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

Tuomas Rintamäki[a], Afzal S. Siddiqui[b,c,*], Ahti Salo[a]

[a]Systems Analysis Laboratory, Department of Mathematics and Systems Analysis, School of Science, Aalto University, Finland
[b]Department of Statistical Science, University College London, UK
[c]Department of Computer and Systems Sciences, Stockholm University, Sweden

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ABSTRACT

Although variable renewable energy (VRE) technologies with zero marginal costs decrease electricity prices, the literature is inconclusive about how the resulting shift in the supply curves impacts price volatility. Because the flexibility to respond to high peak and low off-peak prices is crucial for demand-response applications and may compensate for the losses of conventional generators caused by lower average prices, there is a need to understand how the penetration of VRE affects volatility. In this paper, we build distributed lag models with Danish and German data to estimate the impact of VRE generation on electricity price volatility. We find that in Denmark wind power decreases the daily volatility of prices by flattening the hourly price profile, but in Germany it increases the volatility because it has a stronger impact on off-peak prices. Our analysis suggests that access to flexible generation capacity and wind power generation patterns contribute to these differing impacts. Meanwhile, solar power decreases price volatility in Germany. By contrast, the weekly volatility of prices increases in both areas due to the intermittency of VRE. Thus, policy measures for facilitating the integration of VRE should be tailored to such region-specific patterns.

1. Introduction

The adoption of variable renewable energy (VRE) technologies is having profound consequences for the electric power industry. For example, buttressed by subsidies and priority grid access, solar and wind power generation in Germany comprised 25% of national electricity output in 2013 and facilitated a 30% reduction in CO_2 emissions relative to 1990 levels (von Hirschhausen, 2014). Likewise, neighbouring Denmark has adopted VRE-friendly policies enabling it to meet nearly 40% of its electricity needs through wind (Energinet.dk, 2015). However, similar shares of VRE generation in different electricity markets have resulted in contrasting effects on daily price volatility, which will affect the profitability of conventional power plants. Indeed, via a supply-function equilibrium model, Green and Vasilakos (2010) demonstrate that the incorporation of intermittent renewable resources can increase price volatility in the British electricity industry. Such a change in market will likely lead to an optimal generation mix using more gas-fired plants in the long run (Green and Vasilakos, 2011). Hence, understanding how VRE generation affects price volatility and uncovering the drivers of these effects is important for both power companies and regulators dealing with a transition to a more sustainable energy system.

While fundamental models are often used to examine policy implications, e.g., in terms of transmission expansion to accommodate increased VRE capacity (Egerer et al., 2013), such models need to be sufficiently detailed to capture the subtle changes that we seek to detect here. In particular, building and calibrating large-scale fundamental models with interconnected regions is often confounded by the complexities of deregulated electricity industries and the associated data requirements at the plant level, for example. By contrast, since the electricity industry is one of the few infrastructure industries with liquid markets and publicly available data on prices as well as cross-border transmission flows, we exploit this feature in taking an empirical approach to understand the effects of VRE generation on price volatility in Danish and German electricity markets.

Our methodology is largely based on Mauritzen (2010) who represents the volatility of prices via a seasonal autoregressive

* Corresponding author.
E-mail addresses: tuomas.rintamaki@aalto.fi (T. Rintamäki), afzal.siddiqui@ucl.ac.uk (A.S. Siddiqui), ahti.salo@aalto.fi (A. Salo).

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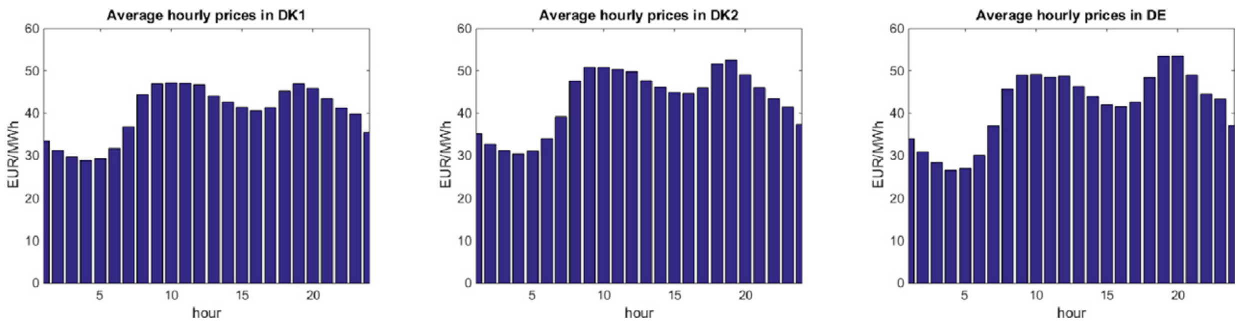


(a) DK1. (b) DK2. (c) DE.

Fig. 1. Average hourly electricity prices for DK1, DK2, and DE from 2010 to 2014.

moving average (SARMA) model in which wind power production is an exogenous variable. This methodology yields results that are straightforward to interpret and makes it possible to develop forecasts for electricity price volatility based on the data from previous days and information on regular consumption patterns. His conclusion is that Danish wind power decreases the daily volatility of the area prices in Denmark. On the contrary, Ketterer (2014) uses a generalised autoregressive conditional heteroscedasticity (GARCH) model and finds that German wind power increases the daily volatility of German electricity prices. Explaining these results using data from the two markets and distilling their implications for electricity markets in general is the objective of this paper.

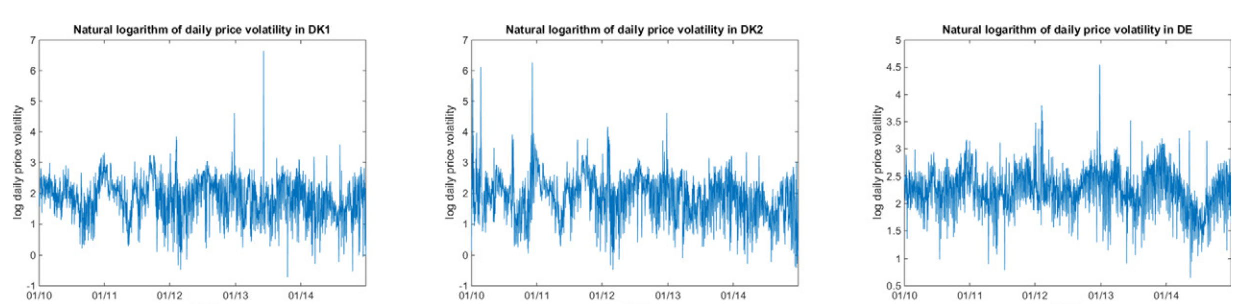
We proceed by first confirming the differing impacts of wind power on price volatility in these two markets and then explaining them by dividing the dataset into peak and off-peak hours with separate regressions for each subset of hours. This allows us to analyse changes in volatility by relating them to supply-curve elasticities and to the patterns of wind and solar power production as well as cross-border exchanges. Partitioning the dataset reveals that wind power output decreases daily price volatility in Denmark because wind speeds are roughly evenly distributed throughout the day. Relative to its average electricity demand, Denmark has high transmission capacity to the Nordic countries with large hydropower reservoirs, which may also explain Denmark's reduction in daily price volatility as both peak and off-peak hour prices are estimated to decrease nearly equally due to wind power generation. In Germany, however, there is an increase in price volatility because of greater wind power output during off-peak hours. Moreover, Germany's cross-border transmission lines are smaller relative to its average electricity demand, and it has limited access to flexible hydro generation. As a consequence, prices diverge as the price-decreasing impact of wind power is amplified during off-peak hours. Over a weekly time horizon, the level and the standard deviation of total VRE generation are found to increase the weekly volatility of electricity prices in both countries.

For producers and consumers alike, our empirical analysis not only corroborates earlier findings but also explains them by proposing plausible drivers. The implication of our results is that the allocation of generation and demand is becoming more important as average power prices decrease, but the achievable profit on different days varies significantly. To prevent intermittent renewable generation from threatening the stability of the power system, investments in flexible generation, extensions to the transmission network, integration of adjacent markets, and demand response will be required in the future. Moreover, additional trading opportunities by both producers and large consumers in intraday and balancing markets may be desirable (Mauritzen, 2015).

This paper is organised as follows. In Section 2, we review the literature on the impacts of VRE on Danish and German electricity markets, in particular. In Section 3, we present our model and analyse the time-series data. Section 4 presents the results for the effects of VRE generation on daily and weekly volatility. Finally, in Section 5, we provide conclusions and discuss directions for future research. Details on model selection and robustness checks are provided in the Appendix.

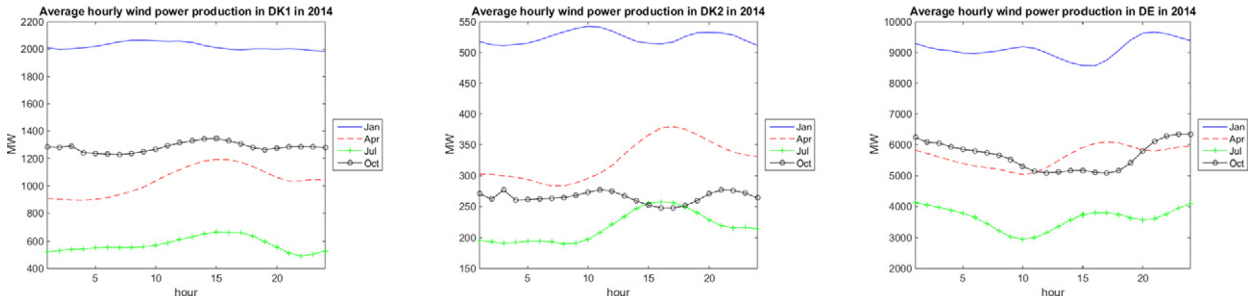
2. Literature review

The adoption of wind and solar generation technologies worldwide has necessitated a need to assess both the availability of resources (Yip et al., 2016) and their impact on electricity markets (González-Aparicio and Zucker, 2015). Many studies have investigated the effect of wind power production on price levels and



(a) DK1. (b) DK2. (c) DE.

Fig. 2. The natural logarithm of daily price volatility of DK1, DK2, and DE prices from 2010 to 2014.



(a) DK1. (b) DK2. (c) DE.

Fig. 3. Average hourly wind power in DK1, DK2, and DE in selected months in 2014.

reached the common conclusion that wind power decreases prices. For example, Jónsson et al. (2010) employ the same hourly Danish wind power forecast data that are used by market players to place their bids. They build a non-parametric regression model to study price levels as well as the distribution of the prices at different wind power levels. Their conclusion is that higher wind power penetration in the day-ahead market decreases Danish prices and volatility substantially.

In Germany, price volatility has been studied by incorporating various market-related measures as exogenous variables (Kalantzis and Milonas, 2013; Frömmel et al., 2014). Only recently have there been studies on the direct effects of growing capacity of wind and solar power on electricity prices. Ketterer (2014) finds that higher wind power production leads to higher daily volatility. Moreover, she notes that regardless of the regulatory change in 2010, which forced the German transmission system operators to publish day-ahead forecasts for VRE generation in their area, the volatility-increasing effect has prevailed. Because the price-decreasing impact of solar power is stable during peak hours (Paraschiv et al., 2014), it is likely that solar power decreases price volatility.

Besides patterns of solar and wind power production, transmission flows also affect the volatility of electricity prices as suggested by the complementarity model by Morales et al. (2011), who use wind power scenarios as inputs. By adopting the same time-series framework as in Mauritzen (2010) and Mauritzen (2013) investigates how wind power affects the cross-border transmission of electricity between Denmark and Norway. His conclusion is that when more (less) wind power is produced in Denmark, exports to (imports from) Norway are higher while Norwegian hydropower plants produce less (more). Zugno et al. (2013) find a similar pattern between Germany and hydro-dominant Austria and Switzerland, but these transmission lines are closer to congestion. Moreover, the flow to the Nordic countries from Germany is low, and the flow to its neighbouring countries with inflexible generation such as France does not respond much to changes in wind power.

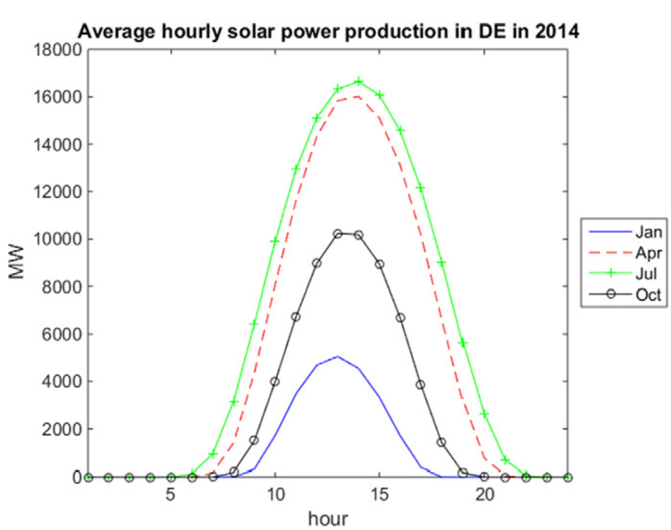


Fig. 4. Average hourly solar power in DE in selected months in 2014.

Building on assumptions about extended cross-border transmission and VRE capacity in 2030, Jaehnert et al. (2013) find that price spikes and dips become more frequent in the European power market. Due to the large price difference between the Nordic and German markets, also additional investments in transmission capacity become optimal. In similar scenarios, Farahmand et al. (2012) find that the integration of Nordic and German balancing markets via simultaneous dispatching can reduce balancing costs considerably because VRE generation forecast errors with opposite signs can be netted.

In addition to explaining the results of Ketterer (2014) and Mauritzen (2010), our approach of dividing the data into off-peak and peak hours contributes to the literature on estimating the impact of renewable generation on electricity price levels (see Würzburg et al., 2013; Mulder and Scholtens, 2013; Paraschiv et al., 2014; Gelabert et al., 2011, for example) by providing insights on how the price-decreasing impact is distributed during the day. To this end, Barthelmie et al. (1996) and Holttinen (2005) suggest that Danish wind power peaks in the afternoon and the effect is more pronounced in summers. On the other hand, He et al. (2012) and Huber et al. (2014) show that German wind power tends to peak at night and also in summer afternoons.

3. Methodology and data

3.1. Model

To estimate the effect of exogenous variables such as wind and solar power on a dependent variable of interest such as electricity price volatility, we use the seasonally adjusted autoregressive moving average (SARMA(p,q)(P,Q)[s]) model (Shumway and Stoffer, 2011):

$$v_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i v_{t-i} + \sum_{i=1}^{q} \beta_i \epsilon_{t-i} + \sum_{i=1}^{P} \alpha_{i\bullet s} v_{t-i\bullet s} + \sum_{i=1}^{Q} \beta_{i\bullet s} \epsilon_{t-i\bullet s} + \epsilon_t + \gamma^{\top} x_t, \quad (1)$$

where v_t is the dependent variable during time period t and x_t a vector of exogenous variables. There are p autoregressive (AR) terms v_{t-i}, q moving average (MA) terms ϵ_{t-i}, P seasonal autoregressive

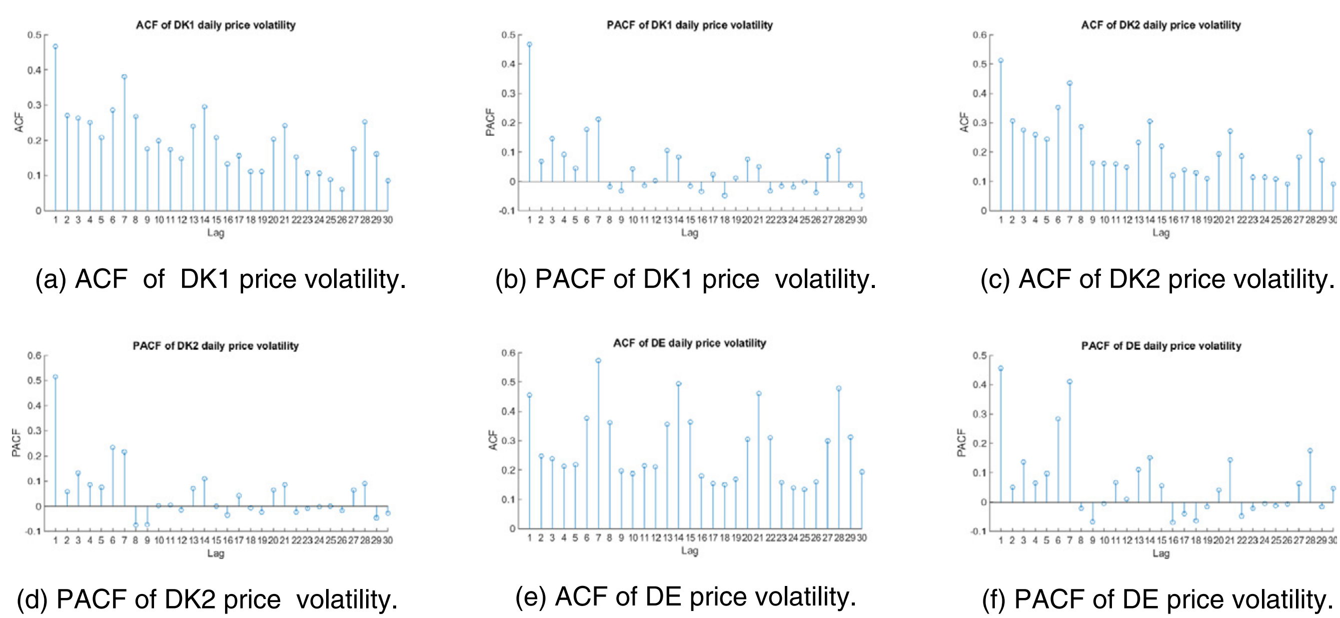
Table 1
Exogenous variables in our models. We take the natural logarithm of all variables except $exim_d^{op1}$, $exim_d^{op2}$, $exim_d^p$, and $exim_w$.

Variable	Explanation
v_d	Standard deviation of hourly prices on day d (€/MWh)
p_d^{op1}	Average off-peak 1 prices on day d (€/MWh)
p_d^{op2}	Average off-peak 2 prices on day d (€/MWh)
p_d^p	Average peak prices on day d (€/MWh)
$wind_d$	Average wind power on day d (MW)
$wind_d^{op1}$	Average off-peak 1 wind power on day d (MW)
$wind_d^{op2}$	Average off-peak 2 wind power on day d (MW)
$wind_d^p$	Average peak wind power on day d (MW)
$wind\_pen_d$	Average wind power penetration on day d
$wind\_pen_d^{op1}$	Average off-peak 1 wind power penetration on day d
$wind\_pen_d^{op2}$	Average off-peak 2 wind power penetration on day d
$wind\_pen_d^p$	Average peak wind power penetration on day d
$solar_d$	Average solar power on day d (MW)
$solar_d^p$	Average peak solar power on day d (MW)
$solar\_pen_d$	Average solar power penetration on day d
$solar\_pen_d^p$	Average peak solar power penetration on day d
vre_d	Average wind and solar power on day d (MW)
vre_d^p	Average peak wind and solar power on day d (MW)
vre_pen_d	Average wind and solar power penetration on day d
$vre\_pen_d^p$	Average peak wind and solar power penetration on day d
$exim_d^{op1}$	Average off-peak 1 export/import on day d (GW)
$exim_d^{op2}$	Average off-peak 2 export/import on day d (GW)
$exim_d^p$	Average peak export/import on day d (GW)
gas_d	Average spot gas price on day d (€/MWh)
v_w	Standard deviation of daily average prices during week w (€/MWh)
$wind_w$	Average wind power during week w (MW)
$wind_w^{std}$	Standard deviation of average daily wind power outputs during week w (MW)
$wind\_pen_w$	Average wind power penetration during week w
$solar_w$	Average solar power during week w (MW)
$solar\_pen_w$	Average solar power penetration during week w
vre_w	Average wind and solar power during week w (MW)
vre_w^{std}	Standard deviation of average daily wind and solar power outputs during week w (MW)
vre_pen_w	Average wind and solar power penetration during week w
$exim_w$	Average export/import during week w (GW)
gas_w	Average gas price during week w (€/MWh)

(SAR) terms $v_{t-i \cdot s}$ with periodicity of s, and Q seasonal moving average (SMA) terms $\epsilon_{t-i \cdot s}$ with periodicity of s with the coefficients α_i, β_i, $\alpha_{i \cdot s}$, and $\beta_{i \cdot s}$, respectively. In other words, the terms v_{t-i} are lagged values of v_t and ϵ_{t-i} Gaussian white noise error terms. The impact of the exogenous variables on price volatility is estimated by the parameter vector γ using R (R Core Team, 2015).

3.2. Summary statistics

Our data for the two Danish areas (Western Denmark, DK1 and Eastern Denmark, DK2) consist of hourly area prices (in €/MWh), forecasted hourly wind power production (in MW), forecasted hourly demand (in MW), and hourly cross-border flows between



(a) ACF of DK1 price volatility. (b) PACF of DK1 price volatility. (c) ACF of DK2 price volatility.

(d) PACF of DK2 price volatility. (e) ACF of DE price volatility. (f) PACF of DE price volatility.

Fig. 5. ACF and PACF plots of DK1, DK2, and DE daily price volatility.

Table 2
The effect of different explanatory variables on DK1 daily price volatility. All coefficients are statistically significant at the 1% level unless otherwise noted.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$wind_d$	−0.0892 (0.0158)		−0.0731 (0.0193)	−0.0906 (0.0194)		−0.0889 (0.0158)
$wind\_pen_d$		−0.0867 (0.0160)			−0.0879 (0.0198)	
$exim_d^{op1}$			0.0641[b] (0.0328)	0.1004 (0.0331)	0.1017 (0.0334)	
$exim_d^{p}$			0.0783[a] (0.0374)	−0.0806 (0.0308)	−0.0850 (0.0307)	
$exim_d^{op2}$			−0.2241 (0.0305)			
Δgas_d						0.3324[c] (0.4080)
α_0	2.3918	1.7080	2.2531	2.3566	1.6605	2.3649
α_1	1.2236	1.2210	1.2546	1.2450	1.2437	1.2210
α_2	−0.2526	−0.2504	−0.2787	−0.2728	−0.2718	−0.2510
α_7	1.0711	1.0706	1.0811	1.0751	1.0747	1.0699
α_{14}	−0.0726	−0.0721	−0.08232	−0.0769	−0.0766	−0.0731
β_1	−0.8635	−0.8632	−0.8698	−0.8669	−0.8666	−0.8625
β_7	−0.9804	−0.9804	−0.9825	−0.9792	−0.9791	−0.9803
AIC	2878.82	2881.50	2820.47	2871.62	2873.72	2879.57
L-B	30	30	28	30	30	30

[a] Significant at 5% level.
[b] Significant at 10% level.
[c] Not significant.

zones DK1-NO2, DK1-SE3, and DK2-SE4 (in MW) in the day-ahead spot market (data source: Nord Pool Spot, 2016). We ignore Danish solar power because of its negligible capacity (Energinet.dk, 2014). For Germany (DE), we use hourly German prices (in €/MWh, Epex Spot, 2016), forecasted hourly wind and solar power production (in MW, EEX Transparency, 2016), forecasted hourly demand (in MW, ENTSO-E Transparency, 2016b), and hourly cross-border flows between Germany and France (in MW, ENTSO-E Transparency, 2016a). We account for fuel prices by including the daily natural gas spot price (in €/MWh, at the NetConnect Germany hub, Bloomberg, 2016). The dataset spans 1 January 2010 to 31 December 2014 and 1 January 2012 to 31 December 2014 for Denmark and Germany, respectively. The dataset for Germany is restricted by public data on cross-border flows.

Because prices are calculated by the exchanges, there are no measurement uncertainties or gaps. We employ VRE and demand forecasts for modelling instead of realised values because only forecasts are available for market participants when determining their bids to the day-ahead market. Thus, prices and volatility are affected by bidding decisions, which might have been different under perfect knowledge of forecast errors. For Germany, there are a few missing days in the ENTSO-E demand forecast time series; for these, we use realised values. Following the convention of the exchanges, we also divide the dataset into three blocks called off-peak 1 hours (from 12

Table 3
The effect of different explanatory variables on DK2 daily price volatility. All coefficients are statistically significant at the 1% level unless otherwise noted.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$wind_d$	−0.0696 (0.0147)		−0.0517 (0.0164)	−0.0604 (0.0165)		−0.0686 (0.0146)
$wind\_pen_d$		−0.0654 (0.0149)			−0.0544 (0.0167)	
$exim_d^{op1}$			−0.0171[a] (0.0418)	−0.0070[a] (0.0430)	−0.0119[a] (0.0433)	
$exim_d^{p}$			0.1462 (0.0481)	−0.0474[a] (0.0416)	−0.0516[a] (0.0416)	
$exim_d^{op2}$			−0.3060 (0.0395)			
Δgas_d						−0.3214[a] (0.4306)
α_0	2.2065	1.7110	2.0966	2.1547	1.7289	2.2035
α_1	1.2329	1.2302	1.2677	1.2313	1.2289	1.2305
α_2	−0.2685	−0.2660	−0.2960	−0.2679	−0.2658	−0.2673
α_7	1.1054	1.1066	1.1078	1.1045	1.1060	1.1046
α_{14}	−0.1058	−0.1069	−0.1081	−0.1050	−0.1063	−0.1050
β_1	−0.8378	−0.8371	−0.8504	−0.8332	−0.8329	−0.8368
β_7	−0.9886	−0.9904	−0.9912	−0.9875	−0.9894	−0.9875
AIC	3159.90	3163.27	3106.16	3162.16	3164.78	3134.09
L-B	30	30	30	30	30	9

[a] Not significant.

Table 4
The effect of different explanatory variables on DE price volatility. All coefficients are statistically significant at the 1% level unless otherwise noted.

	Model								
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
$wind_d$	0.0328[a]		0.0296[a]					0.0367[a]	0.0320[a]
	(0.0146)		(0.0147)					(0.0147)	(0.0148)
$\Delta solar_d$		−0.0379[a]	−0.0350[b]					−0.0205[c]	−0.0339[b]
		(0.0191)	(0.0191)					(0.0191)	(0.0191)
vre_d				0.0187[c]					
				(0.0227)					
$wind\_pen_d$					0.0350[a]				
					(0.0147)				
$\Delta solar\_pen_d$						−0.0466[a]			
						(0.0187)			
vre_pen_d							0.0203[c]		
							(0.0220)		
$exim_d^{op1}$								0.0853	
								(0.0117)	
$exim_d^{p}$								−0.0781	
								(0.0137)	
$exim_d^{op2}$								0.0211[c]	
								(0.0134)	
Δgas_d									−0.3840[c]
									(0.3308)
α_0	1.9167	2.2698	2.0009	2.0691	2.3221	2.2432	2.2764	1.9351	1.9710
α_1	1.1513	1.1657	1.1613	1.1459	1.1525	1.1675	1.1532	1.1508	1.1615
α_2	−0.1622	−0.1752	−0.1711	−0.1576	−0.1633	−0.1773	−0.1637	−0.1623	−0.1716
α_7	1.1764	1.1724	1.1749	1.1717	1.1770	1.1722	1.1737	1.1686	1.1788
α_{14}	−0.1766	−0.1725	−0.1752	−0.1719	−0.1772	−0.1724	−0.1739	−0.1688	−0.1789
β_1	−0.9165	−0.9168	−0.9190	−0.9108	−0.9167	−0.9163	−0.9140	−0.9276	−0.9189
β_7	−0.9896[c]	−0.9911	−0.9870	−0.9885	−0.9890	−0.9910	−0.9898	−0.9888	−0.9914
AIC	487.73	488.60	486.92	492.33	487.13	486.39	491.88	434.13	486.92
L-B	30	30	30	30	30	30	30	30	30

[a] Significant at 5% level.
[b] Significant at 10% level.
[c] Not significant.

AM to 9 AM), peak hours (9 AM to 9 PM), and off-peak 2 hours (9 PM to 12 AM).

Our measure of price volatility for day d in Eq. (1) is the logarithm of the standard deviation calculated from hourly prices p_h and the average daily price $p_d = \frac{1}{24}\sum_{h=1}^{24} p_h$, i.e.,

$$v_d = \ln\left(\sqrt{\frac{1}{24}\sum_{h=1}^{24}(p_h - p_d)^2}\right). \tag{2}$$

As an example of longer time windows, we consider weekly price volatility, which is computed from daily average prices p_d and weekly average prices $p_w = \frac{1}{7}\sum_{d=1}^{7} p_d$.

$$v_w = \ln\left(\sqrt{\frac{1}{7}\sum_{d=1}^{7}(p_d - p_w)^2}\right) \tag{3}$$

We take the natural logarithm to make the time series stationary and to improve the model fit. Also, all exogenous variables x_t in Eq. (1) except for cross-border flows are transformed into natural logarithm form, and, thus, their coefficients γ can be interpreted as elasticities. This assumption of constant elasticity between the exogenous variables and price volatility is more reasonable than assuming that changes in demand, for example, lead to equal changes in price volatility at different demand levels. Because cross-border flows take positive and negative values depending on the direction of the flow, we scale the figures by 1000 MW to obtain values close to those of the logarithmic variables.

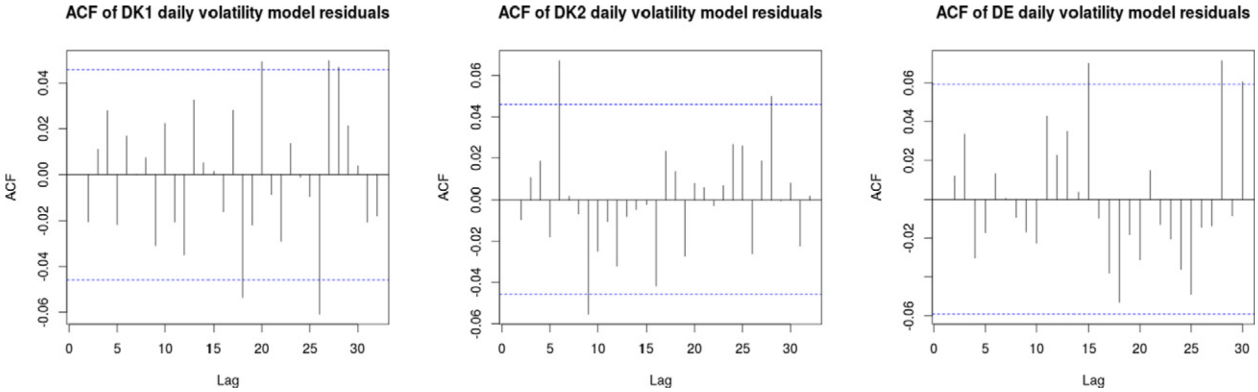
Fig. 1a, b, and c show the average hourly price profile for DK1, DK2, and DE, respectively, resulting from demand patterns. During morning and evening high-load hours, the price is usually driven by thermal plants with higher marginal costs of production. In low-load times, such as night time, prices are set by thermal plants lower in the merit order. On the other hand, Fig. 2a, b, and c show how the daily volatility of DK1, DK2, and DE prices has developed from 2010 to 2014, respectively. There is no clear increasing or decreasing trend in the price volatility of the areas, but the average volatility of Danish prices is lower than that of Germany.

Fig. 3a and b confirm that Danish wind power peaks in the afternoon. In turn, Fig. 3c shows that the production of German wind power is highest at night. The solar power profile in Germany is similar in each month with production only from 6 AM to 8 PM (Fig. 4). We define the wind and solar power penetration during period t as the share of average wind or solar power generation ($wind_t$, $solar_t$) of the average demand ($load_t$) during that period t.

$$wind\_pen_t = \frac{wind_t}{load_t} \quad \text{and} \quad solar\_pen_t = \frac{solar_t}{load_t} \tag{4}$$

3.3. Stability checks

We confirm the stationarity of the time series by applying the augmented Dickey–Fuller (ADF) test. Table 11 in the Appendix shows that all daily time series pass the test at the 10% level until lag 15 except for German solar power, solar power penetration, and gas price, which are differenced to make them stationary. For weekly data, since the gas price, Danish exports, German wind and solar power, and their penetration fail the test already at low lags, we difference these time series. Table 12 in the Appendix shows that all time series pass the test after differencing except for weekly average



(a) DK1. (b) DK2. (c) DE.

Fig. 6. ACF plot of the residuals of the daily price volatility model 1 for DK1, DK2 and DE.

solar power generation and penetration, which reduces the robustness of the results on their impact. In the regressions, we will use the differenced variables prefixed with Δ whenever necessary. For the notation, please refer to Table 1.

Autocorrelation (ACF) and partial autocorrelation functions (PACFs) of the dependent variable in Eq. (1) can be used to specify the order (p,q)(P,Q)[s] of the model. The ACF and PACF of daily price volatility time series from DK1 and DK2 in Fig. 5a, b, c, and d, respectively, and from DE in Fig. 5e and f have high peaks at the first lag and then near multiples of seven indicating a weekly pattern in price volatility (Shumway and Stoffer, 2011). All autocorrelation functions have a downward trend as older data are less relevant.

For both Denmark and Germany, we select the model (1) by stepwise addition of independent variables starting from a SARMA(1,0)(1,0)[7] model, as indicated by the ACF and PACF plots. In the selection process, we omit all exogenous variables x_t and require all coefficients α and β to be statistically significant at the 5% level. If a variable in a particular model (p,q)(P,Q) becomes statistically insignificant, then we do not add new variables because they are likely to be insignificant, too. Also, if the addition of a new variable does not improve the Akaike Information Criterion (AIC) compared to the previous model, then we stop. To compare the candidates obtained in this process, we assess the AIC score, perform the Ljung-Box (L-B) test for residual autocorrelation, 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. The model selection results are reported in Tables 13–15 of the Appendix, where we have omitted models that fail improve the AIC score or have insignificant variables.

We note that the optimal fit would be obtained if model (1) were to be specified separately for each subset of exogenous variables x_t. However, very different specifications could make it difficult to compare the effect of the exogenous variables. Therefore, we present results for alternative model specifications in Tables 16–18 of the Appendix to see the sensitivity of the results obtained using the above process.

4. Results

4.1. Daily volatility

We run separate regressions for both Danish areas, DK1 and DK2, and Germany, DE, to estimate the impact of different explanatory variables on the corresponding area price volatility. For all areas, we obtain the following SARMA(2,1)(2,1)[7] model (see Table 13 in the Appendix for model search iterations):

$$v_d = \alpha_0 + \alpha_1 v_{d-1} + \alpha_2 v_{d-2} + \alpha_7 v_{d-7} + \alpha_{14} v_{d-14} + \epsilon_d + \beta_1 \epsilon_{d-1} + \beta_7 \epsilon_{d-7}. \tag{5}$$

The AR(1) and AR(2) terms account for short-term price volatility development, and the SAR(1) and SAR(2) terms deal with the weekly seasonality in the data. Adding MA(1) and SMA(1) terms provides stochastic parts to the development of the price volatility and improves the fit of the model. Various exogenous variables with the associated parameters, i.e., the term $\gamma^\top x_t$ in Eq. (1), are added to the right-hand side of this model. For example, model 1 for DK1 in Table 2 is

$$\begin{aligned} v_d = {} & \alpha_0 + \alpha_1 v_{d-1} + \alpha_2 v_{d-2} + \alpha_7 v_{d-7} + \alpha_{14} v_{d-14} + \epsilon_d \\ & + \beta_1 \epsilon_{d-1} + \beta_7 \epsilon_{d-7} + \gamma\, wind_d. \end{aligned} \tag{6}$$

In Tables 2 and 3, the main finding is that the coefficient for wind power, $wind_d$, in DK1 at −0.0892 and in DK2 at −0.0696 in model 1 is statistically significantly different from zero at the 1% level according to a Z-test. For both areas, the interpretation is that increasing the amount of daily wind power production by 1% decreases the daily volatility of prices by 0.06–0.09%.[1] The effect is slightly stronger in DK1 than DK2, most likely due to the combination of higher wind power capacity and lower demand in DK1. Moreover, model 2 in Tables 2 and 3 indicates that the higher the wind power penetration, $wind\_pen_d$, is, the lower the price volatility.

Mauritzen (2010) runs similar regressions with a SARMA(2,2)(1,2)[7] model. Our result for DK1 is in line with Mauritzen, but his estimate for the coefficient for DK2 is not statistically significant. The most probable explanation for the difference is that his data span 2002 to 2007, whereas our more recent dataset includes higher wind power capacity in DK2, and, thus, its market impact is likely to be stronger.

In models 3 and 4, we control for exports to and imports from hydro-dominant Sweden and Norway in morning off-peak, peak, and evening off-peak hours ($exim_d^{op1}$, $exim_d^{p}$, and $exim_d^{op2}$, respectively)

[1] Consider a model $\ln y = \alpha + \beta^\top z + \gamma \ln x$. Fixing z, with two different values, x_2 and x_1, we have $\ln y_2 - \ln y_1 = \gamma(\ln x_2 - \ln x_1) \iff \ln\frac{y_2}{y_1} = \gamma \ln\frac{x_2}{x_1} \iff \frac{y_2 - y_1}{y_1} = \left(\frac{x_2}{x_1}\right)^\gamma - 1$. Numerically, the approximation $\frac{y_2 - y_1}{y_1} \approx \gamma\left(\frac{x_2 - x_1}{x_1}\right)$ deviates from the true value of $\frac{y_2 - y_1}{y_1}$ by less than 0.004 percentage points when $\frac{x_2 - x_1}{x_1} = 0.01$ and $|\gamma| \le 0.5$.

Table 5
The effect of different explanatory variables on DK1 price level in each block. All coefficients are statistically significant at the 1% level.

	Block					
Variable	Off-peak 1	Off-peak 1	Peak	Peak	Off-peak 2	Off-peak 2
$wind_d$	−0.1090		−0.0726		−0.0647	
	(0.0092)		(0.0052)		(0.0051)	
$wind\_pen_d$		−0.1153		−0.0791		−0.0667
		(0.0092)		(0.0052)		(0.0051)
$exim_d$	−0.1454	−0.1373	−0.1073	−0.0996	−0.0865	−0.0854
	(0.0183)	(0.0182)	(0.0091)	(0.0091)	(0.0088)	(0.0087)
α_0	4.1465	3.3179	4.1694	3.5878	4.0406	3.5412
α_1	1.1511	1.1505	1.1730	1.1687	1.0622	1.0626
α_2	−0.1922	−0.1904	−0.2240	−0.2195	−0.0933	−0.0922
α_7	0.9475	0.9456	0.9535	0.9533	0.9704	0.9683
β_1	−0.7910	−0.7951	−0.7615	−0.7632	−0.7222	−0.7254
β_7	−0.8791	−0.8835	−0.7990	−0.8082	−0.9359	−0.9391
AIC	792.47	776.51	−1197.78	−1229.52	−1331.94	−1343.87
L-B	30	30	4	4	4	4

and find nearly unchanged coefficients for wind power in both areas. The same is true for wind power penetration in model 5. Because the spot market transmission flows are likely to be endogenous with the price volatility, we cannot draw causal conclusions about their impact (Mauritzen, 2013). However, model 4 for DK1 suggests that exports during morning off-peak hours are positively correlated with daily price volatility, but, during peak hours, the correlation is negative. This is explained by the fact that greater difference between the peak and off-peak hours implies high exports (imports) in the off-peak (peak) hours. By contrast, for DK2, the impact of cross-border exchange is inconclusive in model 4, which can be attributed to the fact that DK2 is connected only to the SE4 bidding area with practically no hydro reservoirs, whereas DK1 is connected to large reservoirs in bidding areas NO2 and SE3 (Nord Pool Spot, 2014). These results are in line with Green and Vasilakos (2012), who find that Denmark exports excess wind power to Norway and Sweden in off-peak hours, in particular, and that the volume of this exchange is higher for DK1 than DK2.

With model 6, we test for the impact of the first difference of natural gas prices, Δgas_d, and find no statistically significant effect on DK1 and DK2 daily price volatility. We note that the daily changes in natural gas spot prices are small, and, thus, they are unlikely to affect short-term bidding behaviour significantly. Moreover, some producers may have longer-term gas contracts instead of relying on spot gas.

Increasing the daily German wind power, $wind_d$, by 1% increases the daily volatility of German prices by 0.03% as indicated by model 1 in Table 4. The result is in line with Ketterer (2014) whose estimate from a rolling regression ranges from 0% to approximately 0.05%. However, when the first difference in daily solar power production, $\Delta solar_d$, increases by 1%, the daily volatility of German prices decreases by 0.04% in model 2. This indicates that also a higher absolute level of solar power leads to lower daily price volatility. Model 3 confirms the signs of the coefficients in the presence of both wind and solar power. Yet, when we combine wind and solar power in variable vre_d in model 4, the coefficient becomes statistically insignificant, which is likely to be caused by the opposing effects of wind and solar power. We arrive at the same conclusions by using the penetration of wind, solar, or the combined generation, i.e., $wind\_pen_d$, $solar\_pen_d$, and vre_pen_d, respectively, as an exogenous variable in models 5–7.

Controlling for the cross-border flow between Germany and France in model 8 keeps the coefficients for $wind_d$ and $\Delta solar_d$ close to the earlier estimates. Positive and negative coefficients for the morning off-peak and peak hour transmission flow ($exim_d^{op1}$ and $exim_d^{p}$), respectively, suggest higher price volatility when exports change to imports during the day. Finally, model 9 shows, in agreement with the result for Denmark, that the first difference of gas prices, Δgas_d, does not have an impact on the daily volatility of German prices.

For all areas, the AIC scores in Table 13 in the Appendix improve after adding the exogenous variables to Eq. (5). In Tables 2–4, we report the lag at which the Ljung-Box test fails at a 1% significance level. The models for DK2 have some autocorrelation at lag 9, but the models for DK1 and DE perform well with all lags. However, Fig. 6a–c show that the ACF plot of the residuals of model 1 for DK1 and DK2 and model 4 for Germany stay within the 95% confidence interval with very few exceptions. As a cross-check, we estimate alternative

Table 6
The effect of different explanatory variables on DK2 price level in each block. All coefficients are statistically significant at the 1% level.

	Block					
Variable	Off-peak 1	Off-peak 1	Peak	Peak	Off-peak 2	Off-peak 2
$wind_d$	−0.0796		−0.0570		−0.0543	
	(0.0068)		(0.0042)		(0.0045)	
$wind\_pen_d$		−0.0813		−0.0596		−0.0557
		(0.0068)		(0.0042)		(0.0045)
$exim_d$	−0.0910	−0.0890	−0.0658	−0.0615	−0.0471	−0.0451
	(0.0205)	(0.0205)	(0.0122)	(0.0122)	(0.0122)	(0.0122)
α_0	3.8882	3.3140	4.0757	3.6436	3.9298	3.5348
α_1	1.1808	1.1804	1.2429	1.2405	1.0707	1.0698
α_2	−0.2303	−0.2301	−0.2909	−0.2889	−0.1073	−0.1070
α_7	0.9019	0.8978	0.9608	0.9605	0.9627	0.9641
β_1	−0.7384	−0.7401	−0.7500	−0.7506	−0.7208	−0.7217
β_7	−0.7794	−0.7766	−0.7912	−0.7949	−0.9186	−0.9220
AIC	623.24	617.20	−1033.78	−1049.23	−842.63	−850.23
L-B	30	30	4	6	5	5

Table 7
The effect of different explanatory variables on DE price level in each block. All coefficients are statistically significant at the 1% the level unless otherwise noted.

	Block									
Variable	Off-peak 1	Off-peak 1	Peak	Peak	Peak	Peak	Peak	Peak	Off-peak 2	Off-peak 2
$wind_d$	−0.3073		−0.1530						−0.1874	
	(0.0156)		(0.0090)						(0.0079)	
$wind\_pen_d$		−0.3243		−0.1667						−0.1915
		(0.0151)		(0.0087)						(0.0078)
$\Delta solar_d$					−0.0528					
					(0.0142)					
$\Delta solar\_pen_d$						−0.0807				
						(0.0138)				
vre_d							−0.3602			
							(0.0158)			
vre_pen_d								−0.3984		
								(0.0145)		
$exim_d$	0.0436	0.0440	0.0187	0.0193	0.0096[c]	0.0107[c]	0.0284	0.0286	0.0444	0.0422
	(0.0107)	(0.0101)	(0.0072)	(0.0070)	(0.0082)	(0.0081)	(0.0066)	(0.0061)	(0.0059)	(0.0058)
α_0	5.8789	2.5388	4.9809	3.2649	3.7043	3.7006	7.0370	3.0252	5.1723	3.1432
α_1	−0.5556	−0.5669	0.9730	0.9757	0.9555	0.9735	0.8819	0.8652	0.5906	0.6052
α_2	0.2948	0.2815	−0.1192[a]	−0.1206[a]	−0.1394[b]	−0.1497[a]	−0.0801[c]	−0.0717[c]	0.0991[c]	0.0924[c]
α_7	0.9167	0.9184	0.9338	0.9327	0.9280	0.9283	0.9322	0.9272	0.9614	0.9586
β_1	0.9225	0.9229	−0.6736	−0.6763	−0.6016	−0.6135	−0.6452	−0.6335	−0.3428[a]	−0.3561[a]
β_7	−0.7339	−0.7575	−0.5912	−0.6016	−0.6093	−0.6152	−0.5658	−0.5863	−0.8166	−0.8258
AIC	601.62	550.09	−223.51	−282.05	−2.58	−22.43	−379.56	−534.03	−829.03	−856.04
L-B	4	4	30	30	30	30	14	14	30	30

[a] Significant at 5% level.
[b] Significant at 10% level.
[c] Not significant.

models (see Table 16 in the Appendix) and find that the estimated parameters for wind and solar power are robust with respect to the specification.

4.2. Analysis of intraday effects

Next, we investigate further why wind power decreases the daily volatility in Denmark but increases it in Germany. Given the hourly price profiles in Fig. 1a, b, and c, the volatility-increasing impact of wind power can be explained if prices in off-peak 1 and 2 decrease more than during peak hours, leading to divergent prices. On the other hand, the volatility will decrease if peak prices decrease more than off-peak prices so that the hourly price profile becomes flatter.

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_d, is replaced by the logarithm of the average price of each block (p_d^{op1}, p_d^p, and p_d^{op2}). Model iteration steps in Table 14 in the Appendix show that the best models for DK1, DK2 and DE are SARMA(2,1)(2,1)[7], SARMA(1,2)(1,2)[7], and SARMA(1,1)(1,2)[7], respectively, using data for peak hours.

However, the addition of exogenous variables to these model causes many variables become statistically insignificant (see Table 17 in the Appendix). Therefore, we step down to a simpler SARMA(2,1)(1,1)[7] model, which for DK1, DK2, and DE differs only by 2.13, 21.64, and 5.25 from the best models in terms of AIC score, respectively. Moreover, the results for different areas can be more readily compared by using a common model. Nevertheless, we consider the best area models in Table 17 of the Appendix. The final SARMA(2,1)(1,1)[7] model is as follows:

$$p_d^b = \alpha_0 + \alpha_1 p_{d-1}^b + \alpha_2 p_{d-2}^b + \alpha_7 p_{d-7}^b + \epsilon_d + \beta_1 \epsilon_{d-1} + \beta_7 \epsilon_{d-7}, \quad (7)$$

where b is the block $\in \{op1, op2, p\}$. Similar to the model in Eq. (6), the exogenous variables are added to the right-hand side of Eq. (7). We note that the instances with a negative average price for a block are removed from our dataset. For DK1, DK2, and DE, there are 13, 10, and 15 such off-peak blocks, respectively. Since the total number of observations is 1813, 1816, and 1081, respectively, we expect that the impact of removing these observations on the coefficients for off-peak blocks is slightly positive at most.

Tables 5 and 6 have the results of the regressions for DK1 and DK2, respectively. The coefficient for average wind power during peak hours, $wind_d^p$, for example, is at the intersection of row $wind_d$ and the column "Peak". Thus, the coefficients for peak-hour wind power, $wind_d^p$, are −0.0726 and −0.0570, respectively, which differ by only 0.01–0.04 units from those for morning and evening off-peak hours, $wind_d^{op1}$ and $wind_d^{op2}$, respectively. Hence, increasing wind power in the peak hours, for example, by 1% causes a 0.07% and 0.06% decline in the average peak price in DK1 and DK2, respectively. Our approximate estimate of the average price-decreasing impact of doubling wind power penetration, $wind\_pen_d$, at 6% is comparable to Jónsson et al. (2010) who estimate that increasing wind power penetration from 20% up to 40% decreases DK1 prices approximately 10%.[2]

Fig. 3a 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. Combined with the small difference between peak and off-peak hour coefficients, this supports the hypothesis that wind power contributes to the flattening of the intraday price profile by decreasing peak prices more than off-peak prices in absolute terms.

Moreover, exchange with the hydro-dominant Nordic countries may contribute to similar flattening of the intraday price curve as the coefficients for peak hour cross-border flows $exim_d^p$ are negative at −0.10 and they differ only slightly from those for morning and evening off-peak hours, $exim_d^{op1}$ and $exim_d^{op2}$, respectively. As the capacities of the associated transmission lines exceed the average DK1 and DK2 wind power forecast in our dataset substantially, the impact of cross-border exchange on DK1 and DK2 electricity prices is significant.

Because the estimated coefficients for the impact of wind power and export in different blocks have higher absolute values for DK1 than DK2, daily DK1 prices are more likely to drop more than daily

[2] Although our estimate is computed using the exact formula $\frac{y_2-y_1}{y_1} = \left(\frac{x_2}{x_1}\right)^{\gamma} - 1$, the estimate is approximate as the true coefficient, γ, is likely to be different at different wind power penetration levels.

Table 8
The effect of different explanatory variables on DK1 weekly price volatility. All coefficients are statistically significant at the 1% level unless otherwise noted.

Variable	Model					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$wind_w$	0.1820[a] (0.0711)		0.1636[a] (0.0790)			
$wind\_pen_w$		0.2098 (0.0723)		0.1969[a] (0.0803)		
$\Delta exim_w$			0.0410[b] (0.0761)	0.0288[b] (0.0759)		
$wind_w^{std}$					0.3653 (0.0731)	
Δgas_w						0.4286[b] (0.5424)
α_0	0.4021[b]	1.8344	0.5223[b]	1.8186	−0.5931[b]	1.6036
α_1	0.3073	0.3059	0.3043	0.3032	0.3030	0.3298
β_4	0.1990	0.1989	0.2027	0.2018	0.1877	0.2100
AIC	427.39	425.81	428.26	426.55	409.97	434.39
L-B	30	30	30	30	30	30

[a] Significant at 5% level.
[b] Not significant.

DK2 prices for a comparable increase in wind power or exports. In agreement with the results in Section 4.1, daily DK1 price volatility is likely to drop more than daily DK2 price volatility due to lower absolute level of prices.

For Germany, Table 7 shows that the coefficients for wind power are −0.1530, −0.3073, and −0.1874 for peak ($wind_d^p$), morning off-peak ($wind_d^{op1}$), and evening off-peak hours ($wind_d^{op2}$), respectively. Similar coefficients are confirmed by wind power penetration, $wind\_pen_d$, too. 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. Indeed, Paraschiv et al. (2014) find that the impact of wind power on German prices has been up to 3.5 times higher in the morning off-peak than in the peak hours, but the difference has decreased over time. 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. This is true especially in morning off-peak hours where the impact is twofold.

In addition, the fact that German wind power peaks during off-peak hours (Fig. 3c) suggests that German off-peak prices can decrease more compared to peak prices in absolute terms, thereby resulting in higher daily price volatility in keeping with the findings of Section 4.1. In practice, this means that morning off-peak prices, in particular, can crash due to the combination of wind power production and low demand. By contrast, peak-hour prices with high demand decrease only slightly.

Increasing the first difference of average German solar power production, $\Delta solar_d$, by 1% decreases peak prices by 0.05% as indicated by Table 7. Furthermore, when we add peak-hour wind and solar power, the parameter estimates for the average combined generation, vre_d, and its penetration, vre_pen_d, are approximately twice as large as the coefficients for wind power, which suggests an equal contribution from solar power. The inconclusive impact of combined VRE generation on German daily price volatility in Section 4.1 can be explained by the fact that the coefficient for wind power in morning off-peak hours at −0.3073 and the coefficient for combined generation in peak hours at −0.3602 are rather close to each other, thereby indicating that these blocks decrease by nearly the same amount. However, because the coefficient for wind power in the evening off-peak hours is less negative at −0.1874, the overall impact of VRE generation on daily price volatility in Germany is likely to be slightly positive on average because evening off-peak hours diverge, which is also supported by the average hourly prices in Fig. 1c.

All the coefficients for cross-border flows between Germany and France, $exim_d$, are positive. Germany is a net exporter over these transmission lines meaning that the higher the export from Germany to France, the higher the German prices. Similar to wind power, the higher coefficients for off-peak hours, $exim_d^{op1}$ and $exim_d^{op2}$, than for peak hours, $exim_d^p$, imply a higher price sensitivity during the off-peak hours. However, the magnitudes of the coefficients for $exim_d$ are relatively small, which indicates that the cross-border exchange with France has a limited correlation with the German price level. Indeed, the possibilities to balance excess VRE generation are limited as the capacity of these transmission lines is only 30% of average VRE forecast in our dataset and the flows to hydro-dominant Austria and Switzerland approach congestion as the VRE penetration grows (Zugno et al., 2013).

The AIC scores of the models for Denmark and Germany improve significantly when external variables are added to the model in Eq. (7). Ljung-Box tests for some models fail already at low lags, which indicate that there is some serial correlation in our models. We estimated models with additional AR and MA terms, which pass the Ljung-Box test up to lag 30, and find that the estimated parameters for DK1, DK2, and DE external variables in Tables 5–7 are robust. Also, Table 17 in the Appendix shows that the results hold with the best area models, too, although they improve the AIC scores only for Germany.

4.3. Weekly volatility

We now extend the analysis to a weekly horizon by specifying a model that includes the weekly price volatility in Eq. (3) and the weekly average wind, solar, and combined production. The general model is

$$v_w = \alpha_0 + \sum_{i=1}^{p} \alpha_i v_{w-i} + \sum_{i=1}^{q} \beta_i \epsilon_{w-i} + \sum_{i=1}^{P} \alpha_{i\cdot s} v_{w-i\cdot s} + \sum_{i=1}^{Q} \beta_{i\cdot s} \epsilon_{w-i\cdot s} + \epsilon_w + \gamma^\top x_w, \tag{8}$$

Unlike the daily models, weekly volatility is affected by several factors such as power plant and transmission line availability and changes in bidding behaviour, which may not have any seasonality. Therefore, we start with the simplest models such as AR(1) and MA(1) but try also a four-week, i.e., monthly, seasonality (Weron, 2014). Table 15 in the Appendix reports the model iterations. For

Table 9
The effect of different explanatory variables on DK2 weekly price volatility. All coefficients are statistically significant at the 1% level unless otherwise noted.

	Model					
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$wind_w$	0.0621[b]		0.0045[b]			
	(0.0720)		(0.0746)			
$wind\_pen_w$		0.0465[b]		−0.0100[b]		
		(0.0729)		(0.0752)		
$\Delta exim_w$			0.2457[a]	0.2533[a]		
			(0.1125)	(0.1122)		
$wind_w^{std}$					0.1842[a]	
					(0.0749)	
Δgas_w						0.2222[b]
						(0.6070)
α_0	1.3173	1.7411	1.6084	1.6122	0.7595[a]	1.6318
α_1	0.3445	0.3465	0.3246	0.3247	0.3459	0.3238
β_4	0.1710[a]	0.1744[a]	0.1642[a]	0.1664[a]	0.1500[a]	0.1555[a]
AIC	498.58	498.92	479.82	479.81	493.48	485.21
L-B	30	30	30	30	30	30

[a] Significant at 5% level.
[b] Not significant.

the Danish areas, models with the monthly seasonality show the best performance, but they are found to be statistically insignificant for Germany. AR(1), which is the best model for Germany, fails the Ljung-Box test with Danish data already at low lags. Therefore, we run SARMA(1,0)(0,1)[4] for Danish and AR(1) for German data:

$$v_w = \alpha_0 + \alpha_1 v_{w-1} + \beta_4 \epsilon_{w-4} + \epsilon_w \tag{9}$$

$$v_w = \alpha_0 + \alpha_1 v_{w-1} + \epsilon_w. \tag{10}$$

In Eqs. (9) and (10), the AR(1) term approximates the current volatility with the previous one. In addition, an SMA(1) term in the Danish model (9) deals with monthly seasonality.

We find that increasing the weekly average wind power, $wind_w$, by 1% increases the weekly volatility of DK1 prices by 0.18% as indicated by model 1 in Table 8. For DK2, the effect is inconclusive in model 1 in Table 9, which may be attributed to lower wind power capacity. These results apply for weekly wind power penetration, $wind\_pen_w$, in model 2. Furthermore, controlling for the first difference of weekly average exports, $\Delta exim_w$, in models 3 and 4 does not change the conclusions for wind power and its penetration. However, the standard deviation of daily average wind power outputs, i.e., the intermittency of daily wind power increases the weekly price volatility by 0.37% and 0.18% both in DK1 and DK2 in model 5, respectively. Similar to the daily volatility results, model 6 shows that the change in weekly average natural gas price, Δgas_w, does not have an impact on the weekly price volatility. Table 18 in the Appendix confirms the conclusions using an alternative ARMA(1,1) model.

In Germany, increasing the first difference of weekly average wind power by 1% increases weekly price volatility by 0.11% as suggested by the coefficient for $\Delta wind_w$ in Table 10. This is supported by the comparative effect of the first difference of weekly average wind power penetration, $\Delta wind\_pen_w$, in model 2. The positive

Table 10
The effect of different explanatory variables on German weekly price volatility. All coefficients are statistically significant at the 1% level unless otherwise noted.

	Model									
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
$\Delta wind_w$	0.1051[b]							0.1095[b]		
	(0.0591)							(0.0597)		
$\Delta wind\_pen_w$		0.1407[a]								
		(0.0593)								
$\Delta solar_w$			−0.1707[c]						−0.1793[c]	
			(0.1130)						(0.1137)	
$\Delta solar\_pen_w$				−0.1432[c]						
				(0.1122)						
vre_w					0.1322[c]					
					(0.1174)					
vre_pen_w						0.1513[c]				
						(0.1096)				
Δvre_w^{std}							0.1083[a]			
							(0.0551)			
$exim_w$								0.0282[c]	0.0289[c]	
								(0.0368)	(0.0383)	
Δgas_w										−2.0427[a]
										(0.8334)
α_0	1.9668	1.9669	1.9676	1.9676	0.7636[c]	2.2393	1.9663	1.9406	1.9408	1.9669
α_1	0.1676[a]	0.1610[b]	0.2058	0.2070	0.1726[a]	0.1759[a]	0.1699[a]	0.1559[b]	0.1963[a]	0.2019[a]
AIC	170.97	168.44	171.96	172.6	173.68	173.05	170.28	172.39	173.39	168.32
L-B	30	30	30	30	30	30	30	30	30	30

[a] Significant at 5% level.
[b] Significant at 10% level.
[c] Not significant.

coefficients for the first differences indicate that higher weekly average wind power is associated with higher weekly price volatility in Germany. However, models 3 and 4 are inconclusive regarding the impact of the first difference in weekly average solar power, $\Delta solar_w$, and its penetration, $\Delta solar\_pen_w$, because the coefficients are statistically insignificant. As in the daily volatility model, the effect is likely negative because the coefficient estimates are negative. Consequently, the impact of weekly average VRE generation, vre_w, and its penetration, vre_pen_w, is inconclusive in models 5 and 6, respectively. Nevertheless, increasing the change in the standard deviation of VRE generation, Δvre_w^{std}, by 1% increases weekly price volatility by 0.11% in model 7. In models 8 and 9, the inclusion of weekly average exports, $exim_w$, does not change the earlier conclusions on the impact of weekly wind and solar power. Counterintuitively, we find a negative impact of the first difference of weekly average gas price, Δgas_w, on the weekly volatility of prices, but the very high coefficient, −2.0427, makes the result unreliable.

The results for Danish and German VRE generation intermittency, $wind_w^{std}$ and Δvre_w^{std}, respectively, can be explained by day-to-day horizontal parallel shifts of the supply curve. When the installed VRE capacity increases, the available supply increases and the parallel shifts are larger, which contributes to the growing weekly volatility. In both countries, the impact can be amplified by highly clustered wind power farms (Elberg and Hagspiel, 2015). However, the average weekly solar power is not found to contribute to the weekly price volatility, which can be explained by the peak-price-decreasing impact of solar power in Germany.

5. Conclusions

Our analyses suggest that wind and solar power production have statistically and economically significant effects on day-ahead price volatility in Denmark and Germany. In the short run, Danish daily price volatility is lower when there is more wind power production. By contrast, wind power increases the daily price volatility in Germany. However, our results are aligned with those of Jónsson et al. (2010), Mauritzen (2010), and Ketterer (2014). In Denmark, the price-decreasing impact of wind power is distributed evenly during different times of day, and there is a peak in average wind power production during peak hours. In Germany, off-peak hours are most sensitive to downward pressure in prices, and wind power is, on average, highest during these hours. Also, we find evidence that the contrasting impact of wind power on price volatility is partly due to the fact that Denmark has access to large hydropower reservoirs in the Nordic countries, whereas Germany's cross-border transmission lines are small relative to the size of its power system and it has limited access to flexible generation capacity. On the other hand, solar power is produced only during peak hours, which decreases daily volatility by decreasing high peak hour prices in Germany. Because wind and solar power have opposite effects on daily price volatility, results on their combined impact are inconclusive.

Our weekly results suggest that the standard deviation of daily average VRE generation increases the weekly volatility of Danish and German prices. These impacts can be attributed to the high day-to-day variability of wind and solar power production. Moreover, the higher the average weekly wind power, the higher the weekly price volatility.

In periods with high price volatility, producers and consumers need to optimise their generation and demand allocation to maximise their profits and to minimise their costs, respectively. From the power system point of view, the adoption of more VRE requires mechanisms to cope with intermittent supply and to decrease balancing costs (Kunz, 2013). The results for Denmark suggest that access to flexible capacity via adequate transmission capacity can reduce short-term volatility. In addition, measures such as i) capacity payments that incentivise flexible plants (Hach and Spinler, 2016), ii) dispersing wind and solar power farms (Elberg and Hagspiel, 2015), and iii) integration of adjacent markets (Farahmand et al., 2012) can be utilised. On the consumer side, enhanced understanding of the causes of volatility can be used to design tariffs that incentivise demand response (Dupont et al., 2014), which is likely to mitigate the costs of balancing caused by the intermittency of VRE.

The limitations of our distributed lag models need to be recognised. First, they estimate a single coefficient to represent the impact of VRE generation on price volatility even if the impact is more dynamic and dependent on the market situation. We have studied only the whole dataset, while the impacts may change over time. Second, the high frequency of trading in electricity markets means that time-series models may not capture processes driving price formation very accurately, which causes errors in the estimated coefficients for VRE. Nevertheless, our checks corroborate the robustness of our findings based on standard time-series methods.

A subject for further research could be to use different modelling techniques. Similar to Ketterer (2014), the impact of wind power on Danish price volatility could be established using a GARCH model. On the other hand, German price volatility could be explored as a function of time and VRE penetration using the non-parametric regression model of Jónsson et al. (2010). Also, the link between VRE generation levels and supply curve elasticities can be established more formally using real supply and demand curve data (see Dillig et al., 2016) or agent-based or complementarity models. Another avenue for future research is to estimate the impact of VRE generation on price volatility in other renewable-rich locations such as Spain, Ireland, and California. Moreover, as the absolute value of the VRE forecast errors is likely to increase when the VRE capacity increases, trading volumes and prices on various intraday markets are subject to change.

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Appendix A. Supplementary data

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