Does renewable energy generation decrease the volatility of electricity prices? A comparative analysis of Denmark and Germany

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February 24, 2014

Abstract

Although renewable energy technologies with zero marginal costs decrease electricity prices, the literature is inconclusive on the impact of the resulting shift in the supply curves on price volatility. Because the risk exposure of conventional generators depends on price volatility, there is a need to understand how this volatility is affected by the penetration of renewables. In this paper, we build distributed lag models with Danish and German data to estimate the impact of renewable energy generation on electricity price volatility. We find that wind power decreases the volatility of daily prices in Denmark due to a flattening of the intraday price profile, but increases the volatility in Germany because of a relatively stronger impact on off-peak prices. Meanwhile, solar power decreases price volatility in Germany. By contrast, the weekly volatility of prices increases in both areas due to the intermittency of renewables.

Keywords: Electricity price volatility, time-series model, wind power, solar power, Nord Pool, EEX

JEL Codes: Q42; C53

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This research has been supported by funding from the STEEM project of the Aalto Energy Efficiency programme.

1 Introduction

On 26 May 2012, Germany set a record by meeting nearly half of its midday electricity demand with solar power [1]. In Denmark, wind power accounted for over 30% of total electricity consumption in 2012 [2]. In Europe but globally as well, the adoption of renewable electricity generation technologies is progressing rapidly as indicated by the average year-on-year investment growth rate of 28% since 2004 [3]. At the same time, the efficiency of renewable energy technologies is improving, and manufacturers are achieving economies of scale that are driving component prices down.

The growing adoption of renewable energy is also a consequence of energy policy, i.e., governments are subsidising investment in renewable energy such as wind and solar power by offering fixed feed-in tariffs for producers, for example. Because of their weather-driven nature and zero short-run marginal costs, large-scale installations of wind and solar power have increasing impacts on both the level and volatility of the market-clearing prices. Indeed, conventional wisdom is that the greater penetration of renewables in Germany is affecting power companies. As a symptom of gloomy market prospects in Continental Europe, Swedish power company Vattenfall announced a $4.6 billion writedown in July 2013 [4].

In this paper, we assess empirically the impact of renewable energy in Denmark and Germany on electricity price volatility. The methodology of this paper is largely based on Mauritzen [5], who models the variation of daily prices as a seasonal autoregressive moving average model (SARMA) in which wind power production is an exogenous regressor. He finds that Danish wind power decreases the daily volatility of the area prices in Denmark. The benefits of this methodology are that its results are straightforward to interpret and that one-day ahead forecasts for electricity prices can be developed based on the data from previous days and information on regular consumption patterns. However, less attention has been paid to exploring possible explanations for the changes in volatility. To investigate these, we divide the data set into peak and off-peak hours and run regressions for each data set separately. This allows us to analyse changes in volatility by relating them to supply curve elasticities and to the patterns of wind and solar power production.

This paper is organised as follows. In Section 2, we review the literature on impacts of renewables on electricity markets. In Section 3, we first analyse time series of Danish area price and wind power data and, then, examine German price and wind and solar power data. Section 4 presents the model for the effects of renewable generation on daily and weekly volatility. Finally, in Section 5, we provide conclusions and discuss directions for future research.

2 Literature review

Estimates about the effect of wind power production on price levels have been reported in many references. The common conclusion is that wind power production decreases prices. Holttinen et al. [6] use the Multi-area Power Market Simulator model, EMPS, in which wind power production is modelled as a must-run supply that decreases spot prices due to zero marginal costs. However, the weekly resolution in EMPS does not capture the intermittent nature of wind power.

Jónsson et al. [7] use hourly data and a non-parametric regression model to provide more detailed results about price levels as well as the distribution of the prices at different wind power levels. They employ day-ahead Danish wind power forecast data that are used when market players place their bids. They model Danish day-ahead area prices as a function of wind power penetration, i.e., the ratio of wind power and demand forecast, and delivery hour. They conclude that higher wind power penetration in the day-ahead market decreases prices and volatility substantially.

In the same time-series framework as in [5], Mauritzen investigates how wind power affects the cross-border transmission of electricity between Denmark and Norway [8]. His conclusion is that when more wind power is produced in Denmark, exports to Norway are higher while Norwegian hydropower plants produce less. When wind power production decreases in Denmark, Norway produces more hydropower and Denmark buys back the wind energy it exported. This supports the suggestion of Green and Vasilakos [9], who state that the large hydropower capacity in Norway, Sweden, and Finland acts effectively as storage for high wind power capacity in Denmark.

In Germany, only recently have there been studies on the effects of growing wind and solar power capacity on electricity prices. Ketterer [10] models the influence of intermittent wind power production on the level and volatility of the electricity prices in Germany by using a generalised autoregressive conditional heteroskedasticity (GARCH) model with logarithmic prices. GARCH models are particularly suitable for the analysis of volatility [11]. Because power markets exhibit a high degree of volatility and volatility clustering [12], GARCH models can also be used to analyse electricity prices. Ketterer finds that higher wind power production decreases the German price level but leads to higher daily volatility. However, she notes that since the regulatory change in 2010, which forced the German transmission operators to publish day-ahead forecasts for renewable generation in their area, the volatility-increasing effect of wind power has decreased, but the effect still remains. Therefore, Ketterer's results are not aligned with those of Jónsson et al. [7] and Mauritzen [5] on the effect of wind power on price volatility.

Würzburg et al. [13] model daily electricity prices in Germany from 2010 to 2012 with a time-series model in which the independent variables are demand, renewable generation, gas price, total export or import, and dummies for weekdays. They find that a 1 GWh increase in total forecasted renewable generation results in a €1/MWh decrease in electricity prices. When they partition renewable generation into wind and solar power components, the price-decreasing effect from both is equal at €1/MWh for each additional 1 GWh of expected generation. They note that the result is counterintuitive as solar power is expected to have a greater impact because it is mainly produced during peak hours. In turn, Weigt [14] utilises realistic data on German conventional plants and develops an optimisation model, which minimises production and start-up costs in Germany while meeting demand and capacity constraints. If wind power is included in the optimisation, then the average price level decreases by over €10/MWh in 2006 and 2007.

Mulder and Scholtens [15] explore the effect of Dutch renewable production on daily Dutch electricity prices from 2006 to 2011. They use a time-series model in which electricity prices are explained by economic and climate factors. The economic factors include, among others, tightness in the market, defined as the demand excluding decentralised generation that is produced close to where it used. Climate factors include wind speeds and the intensities of sunshine in the Netherlands and Germany. Although the share of renewable generation has increased in the recent years, Mulder and Scholtens conclude that it is still so small that renewable generation does not affect Dutch electricity prices. However, they find a weak negative impact on Dutch prices from German wind speed.

Gelabert et al. [16] study the impacts of renewable generation on daily Spanish electricity prices from 2005 to 2010 with a time-series model in which total demand and renewable generation are treated as independent variables. They find that a 1 GWh marginal increase in renewable generation decreased average Spanish electricity prices in 2005 by €3.8/MWh. Although the share of renewables has increased, prices have declined less since 2005, and in 2010 the decrease was only €1.7/MWh. According to Gelabert et al. [16], the explanation for this development is that in Spain, coal plants have recently been replaced by gas plants that are usually setting the price. Furthermore, the increase in renewable generation has discouraged investment in other types of capacity, and some companies exert market power to counter the price-decreasing effect of renewables.

Outside Europe, Woo et al. [17] study the impact of wind power on 15-minute price levels and variance in Texas using a time-series model that includes generation from wind and nuclear, the natural gas price, and demand as exogenous variables. They find that a 1 GWh increase in wind power production decreases electricity prices by $3-$15/MWh in different zones of Texas. Moreover, they forecast electricity prices in Texas with 10% higher installed wind power capacity. They conclude that the variance of electricity prices increases by less than 1% in non-West zones of Texas and by about 5% in West Texas where most of the wind power capacity is situated.

The impacts that renewable electricity generation has on price levels and volatility influence investment decisions. Baringo and Conejo [18] build a mathematical program with equilibrium constraints (MPEC) to determine optimal strategies for investment in wind power for different scenarios of demand and wind power production. They do not consider subsidies for the investor, and all investment costs are recovered from electricity sales. They note that in some scenarios it is not optimal to build all available wind power capacity because electricity prices would fall so much that the profit of the investor would decrease. In [19], Baringo and Conejo use a similar MPEC framework to model a central planner that simultaneously invests in wind power and reinforces transmission lines in an illustrative network with discrete scenarios of demand and wind power production at various levels of subsidies for wind power. They conclude that, in their market model, subsidies are required to promote investments in wind power, and investments in wind power are conditioned by the reinforcements of the transmission network. Pahle et al. [20], too, use an equilibrium approach to study the German electricity market by building a numerical Nash-Cournot model that helps strategic investment decisions of power companies faced with intermittent wind power production and a broad range of exogenous CO_2 prices. Wind power is not subsidised, which allows them to conclude a CO_2 price of at least €128/ton is required before investments in wind power become more profitable than coal or gas condensing plants.

Green and Vasilakos [21] estimate the impact of intermittent wind power generation on hourly equilibrium prices and volumes with data on expected wind power production and demand in Great Britain in 2020. They employ a supply-function equilibrium model in which market players submit their offers consisting of quantities and prices to the electricity exchange. Each player maximises its hourly profit given demand and the supply functions of other players. Both in competitive and duopolistic markets, they find that the volatility of prices is higher when there is more variability in wind power production. They also note that the volatility increases if market power is exercised.

In this paper, we investigate more closely some of the hypotheses from Ketterer [10], Jónsson et al. [7], and Mauritzen [5]. Specifically, we explain the difference in the results for Denmark and Germany by dividing the data set into peak and off-peak hours. Our approach also contributes to the literature that estimates the impact of renewable generation on electricity price levels ([13], [15], and [16], for example) by providing insights on how the price-decreasing impact is distributed during the day. Moreover, we extend the analysis to address the impacts of solar power. Following Mauritzen [5], we apply the methodology at the weekly level to analyse the impact of intermittent renewable energy in the long run. However, instead of using the level of wind power production similar to Mauritzen [5], we take the intermittency of wind power into account by using the standard deviation of wind power production. Specifically, we hypothesise that renewable generation decreases daily volatility but increases volatility at the weekly level in both countries. The hypothesis for daily volatility is motivated by the recognition that renewable generation cuts peak-hour prices, whereas that for weekly volatility by the day-to-day variability of wind and solar energy production.

3 Data and methodology

3.1 Summary statistics

Our data consist of hourly Danish area prices (in €/MWh), realised hourly wind power production (MWh/h) for the two Danish areas (Western Denmark, DK1 and Eastern Denmark, DK2), hourly German (Phelix) prices (in €/MWh), and hourly forecasts for wind and solar power production in Germany (MWh/h). In both areas, there has been a significant amount of renewable production for several years [22]. For Denmark, the dataset spans from 1 January 2007 to 31 December 2013 (2557 daily observations) and for Germany from 30 October 2009 to 31 December 2013 (1524 daily observations).

Because prices are calculated by the exchanges, there are no measurement uncertainties or gaps. Ideally, one should use wind and solar power forecasts for modelling instead of realised values because only forecasts are available for the players when submitting bids to the day-ahead market. For Germany, there were enough earlier forecasts available at EEX Transparency Platform [23], but for Denmark we employed realised values because old forecasts from Nord Pool [24] can be obtained starting from only 2011. Forecasts also remain unchanged, whereas the actual production figures have small errors due to imperfect measurement equipment, and, consequently, they are updated retroactively. Therefore, using realised Danish wind power data instead of forecasts introduces some error into the regressions. However, we assume that this error is random and absorbed by the residuals, in which case the estimated coefficients will have no systematic biases.

To estimate the effect of wind power production on price volatility, we use a distributed lag model with an exogenous regressor as in Equation 1

$$v_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i v_{t-i} + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i} + \sum_{i=1}^{r} \sigma_i w_{t-i}, \tag{1}$$

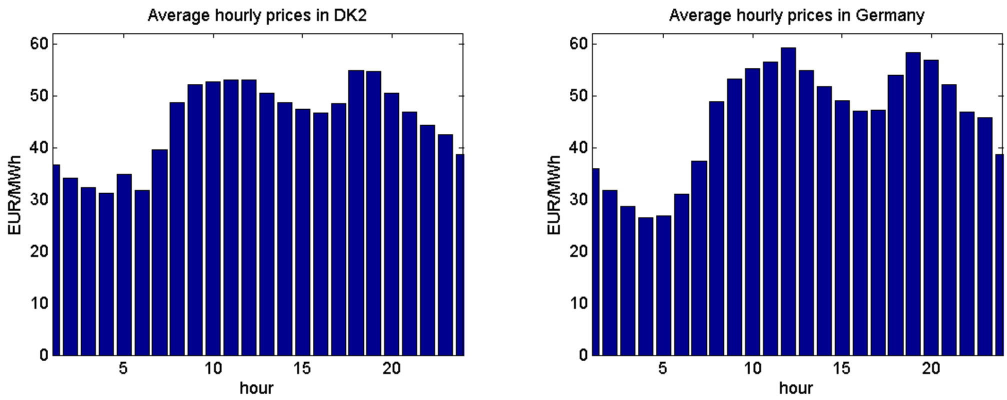
where v_t denotes the logarithm of a measure of volatility and w_t the logarithm of the exogenous wind power production term defined as the sum of the reported hourly production. There are p autoregressive (AR) terms v_{t-i}, q moving average (MA) terms ε_{t-i}, and r external regressors w_{t-i} with the coefficients α_i, β_i, and σ_i, respectively. Because wind and solar power is bid at zero or negative price to the day-ahead market, we can assume that all wind and solar power bids are accepted and affect prices directly through a parallel shift in the supply curve. All variables are transformed into natural logarithm form, and, thus, the coefficients can be interpreted as elasticities. This assumption of constant elasticity between wind power and prices is more reasonable than assuming that changes in wind power production lead to equal changes in prices at different production levels.

Our measure of volatility is the standard deviation calculated from hourly prices in Equation 2.

$$\begin{aligned} &v_t = \ln(V_D) \text{ , where} \\ &V_D = \sqrt{\frac{1}{24}\sum_{h=1}^{24}(P_h - \bar{P})^2} \text{ , and} \end{aligned} \tag{2}$$

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

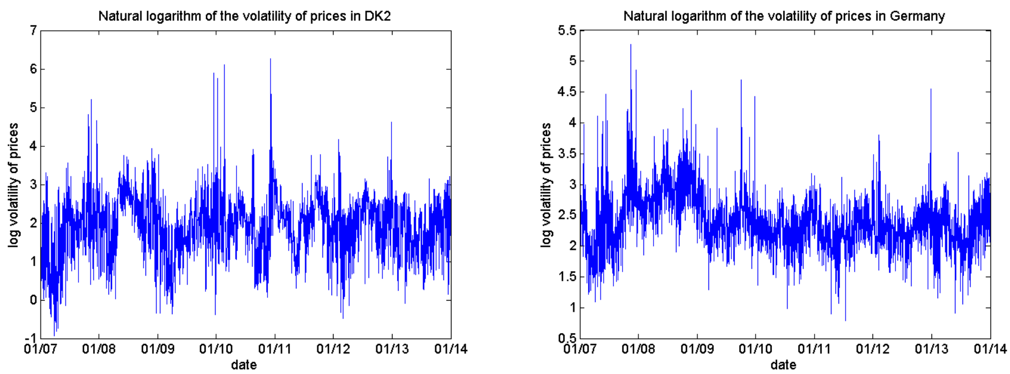
Figures 1(a) and 1(b) show the average intraday price profile for Denmark East (DK2) and Germany, respectively, resulting from demand patterns. During morning and evening high-load



(a) Denmark East

(b) Germany

Figure 1: Average electricity price for Denmark East (DK2) and Germany from 2007 to 2013.



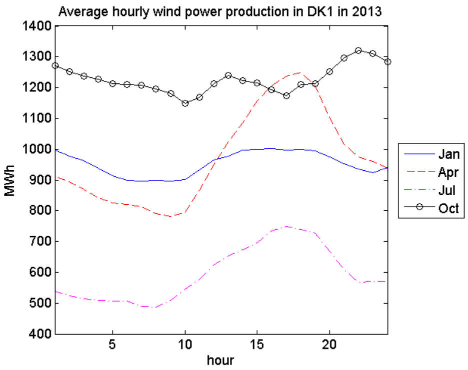
(a) Denmark East

(b) Germany

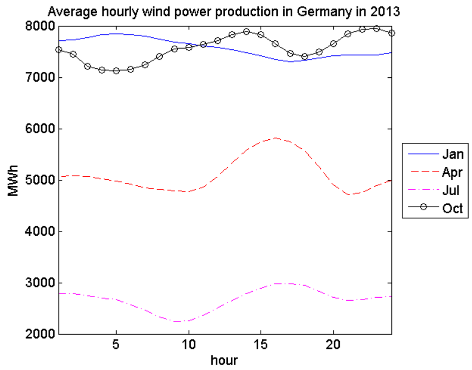
Figure 2: The natural logarithm of daily price volatility of Denmark East (DK2) and German prices from 2007 to 2013.

hours, the price is usually driven by thermal plants with higher marginal costs of production. In low-load times, such as night time, prices are set by thermal plants lower in the merit order.

Figures 2(a) and 2(b) show how the daily volatility of DK2 and German prices has developed from 2007 to 2013, respectively. There is no clear increasing or decreasing trend in the price volatility of the areas, but generally the volatility of DK2 prices is lower than that of Germany. Because condensing plants set German prices in most cases, German price volatility is more stable than that of DK2, which is affected by the cyclical changes in hydro reservoirs in the Nordic region.



(a) Denmark West



(b) Germany

Figure 3: Average hourly wind output in Western Denmark (DK1) and Germany in selected months in 2013.

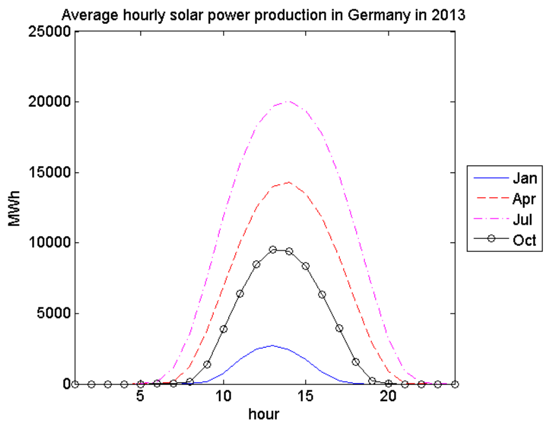


Figure 4: The intraday profile of German solar power in 2013

Figures 3(a) and 3(b) show that on average peak hours from 10 AM to 8 PM are windier than off-peak hours. As a result, there is more must-run supply during peak hours than in off-peak hours. In Denmark, this effect is more pronounced than in Germany, and we hypothesise that this effect is caused by the larger number of wind power turbines on the coast with higher wind speeds. In turn, solar power production in Germany shows a more predictable pattern (Figure 4). However, the profile of solar power production is similar in each month with production only from 6 AM to 8 PM, indicating that solar power is produced only during peak hours.

As an example of longer time windows, we consider weekly price volatility, defined as the standard deviation of daily prices as shown in Equation 3.

$$V_W = \sqrt{\frac{1}{7}\sum_{d=1}^{7}(P_d - \bar{P})^2} \text{ , where} \tag{3}$$

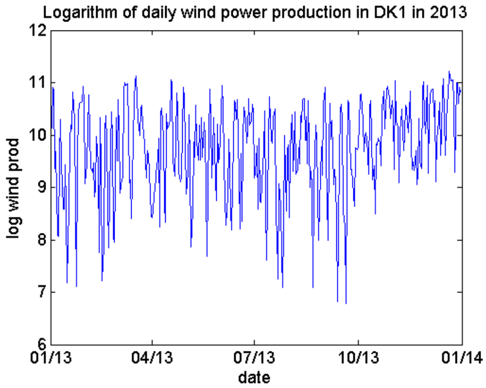
V_W is weekly volatility, P_d price on day d $\frac{1}{24}\sum_{h=1}^{24} P_h$, and

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

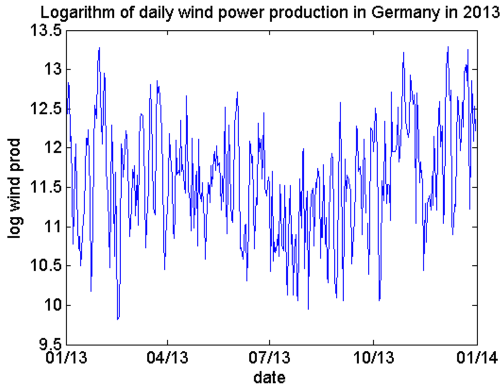
Thus, we have 366 observations for Denmark and 219 for Germany. Also, wind and solar power terms for the weekly model are defined as the standard deviation of daily production in contrast to the daily model where hourly productions are summed up. The reason for the difference is that at the daily level, we explore the impact of high wind or solar power production on the intraday price profile, but at the weekly level, we examine whether or not the variability of wind or solar production levels causes volatility in daily prices during a week. The change is made because it is possible to have approximately the same amount of wind or solar power produced during a week with a stable or fluctuating production profile.

3.2 Stability checks

The variability and lack of patterns of Danish and German wind power are apparent in Figures 5(a) and 5(b), which plot the natural logarithm of daily wind power output in 2012. On the other hand, Figure 6 shows that the production of solar power fluctuates less than that of wind power on a day-to-day basis even though the daily time series is still very volatile. For the model in Equation 1 to be valid, price volatility as well as wind and solar power time series need to be stationary. A visual inspection of Figures 2(a), 2(b), 5(a), 5(b), and 6 suggests that these time series are stationary. We confirm the stationarity of the time series by applying the augmented Dickey-Fuller test [25] with lag orders from 1 to 15 for daily data and 1 to 5 for weekly data. All daily time series pass the test at the 5% level except for the solar power time series, which fails from lag order 10 onwards. From weekly data, German price and solar power data are not stationary from lag order 3 onwards at the 5% confidence level. Moreover, wind and solar



(a) Denmark West



(b) Germany

Figure 5: Natural logarithm of daily wind output in Western Denmark (DK1) and Germany in 2013

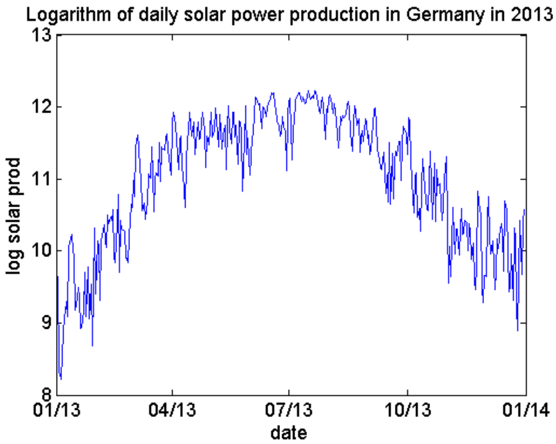
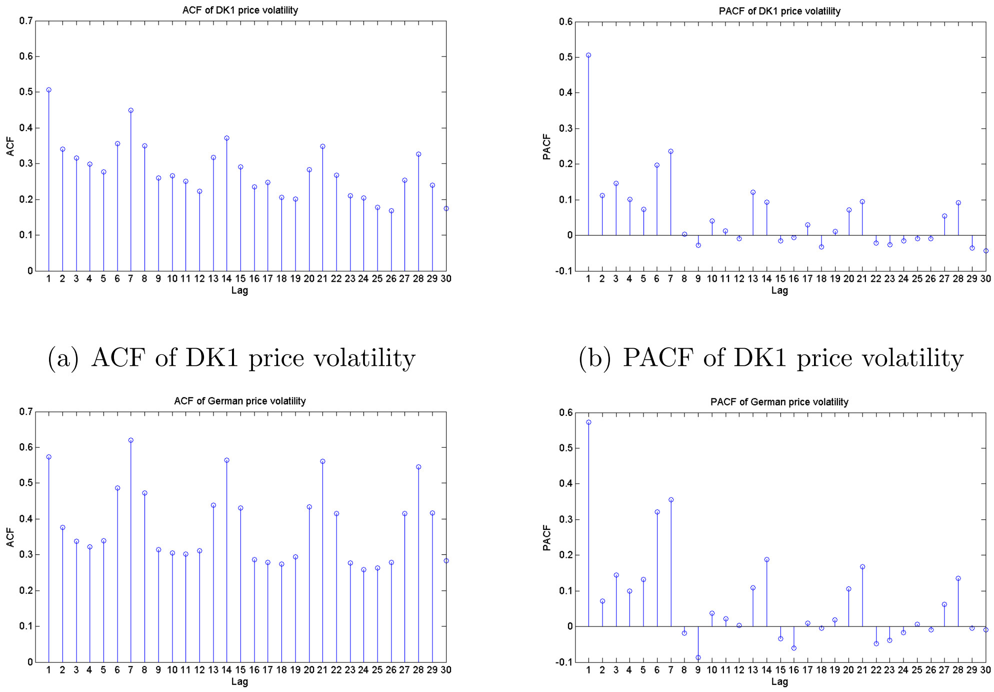


Figure 6: Natural logarithm of German solar power in 2013

power production do not depend on price volatility because the negligible short-run marginal costs of wind and solar power give no incentives for the producers to hold back production.

We use autocorrelation (ACF) and partial autocorrelation functions (PACF) of price volatility, wind, and solar power time series to specify the model. First, the ACF and PACF of daily price volatility time series from DK1 in Figures 7(a) and 7(b), respectively, and from Germany in Figures 7(c) and 7(d) have high peaks at the first lag and then near multiples of seven indicating the weekly pattern in demand. Second, the ACF of daily wind power time series has high peaks at the first few lags as shown in Figures 8(a) and 8(b) for DK1 and Germany, respec-



(a) ACF of DK1 price volatility

(b) PACF of DK1 price volatility

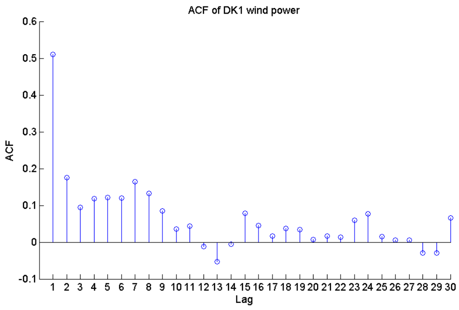
(c) ACF of German price volatility

(d) PACF of German price volatility

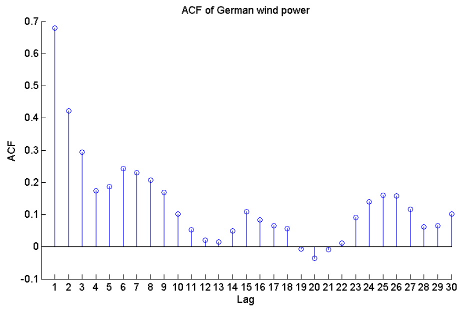
Figure 7: ACF and PACF plots of DK1 and German daily price volatility. The ACF and PACF plots for DK2 are highly similar to DK1.

tively. This suggests that an AR(1) or AR(2) representation is sufficient for wind power. As the ACF of daily solar power time series in Figure 8(c) is flat with every lag due to the smaller day-to-day variability visible in Figure 6, the best ARMA process is determined by starting from the simplest AR(1) representation and by increasing the AR and MA terms iteratively. The same method is used for weekly data because the ACF and PACF plots do not give explicit indications of the appropriate model structure.

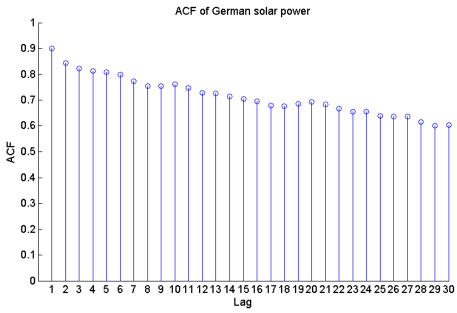
The final model candidates are evaluated by requiring that all coefficients are statistically significant at the 1% level. To compare the candidates, we assess the Akaiki Information Criterion (AIC) and examine the Q-Q, ACF, and PACF plots of the residuals of the models. Because of the large number of observations, we can expect to obtain unbiased estimators and residuals with little serial correlation. Finally, if the parameters of two models were close to each other, then a more parsimonious model would be preferred.



(a) ACF of DK1 wind power



(b) ACF of German wind power



(c) ACF of German solar power

Figure 8: ACF plots of DK1 and German renewable production. The ACF plot for DK2 is highly similar to DK1.

4 Results

4.1 Daily volatility

We run separate regressions using specifications from Section 3.2 for both Danish areas, DK1 and DK2, to estimate the impact of daily wind power production on the corresponding area price volatility. For Denmark, we obtain the following SARMA(2,1)(1,1) model with exogenous terms for total daily wind power production data.

$$v_t = \alpha_0 + \alpha_1 v_{t-1} + \alpha_2 v_{t-2} + \alpha_7 v_{t-7} + \beta_1 \varepsilon_{t-1} + \beta_7 \varepsilon_{t-7} + \sigma_1 w_t + \sigma_2 w_{t-1} \tag{4}$$

The AR(1) and AR(2) terms account for short-term price development, and the AR(7) term deals with the weekly seasonality in the data. Adding MA(1) and MA(7) terms provides stochastic parts to the price development and increase the fit of the model. The estimated coefficients α_i and β_i are given in Table 1 where all coefficients are statistically significant at the 1% level unless otherwise noted. Furthermore, the regressions include a constant labelled α_0 as well as a contemporaneous and a one-day lagged term for wind power. The wind power terms are labelled as w_t and w_{t-1} in Equation 4 and their estimated coefficients are σ_1 and σ_2, respectively. Using a one-day lagged term for the exogenous variable accounts for the autocorrelation in the wind power production data and decreases serial correlation in the model residuals.

In Table 1, an interesting finding is that the contemporaneous terms σ_1 for DK1 at -0.0784 and for DK2 at -0.0766 are statistically significantly different from zero at the 1% level. For both areas, the interpretation is that doubling the amount of daily wind power production leads to about an 8% decrease in the standard deviation of hourly prices. The effect is slightly stronger in DK1 than DK2, which is most likely caused by the combination of higher wind power production and lower consumption in DK1 area.

Mauritzen [5] runs similar regressions with a more complicated SARMA(2,2)(1,2) model. Our result for DK1 is in line with Mauritzen, although he finds that the effect is stronger at

−10%. However, his estimate for the coefficient for DK2 is not statistically significant. The most probable explanation for the differences is that his data spans 2002 to 2007, whereas our dataset has more recent data.

The contemporaneous terms σ_1 for DK1 and DK2 are robust in that minor changes in the model specification affect estimated coefficients only slightly. The lagged terms σ_2 are also statistically significant and robust to specification. However, they do not have immediate economic interpretation because wind power fluctuates considerably from day to day, and the market players have more recent wind forecasts available for the following day.

	DK1	DK2
σ_1	-0.0784	-0.0766
	[0.0126]	[0.0117]
σ_2	0.0563	0.0583
	[0.0123]	[0.0115]
α_0	2.1779	2.2381
α_1	1.2197	1.3039
α_2	-0.2349	-0.3211
α_7	0.9992	0.9996
β_1	-0.8830	-0.8743
β_7	-0.9828	-0.9842
AIC	4128.72	4582.23

Table 1: The effect of Danish wind power production on daily Danish area price volatility. All coefficients are statistically significant at the 1% level. We have reported standard errors in brackets below the exogenous coefficients.

For Germany, we run separate regressions, in which the external regressor affecting price volatility is either the total wind power production, the total solar power production, or the combined wind and solar power in Germany. Compared to the model for Danish areas in

Equation 4, adding an AR(14) term improves the fit. Thus, we have

$$v_t = \alpha_0 + \alpha_1 v_{t-1} + \alpha_2 v_{t-2} + \alpha_7 v_{t-7} + \alpha_{14} v_{t-14} + \beta_1 \varepsilon_{t-1} + \beta_7 \varepsilon_{t-7} + \sigma_1 w_t + \sigma_2 w_{t-1} \tag{5}$$

Table 2 shows that the contemporaneous term, σ_1, for German wind power is positive at 0.0319 - contrary to the negative coefficient estimated for Danish areas. The coefficient for wind power suggests that doubling the daily wind power production increases the hourly volatility of German prices by 3%. Although the direction of the impact is different from the Danish result, it is in line with Ketterer [10] whose GARCH model suggests that wind power increases the daily volatility of German prices.

However, the coefficient σ_1 for daily solar power is negative at -0.0425. The coefficient can be interpreted so that doubling daily solar power production decreases the volatility of hourly German prices by 4%. The absolute value of the coefficient is close to that for wind power, but the opposite sign indicates that the impact is different.

When German wind and solar power time series are aggregated, the effect measured by the coefficient σ_1 is positive at 0.0353. Following the same interpretation, doubling the daily combined output contributes to German price volatility by 4%. The combined output is mostly driven by wind power because in our dataset the average daily wind power output was 224% higher than the average daily solar power output. Consequently, the coefficient for combined output is closer to the coefficient of wind power. However, in the regression with combined output, the constant α_0 is lower than the constant in the regression with only wind power; it is not statistically significant, which may have increased the estimate for the coefficient σ_1 upwards. Also, these regressions include lagged terms for wind, solar, and combined output. As for Denmark, these terms do not have any economic interpretation. For regressions with realised production figures instead of forecasts, the results are quite similar, thereby indicating that the results for Denmark are robust.

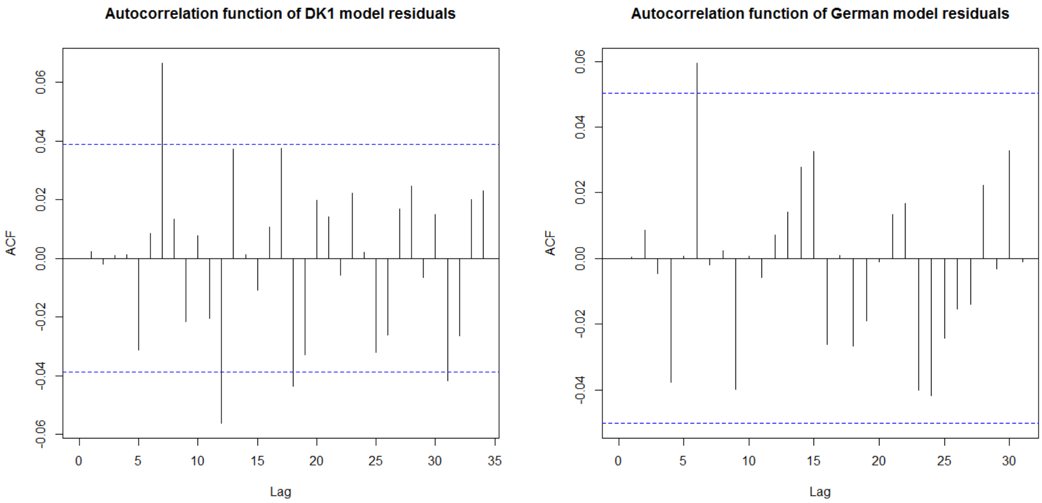
The ACF plots of model residuals are presented in Figures 9(a) and 9(b) for DK1 and German data with wind power as an exogenous term. The model residuals remain within the

	DE (wind)	DE (solar)	DE (combined)
σ_1	0.0319	-0.0425	0.0353[a]
	[0.0123]	[0.0128]	[0.0175]
σ_2	0.0910	-0.0247[a]	0.1164
	[0.0112]	[0.0121]	[0.0147]
α_0	0.8992	3.0174	0.4904[b]
α_1	1.1546	1.1685	1.1679
α_2	-0.1811	-0.2025	-0.1852
α_7	1.1131	1.1071	1.1129
α_{14}	-0.1143	-0.1086	-0.1141
β_1	-0.8925	-0.8897	-0.9001
β_7	-0.9724	-0.9694	-0.9730
AIC	523.58	603.25	538.02

[a]significant at 5%

[b]not significant

Table 2: The effect of German solar, wind, and combined output on daily German price volatility. All coefficients are statistically significant at the 1% level unless otherwise noted. We have reported standard errors in brackets below the exogenous coefficients.



(a) ACF of DK1 model residuals (b) ACF of German model residuals

Figure 9: ACF of DK1 and German model residuals.

95% confidence level with few exceptions at the multiples of seven. Therefore, the models' residuals appear to be normally distributed and serially uncorrelated as required.

4.2 Analysis of intraday effects

To investigate further why wind power decreases the daily volatility in Denmark but increases it in Germany, we divide the data set into three blocks called off-peak 1 hours (from 12 PM to 9 AM), peak hours (9 AM to 9 PM), and off-peak 2 hours (9 PM to 12 PM), according to EEX specification [26]. Given the intraday price profiles in Figures 1(a) and 1(b), the volatility-increasing impact of wind power can be explained if prices in off-peak 1 and 2 blocks decrease more than during peak hours, thereby meaning that prices diverge. On the other hand, the volatility will decrease if peak prices decrease more than off-peak prices, i.e due to the flattening of the intraday price profile.

To test these possibilities, we perform similar regressions as in the previous section for each block, except that the logarithm of the standard deviation of hourly prices v_t and the logarithm of the sum of hourly wind power productions w_t are replaced by the logarithm of the average price p_t and the logarithm of average wind power production aw_t, respectively. We choose the average function because the number of hours varies in the blocks. Using the same procedure of model specification as in Section 3.2, the change of variables leads only to minor modifications. The best models for Denmark and Germany are

$$p_t = \alpha_0 + \alpha_1 p_{t-1} + \alpha_7 p_{t-7} + \beta_1 \varepsilon_{t-1} + \beta_7 \varepsilon_{t-7} + \sigma_1 aw_t + \sigma_2 aw_{t-1} \tag{6}$$

$$p_t = \alpha_0 + \alpha_1 p_{t-1} + \alpha_7 p_{t-7} + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \beta_7 \varepsilon_{t-7} + \sigma_1 aw_t + \sigma_2 aw_{t-1}. \tag{7}$$

The results of the regressions are in Table 3 and 4 for Denmark and Germany, respectively. For DK1 and DK2, the coefficients for peak hours are -0.0706 and -0.0434, respectively, which are slightly lower than the coefficients for evening off-peak hours at -0.0602 and -0.0301 but higher than the coefficients for morning off-peak hours at -0.1116 and -0.0592. For Germany, the coefficients for wind power are -0.1197, -0.2742, and -0.1354 for peak, morning off-peak, and evening off-peak, respectively.

The absolute values of the coefficients reflect the sensitivity of prices to wind power production. The fact that the coefficients for morning and evening off-peak hours in Germany are more negative than the coefficient for peak hours indicates that the supply curves for off-peak hours are more sensitive than the supply curves for peak hours. Thus, if there is an increase in wind power production during off-peak hours, then prices will fall more than in peak hours for a comparative increase in wind output. In Denmark, there is not much difference between the blocks because the coefficients are close to each other.

Figure 3(a) shows that in Denmark there is a peak in wind output during peak hours, which amplifies the total impact of wind power on peak hours relative to off-peak hours. This suggests the idea that wind power contributes to the flattening of the intraday price profile by decreasing peak prices more than off-peak prices in absolute terms. However, the German intraday wind profile in Figure 3(b) is flatter indicating that the output is more stable throughout the day. When this is combined with the fact that coefficients for morning and evening off-peak hours are even lower than that for peak hours, off-peak prices can decrease more compared to peak prices in absolute terms, thereby resulting in higher daily volatility. In practice, this means

	DK1			DK2		
	Peak	Off-Peak 1	Off-peak 2	Peak	Off-peak 1	Off-peak 2
σ_1	-0.0706	-0.1116	-0.0602	-0.0434	-0.0592	-0.0301
	[0.0034]	[0.0070]	[0.0033]	[0.0030]	[0.0046]	[0.0019]
σ_2	-0.0077^a	-0.0208	-0.0052^b	-0.0003^b	-0.0143	-0.0031^b
	[0.0034]	[0.0069]	[0.0033]	[0.0030]	[0.0045]	[0.0019]
α_0	4.2863	4.2302	4.0881	4.0634	3.8507	3.8730
α_1	0.9097	0.9037	0.9834	0.8751	0.8564	0.9802
α_7	0.9935	0.9967	0.9992	0.9901	0.9642	0.9996
β_1	-0.5814	-0.6339	-0.7349	-0.4307	-0.4596	-0.6003
β_7	-0.9047	-0.9565	-0.9898	-0.8853	-0.8698	-0.9913
AIC	-1338.03	2208.37	-1487.33	-1045.99	1203.02	-2730.59

^{a}significant at 5%

^{b}not significant

Table 3: The effect of Danish wind power production on intraday Danish area prices in different blocks. All coefficients are statistically significant at the 1% level unless otherwise noted. We have reported standard errors in brackets below the exogenous coefficients.

that morning off-peak prices, in particular, can crash due to the combination of wind power production and low demand. In contrast, peak-hour prices with high demand decrease only slightly.

When German solar power production is also accounted for, the coefficient for peak hours drops to -0.2347. The result is intuitive because most solar power production takes place during peak hours. However, peak-hour prices do not decrease as much as morning off-peak prices as the coefficient for morning off-peak prices is even lower at -0.2942. In contrast, evening off-peak hours decrease less. Hence, the volatility-increasing effect of the combined renewable output in Section 4.1 can be caused by lower morning off-peak prices and higher evening off-peak prices relative to peak prices.

	DE (wind)			DE (combined)		
	Peak	Off-Peak 1	Off-peak 2	Peak	Off-peak 1	Off-peak 2
σ_1	-0.1197	-0.2742	-0.1354	-0.2347	-0.2942	-0.1382
	[0.0071]	[0.0153]	[0.0067]	[0.0116]	[0.0160]	[0.0068]
σ_2	-0.0071[b]	-0.0130[b]	0.0148[a]	0.0058[b]	-0.0136[b]	0.0149[a]
	[0.0068]	[0.0147]	[0.0064]	[0.0104]	[0.0153]	[0.0064]
α_0	4.7895	5.7836	4.7646	5.9333	5.9603	4.7883
α_1	0.8981	0.9289	0.9152	0.8798	0.9262	0.9154
α_7	0.9900	0.9989	0.9942	0.9904	0.9987	0.9943
β_1	-0.5412	-0.4897	-0.4929	-0.5352	-0.4893	-0.4939
β_2	-0.1099	-0.2263	-0.1613	-0.1032	-0.2257	-0.1617
β_7	-0.8527	-0.9768	-0.9509	-0.8516	-0.9742	-0.9511
AIC	-557.05	1483.00	-1077.84	-656.62	1468.96	-1081.65

[a]significant at 5%

[b]not significant

Table 4: The effect of German wind output on different blocks. All coefficients are statistically significant at 1% level unless otherwise noted. We have reported standard errors in brackets below the exogenous coefficients.

4.3 Weekly volatility

We next extend the analysis to a weekly horizon by specifying a weekly model that includes the standard deviation of daily prices in Equation 3 and the standard deviation of daily renewable production. Our aim is to explore if wind power, for example, contributes to the weekly volatility of Danish and German prices due to the day-to-day variability of wind power production.

The best regression model selected using the same procedure as in Section 3.2 is the ARMA(1,1) model

$$v_t = \alpha_1 v_{t-1} + \beta_1 \varepsilon_{t-1} + \sigma_1 w_t. \tag{8}$$

Weekly volatility depends on several factors. Unlike in the daily model, the random spikiness of the data, in particular, cannot be explained with demand patterns. In Equation 8, the AR(1) term approximates the current volatility with the previous value along with a MA(1) term that generates randomness. All variables have been transformed into natural logarithm form as before.

Table 5 shows the results from the regression for Danish data. Coefficients for DK1 and DK2 wind power, σ_1, are clearly positive at 0.1890 and 0.2064, respectively. The coefficients can be interpreted so that doubling the standard deviation of weekly wind power output in DK1 and DK2 areas increases the weekly volatility of these areas prices by 19% and 21%, respectively. Other statistically significant model candidates give slightly smaller coefficients.

The results can be explained by day-to-day horizontal parallel shifts of the supply curve. When the installed capacity is increasing, the available supply is increasing and the parallel shifts are larger which contributes to the growing weekly volatility. Mauritzen [5] uses an AR(3) model to estimate the weekly impact of Danish wind. Contrary to our results, he finds the effect of DK2 wind power on DK2 price volatility is negative, while the impact of DK1 wind power on DK1 price volatility is positive. We question the robustness of the results because he notes that the coefficients are statistically significant at the 10% level even if the reported standard deviations are, in some cases, larger than the coefficient estimates itself.

	DK1	DK2
σ_1	0.1890	0.2064
	[0.0193]	[0.0097]
α_1	0.9435	0.8283
β_1	-0.6419	-0.5989
AIC	646.11	729.71

Table 5: The effect of the standard deviation of the weekly Denmark wind power production on weekly Denmark prices volatility. All coefficients are statistically significant at the 1% level unless otherwise noted. We have reported standard errors in brackets below the exogenous coefficients.

Table 6 shows the results for Germany. Wind power is the external regressor in the first, solar in the second, and the sum of wind and solar power in third column. The corresponding coefficients, σ_1, are 0.17, 0.20, and 0.18, which means that doubling the standard deviation of weekly wind, solar, and the combined output increases the weekly German price volatility by 17%, 20%, and 18%, respectively.

5 Discussion and conclusion

The share of renewable energy of total energy consumption is growing in Europe because of EU decarbonisation targets. Denmark and Germany have large shares of wind and solar power facilitated by their national policies. Consequently, we have chosen these two countries to explore the impact that renewable energy has on liberalised electricity markets. Our hypothesis is that wind and solar power decrease the volatility of daily prices because they decrease the high peak prices relative to lower off-peak prices. In longer time windows, we hypothesise that wind and solar power increase volatility due to their intermittent nature.

Our analyses suggest that wind and solar power production have statistically and economically significant effects on day-ahead prices in Denmark and Germany. In the short run, the

	DE (wind)	DE (solar)	DE (combined)
σ_1	0.1743	0.2027	0.1754
	[0.0114]	[0.0071]	[0.0115]
α_1	0.9900	0.8523	0.9901
β_1	-0.9428	-0.6975	-0.9434
AIC	261.43	300.19	259.33

[a] not significant

Table 6: The effect of the standard deviation of the weekly German wind, solar and combined production on weekly German price volatility. All coefficients are statistically significant at 1% level unless otherwise noted. We have reported standard errors for the exogenous terms in brackets.

daily volatility of Danish prices is lower when there is more wind power production. In contrast to Denmark, wind power increases the daily volatility of prices in Germany. Hence, our hypothesis is not fully confirmed. However, our results are aligned with those of Jónsson et al. [7], Mauritzen [5], and Ketterer [10], and we endeavour explain them via analysis of intraday prices. We have argued that this discrepancy between the impacts of wind power can be attributed to different intraday production profiles and different elasticities of supply curves during different times of a day. In Germany, off-peak hours are most sensitive to downward pressure in prices, and wind power is, on average, rather evenly distributed throughout the day. As a result, prices during off-peak hours decrease more relative to those in peak hours, which means that prices are diverging and standard deviation increases. In Denmark, however, the price-decreasing impact of wind power is distributed more evenly during different times of day, and there is a peak in average wind power production during peak hours. Thus, the standard deviation decreases when the overall price level decreases.

Solar power is produced only during peak hours, which decreases daily volatility by decreasing high peak hour prices. However, when wind and solar power are generated simultaneously in Germany, the daily price volatility increases. In our data set, the average daily output from wind power is 224% higher than the average daily solar power output. This suggests that, on average, wind power is the dominant component in the total price impact of wind and solar power.

Although our weekly results are not as robust as the daily ones, they suggest that wind and solar power increase the weekly volatility of Danish and German prices. This can be attributed to the high day-to-day variability of wind and solar power production because both wind and solar power depend on weather. On a windy day, for example, the price level can be low, but on the following day the price level can be high if the zero-priced supply from wind power is very low.

Our distributed lag models have several limitations. First, they estimate a single coefficient to represent the impact of renewable energy output on price volatility even if the impact is more dynamic and dependent on the market situation. Second, the high volatility of electricity markets means that time-series models do not necessarily model the price development very accurately, which causes errors in the estimated coefficients for renewable energy.

A subject for further research is to use different modelling techniques. In particular, the link between renewable energy production profiles and supply curve elasticities can be established more formally. If German supply is more inflexible than Danish supply during off-peak hours, then high volumes of renewable energy can cut off-peak prices more relative to peak prices. Moreover, the differences in cross-border transmission capacities between Denmark and Germany can also be taken into account. As Mauritzen [8] states, Norway is effectively acting as storage that absorbs Danish wind power during off-peak hours by lowering its hydropower production.

Our results for Nord Pool and EEX suggest that the day-ahead price is affected by the forecasted wind and solar power profiles. In extreme cases, the combination of low demand and very high supply from renewable sources can lead to very low or even negative prices which are below the marginal costs of production. Germany, in particular, exhibits occasionally lower prices during peak hours than base hours. Before the large-scale penetration of wind and solar power in Europe, power companies used to profit from peak prices, but now they are facing diminishing returns [27].

Outside Germany and Denmark, renewables have been found to decrease prices in Spain [16] and Texas [17]. Also, Woo et al. [17] forecast that price volatility in Texas increases in case of higher installed wind power capacity. Thus, the price impacts of renewables are not limited to the two countries we have analysed but similar development is likely to exist in other countries as well, provided that the capacity is large enough. In the Netherlands, for example, there is no evidence of price impact yet because the installed capacity is still relatively small [15].

The current policies for supporting renewables may lead to lower prices, and, thus, discourage investment. Ultimately, this can lead to problems in securing the supply of electricity. The adoption of more renewable energy requires mechanisms to cope with intermittent supply. Moreover, wind power production is often geographically dislocated from consumption, which can pose challenges for transmission network management. In [28], the European Commission identifies the capacity mechanism, i.e., support payments for conventional generators, as a means for securing supply. Following a recommendation from the German Federal Ministry of Economics and Technology [29], the new German coalition seeks to create a capacity mechanism in Germany [30]. Consequently, equilibrium models similar to [18] and [20] are needed to explore what kinds of energy policies would promote investments in renewables while maintaining the security of supply and allowing power companies to make reasonable profits.

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