours. After the jump, the supply curve stays rather flat because an array of similar conventional production plants are brought online. In peak hours, the demand is so high that the intersection point is in the stable part of the curve. Only in high volumes, the slope of the supply curve increases significantly when gas turbines, for example, are brought online.



(a) Phelix aggregated bid curves in hour 5



(b) Phelix aggregated bid curves in hour 9

(c) Phelix aggregated bid curves in hour 22

Figure 29: Phelix aggregated supply (grey) and demand (orange) curves in one hour in the off-peak 1, peak and off-peak2 blocks on 5 February 2013. Thanks to the EEX policy not to offer data openly for research, the average slopes for each supply curve have been calculated using the auxiliary lines added by me. Image source: Epex spot.

Table 6: The effect of German wind output on different blocks. All coefficients are statistically significant at 1% level unless otherwise noted.

	Peak	Peak stdev	Dip	Off-peak 1	Off-peak 2
$de - wind_t - avg$	-0.0979	NA	-0.1084	-0.2468	-0.1107
	[0.0061]	NA	[0.0067]	[0.0169]	[0.0071]
$de - wind_{t-1} - avg$	0.0133^a	NA	0.0191	-0.0187^c	0.0172^a
	[0.0061]	NA	[0.0067]	[0.0169	[0.0071]
$de - wind_t - sum$	NA	0.0343^a	NA	NA	NA
	NA	[0.0161]	NA	NA	NA
$de - wind_{t-1} - sum$	NA	0.0212^c	NA	NA	NA
	NA	[0.0161]	NA	NA	NA
$constant$	4.6007	1.1008	4.6037	5.5475	4.5414
	[0.3312]	[0.2403]	[0.2903]	[0.2292]	[0.1459]
α_1	1.1480	1.1118	1.1098	-0.0629^c	1.2496
α_2	-0.1958	-0.1532	-0.1561	0.2685	-0.2704
α_7	0.9976	0.9178	0.9949	0.9862	0.9885
β_1	-0.7421	-0.8225	-0.7712	0.6085	-0.8288
β_7	-0.9248	-0.7924	-0.8992	-0.9144	-0.9515

[a] significant at 5% level
[c] not significant

4.2.3 Weekly model

Similar to Denmark west, the correlation between the difference in consecutive daily Phelix prices and the difference in consecutive daily wind power produced in Germany is rather high at -0.42. For solar power production, the same correlation is only -0.043. Therefore, the windier it is, the lower the daily price level is, but the same does not go for solar power. As earlier, my hypothesis is that the weekly volatility increases because of the intermittent nature of renewable generation power. As with the weekly model for Denmark, I run regressions with both total renewable generation and the weekly standard deviation of renewable generation given by the Equation 7. I ran three regressions with both variable types: solar power, wind power, and combined output. The idea is again that total output does not necessarily tell anything about the variation of the production levels but the weekly standard deviation captures the evident correlation between daily price and production levels better.

The results are presented in Table 7 where Phx is short for Phelix and the variables are the same as earlier. The model is again ARIMA(1,1,0) given by Equation 8. Integrating greatly improves the fit to the weekly volatility time series. Mere AR(p) or MA(q) processes do not deal with the zig-zag nature of the original time series properly.

When the exogenous variables are total productions, only the coefficient for wind power is significant at 0.1664. Hence, weekly wind power output should increase the weekly volatility. Further conclusions cannot be made for solar power and combined output. After changing the exogenous variables to weekly standard deviations, only solar power is not statistically significant. The coefficient for wind power is 0.1520 and 0.1742 for combined output. Therefore, the standard deviation of wind power and combined output has a substantial increasing effect on the weekly volatility. However, I have only three complete years of renewable generation data so it is not reliable to assess whether the standard deviation has increased. The fit of the weekly model with the standard deviation of wind power output is shown in Figure 30.

As with the Danish model, none of the models is validated by diagnostic tests although the coefficients are statistifically significant. Again, the residuals of the models do not conform to the assumptions of generalized linear model. Adding high-order AR terms improves the situation, but the results do not differ significantly so I stick to the same model for consistency. As the weekly volatility is dependent on numerous factors, an ARIMA model does not capture the randomness of the data. Therefore, the coefficient are not reliable. However, the results can be explained qualitatively.

The positive coefficients for total weekly wind power output and the standard deviation are again supported by the merit order effect. Similar to Denmark, Figure 25 shows how applying wind power shifts the supply curve to right. The correlation between daily wind power and price levels refers to the price decreasing shift in supply curve. The total daily output in Figure 16(b) is a purely stochastic process which leads the supply curve to oscillate horizontally. The oscillation is strengthened by more stochastic production or higher capacity, resulting into increased long-term volatility. Hence, the positive coefficients for the standard deviation and the total weekly wind power output. The combined output is largely driven by wind power so its coefficients are also positive.

The statistical insignificance for solar power coefficients results possibly from its relatively small share in production mix. As the autocorrelation structure of solar power suggested, the observations for solar production are similar. Thus, solar power production level is more predictable than wind power. Moreover, being prevalent only in peak hours, solar power is more predictable also timewise. Therefore, the effect of solar power on the supply curve is not as random as the effect of wind power. With the daily data, I find that solar power has negative effect on the daily volatility, and I suggest that this applies also to weekly volatility. However, more data would be needed to confirm that.

Table 7: The effect of the standard deviation of the weekly Denmark wind power production on weekly Denmark price volatility. All coefficients are statistically significant at 1% level unless otherwise noted.

	Phx (solar)	Phx (solar)	Phx (wind)	Phx (wind)	Phx (res)	Phx (res)
$de - solar_t$	-0.1835^c	NA	NA	NA	NA	NA
$de - solar_t - std$	NA	-0.0350^c	NA	NA	NA	NA
$de - wind_t$	NA	NA	0.1664^a	NA	NA	NA
$de - wind_t - std$	NA	NA	NA	0.1520^a	NA	NA
$de - res_t$	NA	NA	NA	NA	0.1708^c	NA
$de - res_t - std$	NA	NA	NA	NA	NA	0.1742
a_1	-0.4809	-0.4763	-0.4644	-0.4641	-0.4641	-0.4682

[a] significant at 5% level

[c] not significant

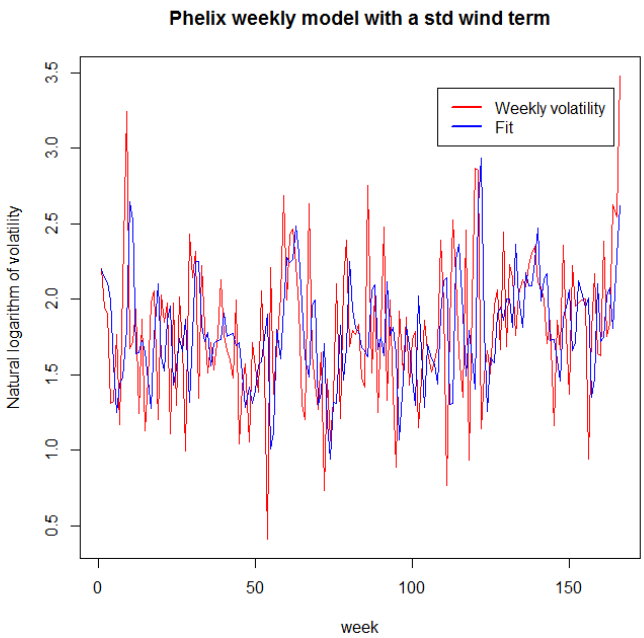


Figure 30: The fit of the weekly model for Phelix with the standard deviation of wind power production as an exogenous variable

5 Conclusions

New technology development has made it possible to utilize uncontrollable natural sources such as wind and photovoltaic effect in energy generation. However, only the objectives to improve energy efficiency, to reduce greenhouse gas emissions, and to secure energy supply in times of reducing oil reserves has turned renewable energy into a boom. The reform is made possible by the fact that general public has started to adapt to the idea of global warming and new green technologies. Hence, renewable energy generation has started to gain considerable political advocacy. Concrete examples of this development are the renewable energy policies in the EU. I have researched the cases of Germany and Denmark where renewable energy now makes up over 20% of the gross electricity production. However, these large amounts of intermittent eletricity production set challenges for the electricity market and the design of the power system. Given the ambitious renewable energy goals in the EU, it is becoming more and more important to understand the underlying reasons for these challenges.

The results I present show that wind and solar power production levels change considerably from month to month with the maximum output occurring during the peak hours. The negligible marginal costs of renewable generation cause daily price levels to decrease in Denmark and Germany as traditional fossil fuel-based generation is displaced. Both wind power generation in Denmark and solar power generation in Germany decrease also daily volatility. This is caused by output peak cutting the peak hour prices. The results for Danish wind are not only in line with Mauritzen's [10] results but also with Jónsson et al [4] who use different methodology. This confirms the robustness of the results. Moreover, the results for German solar power prove the remark of Bundesnetzagentur [8] that the price spread between peak and off-peak hours decreases when there is solar power available.

However, German wind power increases German daily price volatility. The result is in line with Ketterer [5]. When the German data are divided into peak and off-peak hours, I notice that windy conditions during the off-peak 1 hours (00-07) can cause a crash in prices. In fact, the average intraday wind output curve is so flat that there is not much difference in wind output between off-peak and peak hours. Daily volatility increases because prices in off-peak 1 hours lower too much relative to peak and off-peak 2 prices, which remain close to each other. The same effect is observed also in Denmark but it is dampened by two factors. First, the price-decreasing effect wind power has on off-peak 1 hours is not nearly as strong as in Germany. Second, wind power output in off-peak hours is much lower than in peak hours in Denmark.

For both Denmark and Germany, I find that the volatility of prices increases in longer term due to the intermittent nature of wind power. Mere German solar power does not have a statistically significant effect on weekly volatility. Because of the negligible costs, wind and solar power push the prices down effectively, but in case of bad weather conditions electricity producers need to rely on high-priced backup generation from flexible gas turbines, for example. Hence, renewable generation has a disruptive effect on otherwise more predictable supply and demand balance causing the daily price levels to do great jumps from day to day.

Moreover, I find that the standard deviation of daily wind power outputs in a week increases the weekly volatility of prices in Denmark and Germany. For Denmark, which I have more data, I note that the standard deviation of wind power output has increased while the production capacity has increased. For Germany, which I lack old historical data, I cannot not make similar conclusion but it is reasonable to assume that the standard deviation of production increases when the capacity itself increases. The increase in weekly volatility of prices can be constrained if the increase in the standard deviation of wind power output is dealt with limiting production in some hours, optimizing the placement of turbines, and designing the turbines differently, for example.

All the statistically significant coefficients for renewable energy are economically significant. For instance, German daily wind power has a 4.3% increasing effect on daily volatility of prices if the wind power output increases by 100%. Such increases in daily output are not rare due to the unstable nature of wind power generation. Renewable electricity production has transformed from a small phenomenon to a real market maker that needs to be taken into account in day-ahead eletricity trading and, above all, when industry makes decisions based on the electricity price development.

Given the EU energy policies, the renewable capacity continues to increase in Germany and Denmark, and in all other countries belonging to Nord Pool and EEX. By 2020, Denmark is estimated to have a 51.9% share of renewable energy of total energy consumption compared to the current share of around 38%. For Germany, the same figure is 36.6% while the current is just over 20%. The price impacts I have presented depend on the total amount of production and the variations in it. Hence, the impacts become more stronger unless the production mix or market design changes. It is not straight-forward to make similar conclusions for Sweden and Finland, for example, because they have hydro power that can buffer the intermittency of renewable generation.

Lower electricity prices do not encourage new investments in electricity generation. In addition, higher price volatility in longer term introduces uncertainty which increases risk. It is important to notice that renewable generation decreases prices so the upside risk is very limited. Concurrent increases in renewable capacity in geographically close EEX and Nord Pool countries may lead to temporary over-supply situations where cheap power is trapped. Although backup generation is becoming more and more important to secure supply, low utilisation rates and high fuel costs may make investing unprofitable. The situation is also increasing the costs of utility companies as conventional capacity needs to be adapted to the new environment through updating to more flexible electric boilers, for example. Especially the low first off-peak hour prices can decrease the profitability of conventional plants that have high start-up costs. When all these are taken into account, the headline of the UBS investment report "Renewables to wipe out 50% of profits" does not sound so striking anymore.

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A All coefficients of the Danish intraday model when data are divided into peak, off-peak 1 and off-peak 2 hours.

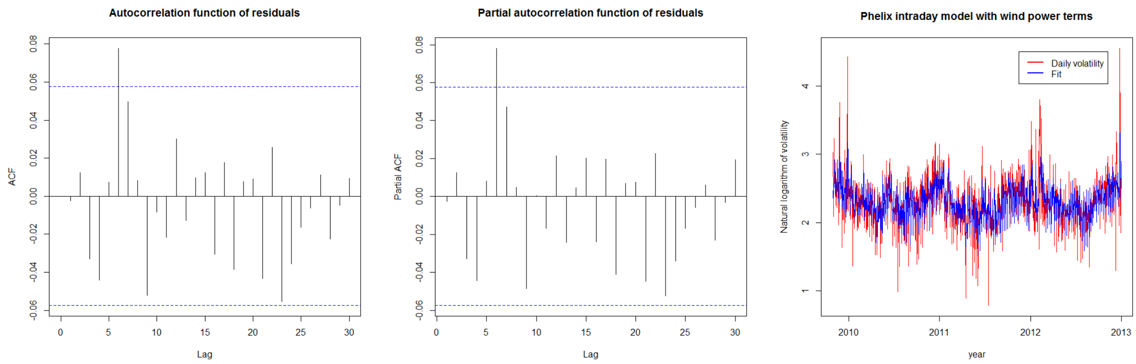
Table 8: The effect of Danish wind power production on intraday Danish area prices in different blocks. All coefficients are statistically significant at 1% level unless otherwise noted.

	Peak east	Off-peak 1 east	Off-peak 2 east	Peak west	Off-peak 1 west	Off-peak 2 west
$de - wind_t$	-0.0413	-0.0557	-0.0287	NA	NA	NA
	[0.0034]	[0.0048]	[0.0021]	NA	NA	NA
$de - wind_{t-1}$	0.0006^c	-0.0131	-0.0035^c	NA	NA	NA
	[0.0034]	[0.0048]	[0.0021]	NA	NA	NA
$dw - wind_t$	NA	NA	NA	-0.0681	-0.1112	-0.0597
	NA	NA	NA	[0.0035]	[0.0074]	[0.0036]
$dw - wind_{t-1}$	NA	NA	NA	-0.0066^b	-0.0202	-0.0046^c
	NA	NA	NA	[0.0035]	[0.0074]	[0.0036]
constant	4.0666	3.8145	3.8649	4.2672	4.2054	4.0768
α_1	1.3605	1.2551	1.1176	1.2547	1.2184	1.0935
α_2	-0.3687	-0.2744	-0.1292	-0.2694	-0.2389	-0.1049
α_7	1.0000	0.9984	0.9995	0.9986	0.9987	0.9988
β_1	-0.8606	-0.8132	-0.6879	-0.8333	-0.8575	-0.7871
β_7	-0.8875	-0.8807	-1.0099	-0.8796	-0.8730	-0.9842
β_{14}	-0.1078	-0.1011	0.0178^c	-0.0762	-0.1038	-0.0046^c

^{b} significant at 10% level

^{c} not different from zero

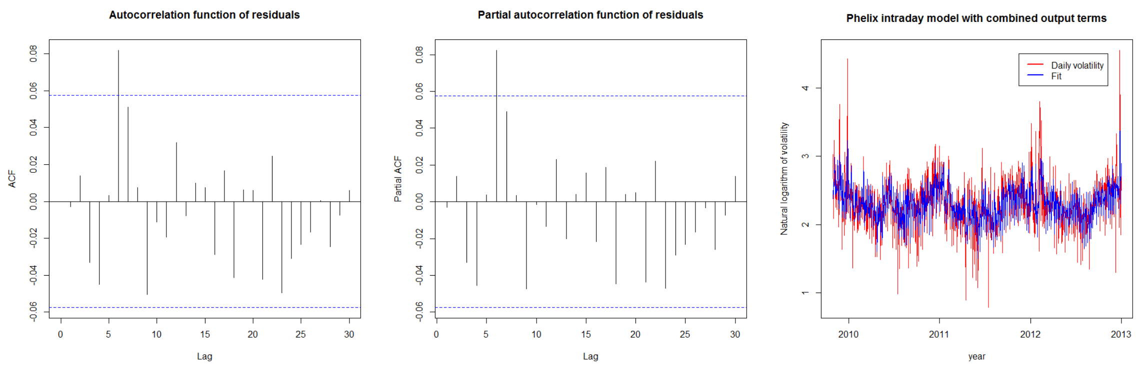
B Diagnostic figures of the German intraday model when the exogenous variable is wind power



(a) Autocorrelation function of Phelix intraday model residuals (b) Partial autocorrelation function of Phelix intraday model residuals (c) Phelix model vs. actual time series

Figure 31: First and second row: Autocorrelation and partial autocorrelation functions of the model residuals with 95% confidence intervals. Third row: The actual daily volatility time series and model fit.

C Diagnostic figures of the German intraday model when the exogenous variable is combined output



(a) Autocorrelation function of Phelix intraday model residuals (b) Partial autocorrelation function of Phelix intraday model residuals (c) Phelix model vs. actual time series

Figure 32: First and second row: Autocorrelation and partial autocorrelation functions of the model residuals with 95% confidence intervals. Third row: The actual daily volatility time series and model fit.