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The impact of offshore wind energy on Northern European wholesale electricity prices

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ABSTRACT

Offshore wind energy is experiencing a rising importance for many electricity markets. While the effects of wind energy overall on electricity prices have been thoroughly studied, it remains unknown if offshore wind has a different impact on electricity prices than onshore wind. The aim of this paper is therefore to estimate the effect of offshore wind energy on wholesale electricity prices and how it differs to the impact of onshore wind. For this purpose, we propose three time series models to describe the development of electricity prices in Germany, Western Denmark and Great Britain from 2015–2018. We focus on the impact on the level and volatility of electricity prices using different time series models such as AR-GARCH or ARMA. Following these models, we can identify that onshore and offshore wind power do have a significantly different impact on wholesale electricity prices in the investigated countries. Based on our results, we discuss the implications of our findings for electricity markets and policy makers.

1. Introduction

Advancing climate change intensifies the urgency to decarbonise the electricity generation and to increase the share of renewable energy sources. In Northern Europe, one of the most important renewable energy source is wind energy, with an ever-rising share of the total electricity generation. Due to technical developments and innovations, offshore wind energy is experiencing even higher growth rates and accounts for a substantial part of the total electricity generation in various Northern European countries by now [4]. The expansion of offshore wind energy is politically promoted due to a higher and more constant electricity feed-in and is indispensable for achieving the climate policy goals of many European governments and the European Union.[1]

A rising share of wind energy has a substantially differing effect on wholesale electricity prices compared to the impact of power generated by conventional power plants. Two characteristics of wind power are mostly responsible for this difference. Firstly, wind is freely available. Thus, electric power can be harvested from wind with almost no variable costs, reducing wholesale electricity prices. This effect is known as the merit-order effect and widely supported throughout the literature [5–7]. Secondly, wind is not a controllable variable and is subject to strong fluctuations, which is believed to increase the volatility of electricity prices. Most empirical studies confirm this volatility-enhancing effect, especially over larger time windows [8–10]. In many countries, these influences are magnified by legal frameworks specifying that electricity from renewable energies, including wind energy, must be purchased and fed-in with priority [9]. We provide a more detailed summary of the most important empirical studies below.

1.1. Contributions

In the short run, wind energy mostly influences electricity price levels through the merit-order effect [11–13]. The merit-order curve

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[1] See, for instance, [1], [2] or [3].

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describes the supply curve of all power generators, which offer electricity at their marginal costs. As wind energy has very low marginal costs, its emergence moves the majority of the merit-order curve rightwards, thereby crowding out more expensive conventional power generators and lowering electricity prices. Throughout the empirical literature, the merit-order effect is confirmed, although its estimated size differs significantly [5]. The magnitude of the effect depends on the steepness of the supply curve [14]. The steeper the curve at the original intersection of supply and demand, the stronger the merit-order effect will be. For different regions, different times of the day are observed to be more sensitive to wind feed-in than others. For example, Rintamäki et al. [10] and Paraschiv et al. [15], find that prices are more sensitive during times of lower demand in Germany, while prices are found to be more sensitive during peak demand times in Denmark [10] and Texas [16]. Huisman and Stet [17] observe that the merit-order effect differs by price quantile in Germany. The merit-order effect is highest during times with low and high quantile prices, while in between the impact is lower.

In contrast to the impact on price levels, the factors impacting the relationship between wind energy and electricity price volatility are multiple and more complex [10]. Therefore, the empirical studies are less consistent regarding the sign and magnitude of this impact [6,9,10,18].

Mauritzen [14] studied the effect of wind power generation on electricity price volatility in Denmark through different time series models. He found that wind power reduces intraday volatility of hourly prices, while it increases the volatility measured over larger periods. Following the approach by Mauritzen [14], Rintamäki et al. [10] confirmed Mauritzen's findings for Denmark. For Germany, on the contrary, they found that additional wind penetration increases both intraday volatility and volatility measured over larger periods. They argue that the intraday volatility is mostly impacted by the elasticity of prices and the distribution of the wind feed-in at different times of the day, respectively. If peak prices are lowered more significantly than off-peak prices, on average, this will lead to an intraday volatility-reducing impact. At the same time, they believe the volatility measured over larger time frames to be mostly caused by the intermittent nature of the wind feed-in. Following their non-parametric regression, Jónsson et al. [19] concluded that higher wind power penetration is associated with lower intraday electricity price volatility in Western Denmark. Ketterer [9] confirms the volatility-enhancing effect of wind energy on daily aggregated electricity prices for the German-Austrian market through her time series model. Additionally, she finds that a regulatory change, reducing the feed-in uncertainty for spot market participants lowered electricity price volatility significantly. In a study on New Zealand, Wen et al. [6] find the impact on volatility to differ by season.

Lichter et al. [20] were the first to empirically investigate the relationship of offshore wind energy and electricity prices, using a time series model similar to [9]. However, they did not control for onshore wind energy, which is highly correlated to offshore wind energy. As we will show in our analysis, this can lead to biased results through the omitted variable bias.

1.2. Motivation

However, these studies primarily refer to onshore wind energy as offshore wind energy was mostly not yet as relevant during the investigated periods. Due to the significantly lower roughness of the sea surface, the feed-in from offshore wind turbines is more constant and stronger than the feed-in from onshore plants [21–23]. Additionally, the offshore wind power feed-in is often less correlated to the total wind feed-in and follows different feed-in patterns over the day. Therefore, the question arises to what extent these differing feed-in characteristics translate into a differing impact on electricity prices.

This question has not yet been empirically tackled in scientific research and will build the core of this analysis. Using different time series models, we investigate the impact of offshore wind energy on the magnitude of electricity prices as well as on its volatility. First, we will estimate an AR-GARCH-model, capturing both the impact on the volatility and magnitude of daily electricity prices. Through ARMA-models, the last two models will solely estimate the impact on the volatility. While the first model covers the volatility measured over a shorter, daily time frame, the latter will again investigate the volatility of daily prices over weekly periods. We will introduce the onshore feed-in as a control variable to learn whether and how the impact of the two wind power generating technologies differs and to identify the factors these findings can be attributed to.

To explore the effects of different regulatory frameworks and market characteristics, we will consider the three regions with the highest offshore wind power generation in Europe: Great Britain, Western Denmark and Germany[2] (see Fig. 1). While Germany and Great Britain experienced a strong offshore capacity growth during the investigated period, Western Denmark has the highest share of offshore wind power generation relative to its total electricity generation in the world [4]. Due to its very high exposure to wind energy, it might provide valuable insights for other regions aiming to follow their example.

2. Data and methodology

This analysis aims to determine the sign and magnitude of the impact of offshore wind energy on mean electricity prices and its volatility. To this end, we will develop three time series models. While the first model captures the effect on mean prices and the volatility in an integrated approach through an AR-GARCH model, the last two models solely investigate the impact on electricity price volatility through an ARMA model, each focusing on the volatility over different time horizons (see Table 1). This analysis covers the four years from 2015–2018 for Germany,[3] Western Denmark and Great Britain. As the German bidding zone was reorganised in October 2018, we did not consider the last quarter of 2018 for Germany.

2.1. Model preparation

2.1.1. Introduction of dependent and independent variables

Dependent variables

Following Mwampashi et al. [7], Clò et al. [27], Gelabert et al. [28] and Ketterer [9], we use daily electricity prices as our dependent variable for the first time series model. Clò et al. [27] and Gelabert et al. [28] support this approach and argue that daily aggregated prices are less noisy than hourly prices. According to [15] and [17] hourly electricity price data should not be treated as one single time series. Rather, each hour of the day forms an individual time series, due to greater variations of underlying drivers within a day than from one day to the other (at the same hour). Thus, when using hourly prices, one should form 24 independent time series for each individual hour. We therefore decide to follow the approach of the aforementioned studies [7,9,27] and use daily electricity prices as dependent variable which allows for a more comprehensive interpretation of results.

[2] Many European countries are split up into bidding zones, with separate electricity markets and prices. In order not to dampen the quality of our data, we do not merge the bidding zones into one country and study the bidding zones separately. For the UK and Denmark, the remaining zones were not included in our analysis, as offshore wind energy is not as relevant in these regions [25].

[3] Until September 2018, Germany, Luxembourg, and Austria formed one bidding zone with one common market and wholesale electricity price. As there are no offshore wind parks in Austria nor Luxembourg (and the Austria and Luxembourg only account for roughly 5% of total wind generation in the bidding zone), we will refer to this bidding zone as "Germany" throughout this paper, yet all data is based on the three countries [26]. From October 2018 onward, Austria forms its own bidding zone with separate electricity prices.

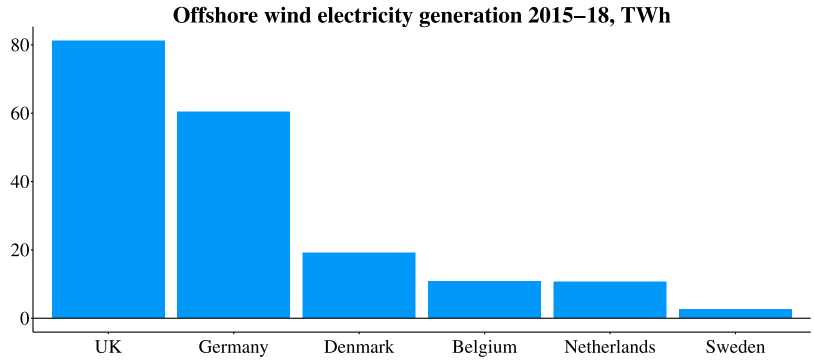

Fig. 1. European countries with the largest offshore wind power generation over 2015–2018 [24].

Table 1
Overview on the main models. In all models, the applied data is adjusted for trends and seasonalities. In most models, we will additionally control for net exports.

	Model	Formula	Dependent variable	External regressors
Model 1.A	SARX(p)(P) [7]-GARCHX(1,1)	(11) & (12)	Wholesale electricity price (1)	Offshore feed-in & Total load
Model 1.B	SARX(p)(P) [7]-GARCHX(1,1)	(11) & (12)	Wholesale electricity price (1)	Offshore feed-in & Onshore feed-in &
Model 2	SARMAX (p,q)(P,Q) [7]	(13)	Daily electricity price volatility (2)	Offshore feed-in & Onshore feed-in
Model 3.A	ARMAX(p,q)	(14)	Weekly electricity price volatility (4)	Offshore feed-in & Onshore feed-in
Model 3.B	ARMAX(p,q)	(14)	Weekly electricity price volatility (4)	Log sd of offshore[a] & onshore feed-in[a]

[a]This term expresses the logarithmised standard deviation of the daily feed-in over one week.

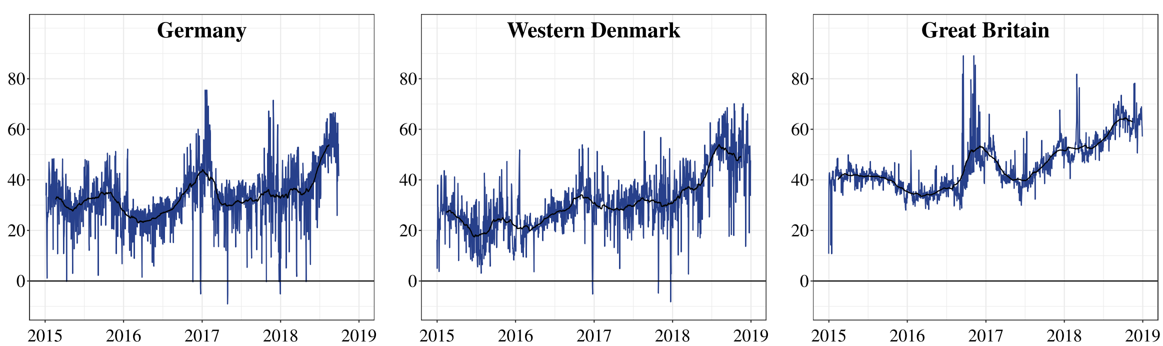

Fig. 2. Daily electricity price development from 2015–2018 for Germany [EUR/MWh], Western Denmark [EUR/MWh] and Great Britain [GBP/MWh] as defined in (1). The black lines represent the 90-days rolling average. Prices for Germany not visualised after reorganisation of German bidding zone from October 2018 onward.

The daily electricity price p_t, is defined as the unweighted average of the hourly electricity prices p_h on a particular day t, thereby following [9], [27] and [10]:

$$p_t = \frac{1}{24} * \sum_{h=1}^{24} p_h \tag{1}$$

Fig. 2 demonstrates its development for the different regions. Particularly striking is the occurrence of negative prices. During these times offtakers receive money when buying electricity on wholesale markets.

The second model investigates the impact of offshore wind power on daily electricity price volatility. Following Rintamäki et al. [10] and Mauritzen [14], we define daily volatility as the logarithmised standard deviation v_t of the hourly electricity price p_h over the day:

$$v_t = \ln \sqrt{\sum_{h=1}^{24} (p_h - p_t)^2} \tag{2}$$

The daily volatility of electricity prices is demonstrated in Fig. A.1.

In the last model, we will study volatility over a weekly horizon. Analogous to the daily volatility, we specify weekly volatility v_w as the logarithmised standard deviation of the average daily electricity price p_t over the week, again following Rintamäki et al. [10] and Mauritzen [14] approach:

$$p_w = \frac{1}{7} * \sum_{t=1}^{7} p_t \tag{3}$$

$$v_w = \ln \sqrt{\sum_{t=1}^{7} (p_t - p_w)^2} \tag{4}$$

Through calculating the weekly volatility based on daily electricity prices, we can capture the volatility of daily electricity prices, which are differently impacted than the intraday volatility of hourly prices [10].

Independent variables

In our time series model, we will also consider external variables as independent variables. For most external variables, we will calculate

Table 2
Pearson correlation coefficients of the filtered onshore and offshore feed-in over different time horizons.

	Germany	Western Denmark	Great Britain
Sum of feed-in			
Hour	0.66	0.79	0.75
Day	0.68	0.83	0.74
Week	0.73	0.80	0.75
Volatility of feed-in			
Week[a]	0.42	0.52	0.23

[a]Defined by ((4).

the sum over the respective period. In this paper, we aim to study the impact of offshore and onshore wind energy on wholesale electricity prices. We therefore consider offshore and onshore wind power feed-in as main independent variables of our models (see Fig. A.2). Following Verbeek [29], to estimate the impact of a specific independent variable, it is not necessary to include all potential variables, as long as the omitted variable bias is prevented by considering the variables correlated to the independent variable of interest (in this case the onshore wind feed-in is correlated to the offshore wind feed-in). Considering electricity prices of neighbouring markets leads to endogeneity problems due to inter-dependencies with the dependent variable (prices of domestic electricity market) and are therefor not considered [29]. Main papers in the literature follow a similar approach [7,9,10]. In addition, we will control for electricity demand and net electricity exports (see Figs. A.3 and A.4) to increase the robustness of our results similarly to [7,9,27].

Thus, in most models, we run regressions incorporating different highly inter-correlated independent variables (see Table 2). This can lead to multicollinearity [29]. Multicollinearity does not result in biased coefficients, but in both less precise and less significant ones, as multicollinearity causes a greater standard error of the independent variables [29]. We will consider this when interpreting the coefficients of our models. Additionally, we will account for this factor by also considering a regression model with interaction terms for each model where multicollinearity probably applies.[4] The interaction term expresses the common effect of the correlated independent variables on the dependent variable and can help to interpret the results and increase its informative value when multicollinearity is probably at play [31]. In order to achieve this, it is important that all independent variables are centred around their means, which they do in all models. Centring also helps to reduce the impact of multicollinearity when the goal is to identify the contribution of a particular variable [32]. Additionally, we will perform various stability checks such as rolling regressions to confirm the stability and robustness of our results. The relatively high number of observations also helps alleviate the problem of multicollinearity [29]. Omitting one variable, however, is not a solution to this problem in our case. As we will show below, this leads to very biased results through the omitted variable bias. Following the above modifications of the independent variable, we test for multicollinearity using the Variance Inflation Factor. It measures the extent to which the variance of the estimation coefficient is increased due to collinearity between independent variables [33]. A result greater than ten is usually perceived as a strong indicator for multicollinearity [33]. Following the test, no model passes this threshold in any of the countries, and even stays below five in all cases. Thus, multicollinearity does not pose a major concern in our models, despite the relatively high correlation. The results are depicted in Table A.1 in the Appendix.

[4] Usually, the interaction term $x_1 \times x_2$ is defined as the product of the two vectors of the original variables x_1 and x_2 [30].

2.1.2. Filtering trends and seasonalities

In order to construct a time series model, it is necessary for the dependent and independent variables to be stationary [34]. A time series is stationary if both its mean and autocovariance function are independent of the time [35]. For this purpose, we assume a linear relationship between the variable x_t, the deterministic component s_t and a stationary stochastic process y_t:

$$x_t = s_t + y_t \tag{5}$$

The graphs A.1, A.2, A.3 and A.4 illustrate that most variables represent a cyclical component over the year. Additionally, electricity prices and demand also reveal a weekly seasonality. In order to filter time series data, trigonometric functions are often used in the literature in order to avoid jumps in the data [36–38]. Therefore, the following model is applied to filter the temporal components of the independent and dependent variables:

$$x_t = \underbrace{\beta_0 + \overbrace{\beta_1 t}^{trend} + \overbrace{\gamma_1 \cos(t * \frac{2\pi}{365})}^{yearly} + \overbrace{\delta_1 d_t}^{weekly}}_{s_t} + \underbrace{\epsilon_t}_{y_t} \tag{6}$$

We filter the trend through a linear function, as the describes the data best. Since most variables are subject to yearly seasonal fluctuations peaking in the winter, we use a cosine function to filter these components. The strong effect of weekends on electricity prices, demand and net exports is considered by the dummy variable d_t, which reflects the weekends.[5] Thus, a linear regression is used to determine the coefficients β_0, β_1, γ_1 and δ_1, which are necessary to determine the seasonal component s_t of the variable x_t at any given time t. The residual ϵ_t of the linear regression (6) now corresponds to the stochastic process y_t from Eq. (5). Hence, y_t stands for the detrended and deseasonalised dependent or independent variable and will form the respective variable in our time series models presented below. We follow this procedure for the dependent and independent variables of our first two models with few exception for some variables where slight variations proved to capture the seasonality better (see a more detailed overview in Table A.2).[6]

For the last model, which studies weekly volatility and weekly aggregated variables, the filtering process is slightly different, as weekly effects are not observable and the year only has 52 weeks.

$$x_t = \underbrace{\beta_0 + \beta_1 t + \gamma_1 \cos(t * \frac{2\pi}{52})}_{s_t} + \underbrace{\epsilon_t}_{y_t} \tag{7}$$

We will follow this procedure for all the dependent and independent variables used in the weekly model (see Tables A.3, A.4, A.5 and A.6).

As our first model considers the arithmetic mean and variance, it is particularly prone to outliers of its dependent variable, the daily electricity price. Therefore, we will filter outliers before filtering the temporal components of the daily electricity price. Outliers are defined as the values exceeding a predefined threshold for a specific weekday. They are replaced by the value of the respective limit.[7] The outliers modified through this procedure account for 0.7%–1.3% of the total data set depending on the region. After filtering temporal components of the electricity price we repeat this procedure again.[8] As significant outliers were only observed in the first model, we will only follow this procedure for this model.

[5] Electricity demand offers a strong weekly seasonality, with demand being significantly lower on weekends when industrial and commercial consumption is lower. This also impacts electricity prices and net exports [39–41].

[6] The results of these regressions are found in Tables A.3, A.4, A.5 and A.6.

[7] The limit is defined as the triple standard deviation from the average value of a certain weekday. The same procedure is also followed by Ketterer [9] and Mugele et al. [42].

[8] Now, 0.6%–1.5% of the data set are modified.

2.2. Selection of the appropriate models

2.2.1. Estimating daily electricity prices

In the first model, we estimate the impact of offshore and onshore wind energy feed-in on the level and volatility of daily electricity prices through an SAR-GARCH model. Since the variance of electricity prices is heteroskedastic and thus conditionally dependent on the past, GARCH models[9] are suitable for modelling the time series [43]. To incorporate additional properties such as a strong tendency to return to the mean, a weekly seasonality, a long memory, and volatility clusters, an SAR(p)(P)[s,s+1]-GARCH(1,1) process[10] is particularly appropriate to model electricity prices[11] and is also often used in the literature for this purpose [9,36,42]).

Our data is shown to fit the typical characteristics of power prices. Examining the autocorrelation plot and the partial autocorrelation plot (see Fig. A.5), we observe that electricity prices are autocorrelated[12] and have a long memory, a typical property of electricity prices [44, 45]. Additionally, we test for autoregressive conditional heteroskedasticity as proposed by Engle [46] and confirm this hypothesis with high significance.[13][14]

$$y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=1}^{P} (\phi_{i\cdot s} y_{t-i\cdot s} + \phi_{i\cdot s+1} y_{t-(i\cdot s+1)}) + \epsilon_t \tag{8}$$

$$\epsilon_t = \sigma_t \eta_t \quad where\, \eta_t \sim i.i.d.\, N(0,1) \tag{9}$$

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{10}$$

Formula (8) lays out the SAR(p,q)(P,Q)[s] model in sigma notation. The coefficients ϕ_i and $\phi_{i\cdot s}$ express the influence of the preceding filtered electricity prices y_{t-i} and $y_{t-(i\cdot s+1)}$ on the filtered electricity price y_t. To account for the observed weekly seasonality, the coefficient $\phi_{i\cdot s}$ marks the impact of P seasonal autoregressive (SAR) terms $y_{t-i\cdot s}$. In the case of weekly seasonality, s is set to 7. The electricity prices are filtered for temporal components in accordance with formula (6).

The influence of the preceding squared error term ϵ_{t-1}^2 on the conditional variance σ_t^2 in (10) is expressed by the coefficient α and is generally referred to as the ARCH term [46]. The influence of the past conditional variance σ_{t-1}^2 is expressed by the coefficient β and is commonly defined as the GARCH term [47].

In order to include external regressors, the SAR(p)(P)[s,s+1]-GARCH(1,1) model can be extended to an SARX(p)(P)[s,s+1]-GARCHX(1,1) model.[15] The additional variables are simply added to the "conditional mean equation" (8) and the "conditional variance equation" (10):

$$y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=1}^{P} (\phi_{i\cdot s} y_{t-i\cdot s} + \phi_{i\cdot s+1} y_{t-(i\cdot s+1)}) + \sum_{j=1}^{m} \theta_j w_{tj} + \epsilon_t \tag{11}$$

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \sum_{k=1}^{s} \gamma_k w_{tk} \tag{12}$$

To form the mean Eq. (11) Eq. (8) is extended by the adjusted external regressors w_{tj}. For the variance Eq. (12), the adjusted external regressors w_{tk} are added to the variance Eq. (10). The coefficients θ_j and γ_k describe the influence of these external regressors on the adjusted electricity price y_t, and the conditional variance of the adjusted electricity price σ_t^2, respectively. When estimating this model, the choice of external regressors will vary (see next section and Table 1).

The distribution of the residuals demonstrates that the distribution is heavy-tailed (see Fig. A.8). Thus, considering the quantile–quantile plots (QQ-plots) for the different regions, we observe that assuming a normal inverse Gaussian distribution of residuals provides the best fit to the data.[16] Under this assumption, the individual plots are closest to the assumed distribution of the residuals.[17] Therefore, we assume normal inverse Gaussian distributed residuals for all AR-GARCH models. Jónsson et al. [19] and Dev and Martin [48] also advocate for using alternatives to the normal distribution. Jónsson et al. [19] argue that assuming a normal distribution can lead to strong distortions.

2.2.2. Estimating the intraday volatility of electricity prices

Our second model investigates the impact of offshore wind energy on intraday electricity price volatility, the logarithmised daily standard deviation of electricity prices defined in formula (2) and filtered by (6). Considering the ACF and PACF plots,[18] we observe autocorrelation in the time series v_t, which implies that current values are correlated to preceding ones[19] [35]. Additionally, we observe strong weekly, seasonal components in the ACF and PACF plots. To account for the impact of preceding periods and the weekly seasonality, a SARMA (p,q)(P,Q)[s] model is usually applied and recommended. To incorporate external variables, we again extend it to a SARMAX (p,q)(P,Q)[s]-model [34].

$$y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{k=1}^{q} \theta_k \epsilon_{t-k} + \sum_{i=1}^{P} \phi_{i\cdot s} y_{t-i\cdot s} + \sum_{k=1}^{Q} \theta_{k\cdot s} \epsilon_{t-k\cdot s} + \sum_{j=1}^{m} \gamma_j w_{tj} + \epsilon_t \tag{13}$$

The first part is known as the AR-process and analogue to (11). In addition to (11), we also consider a MA-process, which describes the influence q preceding error terms ϵ_{t-k} on the intraday electricity price volatility y_t. The impact of each individual preceding error term ϵ_{t-k} on the volatility y_t is expressed by the coefficient θ_k. The coefficients $\phi_{i\cdot s}$ and $\theta_{k\cdot s}$ mark the impact of P seasonal autoregressive (SAR) terms $y_{t-i\cdot s}$ and Q seasonal moving average (SMA) terms $\epsilon_{t-k\cdot s}$. In the case of weekly seasonality, s is set to 7. The coefficients δ_j describe the influence of the external regressors w_{tj} on the intraday volatility. As external regressors, we include the previously introduced and filtered variables, namely the daily sum of offshore feed-in as w_{t1} and the onshore feed-in as w_{t2} (see Table 1). This model forms the second model of our analysis and is closely related to the models of Rintamäki et al. [10] and Mauritzen [14].

2.2.3. Estimating the weekly volatility of electricity prices

In the last model, we will study the impact of offshore wind energy on the weekly volatility of electricity prices. Examining the ACF and PACF plots, we find some degree of autocorrelation,[20] but no clear seasonal effects. Therefore, we will apply an ARMAX model here. An ARMAX(p,q) model is closely related to the previous model (13) and is structured as follows:

$$y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{k=1}^{q} \theta_k \epsilon_{t-k} + \sum_{j=1}^{m} \delta_j w_{tj} + \epsilon_t \tag{14}$$

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[9] GARCH is an abbreviation for "generalised auto-regressive conditional heteroskedasticity".

[10] SAR is an abbreviation for "seasonally adjusted autoregressive".

[11] Note that extending a SAR(p)(P)[s] model to a SAR(p)(P)[s, s+1]-model is not encountered in the literature. However, the observed seasonal patterns of the time series occurring also after the day after a seasonal cycle is completed necessitate this very model in order to describe the data appropriately.

[12] The Box–Ljung test can also be applied to test for autocorrelation and confirms this hypothesis for all countries [34].

[13] Both the Portmanteau-Q test and the Lagrange-Multiplier test confirm this hypothesis with a p-value of <0.0001 for all regions [43].

[14] Similar results were obtained by Ketterer [9] and Lichter et al. [20].

[15] The "X" stands for external regressor or external regressors.

[16] In total, we tested nine different distributions of the residuals.

[17] Further, we find that the AIC and BIC values to be lowest when assuming a normal inverse Gaussian distribution, which confirms our hypothesis.

[18] see Fig. A.6 in the Appendix.

[19] The Box–Ljung test also confirms autocorrelation for all regions.

[20] See Fig. A.7 in appendix. The Box–Ljung test also confirms this hypothesis for all regions with a significance level of $p < 0.00001$.

Table 3
Model 1.B with and without the interaction term. As the autoregressive parameters do not change significantly after including the interaction term, we do not demonstrate them here. For the autoregressive parameters, see Table A.7.

	Germany		Western Denmark		Great Britain	
	With interaction term	Without interaction term	With interaction term	Without interaction term	With interaction term	Without interaction term
mean equation						
Offshore	-1.03^{***}	-0.94^{***}	-6.91^{***}	-7.30^{***}	-0.66^{***}	-0.65^{***}
	(0.15)	(0.15)	(1.15)	(1.08)	(0.08)	(0.08)
Onshore	-0.78^{***}	-0.81^{***}	-4.46^{***}	-4.29^{***}	-0.57^{***}	-0.58^{***}
	(0.03)	(0.03)	(0.44)	(0.40)	(0.05)	(0.05)
Interaction	-0.06^{***}		1.07		−0.02	
	(0.02)		(0.96)		(0.03)	
variance equation						
Offshore	0.00	0.07	1.08	0.00	0.17	0.17
	(0.28)	(0.31)	(3.02)	(4.23)	(0.12)	(0.12)
Onshore	0.00	0.03	3.04^{*}	2.42^{*}	0.00	0.00
	(0.05)	(0.06)	(1.27)	(1.12)	(0.07)	(0.08)
Interaction	0.00		20.87^{***}		0.23^{**}	
	(0.04)		(6.05)		(0.08)	
R^2	0.83	0.83	0.71	0.71	0.77	0.77
Log likelihood	−3734	−3740	−4170	−4177	−3279	−3286
AIC	5.50	5.51	5.74	5.74	4.52	4.52
BIC	5.58	5.58	5.81	5.81	4.59	4.59
Ljung–Box Test	0.35	0.28	0.24	0.10	0.31	0.35

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

The weekly electricity price volatility y_t refers to the logarithmised weekly standard deviation which was derived in (4) and filtered by (7). As external regressors, we will include the weekly sum of offshore feed-in as w_{t1} and onshore feed-in as w_{t2}. In a second variation of this model, we will include the volatility of the offshore and onshore feed-in as independent variables w_{t1} and w_{t2}. It is derived analogously to the electricity price volatility through Eq. (4). This model helps us understand how the intermittency of the offshore and onshore feed-in influences electricity price volatility over a longer time frame and whether it influences electricity price volatility more prominently than the magnitude of the feed-in itself.

3. Results and discussion

3.1. Estimating the impact on daily electricity prices

First, we choose the appropriate number of autoregressive parameters to be included in the model by minimising the BIC values. Thus, we decide to estimate a SARX(3)(3)[7,7+1]-GARCHX(1,1)-model in all regions[21] (see (11) and (12)). Both the ACF and PACF plots, as well as the Box–Ljung and Durbin–Watson tests do not confirm significant autocorrelation of the residuals in most regions.[22] Therefore, we conclude that the models perform rather well on the estimated data. The results of this model are illustrated in Table A.7. We observe neither explosive processes in the mean equation, nor in the variance equation, as the sum of autoregressive parameters ϕ_i is below one, and $\alpha + \beta < 1$. This means that both processes have a tendency to return to the mean and are thus stationary, which holds in all regions [43]. In all regions, we observe a significant merit-order effect of offshore wind energy. In the first model specification, an increase in 1 GWh of offshore wind energy feed-in has a significantly stronger effect on electricity prices than a 1 GWh decrease in demand. This difference is most staggering in Germany, where results differ fivefold and are in line with [20]. Therefore, we suspect the effect of offshore wind energy feed-in to be overestimated when not considering the onshore wind energy feed-in, as both feed-ins are highly correlated. Thus, the offshore wind feed-in probably carries explanatory power from the not considered onshore feed-in in this model and is therefore overestimated. This effect is also known as the *omitted variable bias* [29]. In the next model, we therefore consider the feed-in from both technologies jointly and confirm the merit-order effect for both.[23] This finding is in line with [5], [19] and [9] who confirmed the merit order effect of wind energy. All coefficients for the offshore feed-in are significantly lower than in the first model, which confirms the omitted variable bias following the definition of Verbeek [29] and Greene [50].[24] The difference is most significant in Germany, where the share of offshore feed-in of the total wind feed-in is the smallest.

In Western Denmark, the price-reducing impact of offshore wind is significantly greater than the one of onshore wind energy. Following a t-test on the difference of the two coefficients, we find that the difference is significant on a 2% level.[25] Also estimating the model with the interaction term confirms this hypothesis, as the interaction term is insignificant but positive in Denmark. Thus, the merit-order effect of offshore wind energy is significantly greater than the merit-order effect of onshore wind energy in Western Denmark. This finding is robust and confirmed throughout various model specifications and under different control variables (see 3.4 Alternative model specifications). In Germany

[21] Modelling is performed using the ugarchfit function, which fits univariate AR-GARCH models. The corresponding "*rugarch*" package was developed by Ghalanos [49].

[22] See ACF and PACF plots of the residuals in Fig. A.9 in the appendix. Only in Great Britain, some patterns of autocorrelation remain in the residuals. As the autocorrelation was significantly reduced when comparing it to the autocorrelation of the dependent variable, and the Durbin–Watson test does not support the hypothesis of autocorrelation, we conclude that this model performs necessarily well and its results can still be interpreted.

[23] In the next model, we will not consider demand anymore, as it is not correlated to the wind feed-in and should therefore not influence the magnitude of the coefficients.

[24] According to [29], the omitted variable bias is present when an independent that is correlated to an other independent variable is omitted from the model while it has a significant impact on the dependent variable. This case applies here for onshore wind as proven by the correlation in Table 2 and the highly significant coefficient for onshore wind in Tables 3 and 4. As onshore wind and offshore wind are correlated and both have a significant coefficient, both variables should be considered in the model.

[25] We state the null hypothesis $H_0 : \gamma_2 - \gamma_1 > 0$. To conduct a t-test on this hypothesis, we must first derive the t-value. $t = \frac{\gamma_1 - \gamma_2}{\sqrt{SE(\gamma_1)^2 + SE(\gamma_2)^2}}$. γ_2 and γ_2 mark the coefficient for offshore and onshore feed-in respectively, in this case [51].

and Great Britain, the coefficients for the onshore feed-in are also higher, but not significantly so.

The positive coefficient of the interaction term in Western Denmark helps to explain this finding, as it suggests the marginal impact of an additional unit of wind feed-in to be declining[26] (see Table 3). Thus, the higher the feed-in, the lower the merit-order effect of an additional unit of wind energy.[27] As the average onshore feed-in is significantly greater than the average offshore feed-in and both feed-in sources are not perfectly correlated, the onshore feed-in will have a lower average impact on the electricity price. Hence, the magnitude of its coefficient must be lower.

In Great Britain and Germany, the interaction term is negative and very close to zero. This indicates that the marginal impact of the wind feed-in is not declining, but constant or even slightly increasing.[28] To understand the different result, one must consider the different relevance of wind energy in the different electricity markets. While wind generation is very relevant and often exceeds the total electricity demand in Western Denmark, it is less prominent in Germany and Great Britain. During the investigated period, on 14% of the days, the total wind feed-in was higher than the total electricity demand in Western Denmark for that day. Thus, a large portion of the generated wind energy had to be exported. When wind is exported, the total price elasticity is bound to be lower, as a greater overall market is served, where the Danish wind has a relatively lower relevance in. Thus, the marginal impact of wind energy on the electricity price will inevitably decrease. In Germany and Great Britain, on the contrary, the total electricity demand was not exceeded by the wind feed-in on a single day. Hence, the wind can always crowd out other generation forms and might therefore even lower the prices stronger, depending on the generation mix and the merit-order curve at a particular time.

Thus, the trends observed in Western Denmark might also be awaiting the British and German electricity markets with a further rising relevance of wind energy. This observation is not only valid for these two technologies, but can also be transferred to any feed-in which is less correlated to the total feed-in when the marginal impact of an additional unit of feed-in is declining. This finding has implications for the planning and allocation of wind plants in regions with high wind feed-in. Instead of only focusing on the total expected feed-in, central planners should also consider the correlation of the wind power generation of new plants to the power generation patterns of the overall wind energy grid.

A higher impact on electricity prices is associated with a higher market value and is potentially welfare-enhancing as it helps to compensate for the cost of state-backed support schemes [27]. Hence, to a certain extent, this model advocates the further expansion of offshore wind energy capacities. Still, the validation of the merit-order effect does not necessarily imply that wind energy lowers electricity prices over larger time periods [52,53]. Similar to the short run, the electricity prices also depend from the generation capacities in the long run. A rising share of renewable generation plants could alter the capacity mix towards more flexible technologies with higher compatibility to intermittent energy sources. These technologies often have higher marginal costs and would, therefore, raise electricity prices in the future [52].

Regarding the impact on the conditional variance, the models convey that offshore wind energy does not significantly impact volatility. Through out all models, only the coefficient for the onshore wind feed-in is significant in Denmark. However, its significance might be underestimated due to multicollinearity. When including the interaction term, the interaction term is highly significant in Denmark and Great Britain. This indicates the collective feed-in of both technologies to impact the conditional variance most, while the offshore and onshore feed-in are probably not impacting it differently. The results from this model are only partially in line with the literature. Papers that studied the conditional variance through GARCH models also had mixed findings [9,20]. However, in different approaches to describe the impact on volatility, it is mostly found to be significantly positive [10,18,27]. In order to better describe the impact on volatility we will further investigate this relationship in the next sections.

3.2. Estimating the impact on intraday volatility

In the second model, we estimate the impact of offshore and onshore wind energy feed-in on the intraday volatility, which we defined as the logarithmised standard deviation of hourly electricity prices. Minimising the BIC values, we decide to estimate a SARMAX(1,2)(1,1)[7]-model in Germany and Great Britain, and a SARMAX(3,2)(1,1)[7]-model in Western Denmark (see formula (13)).[29] The results are illustrated in Table 4. As the sum of the estimated autoregressive parameters ϕ_i and θ_i is lower than one, we confirm the model to be stationary. Additionally, both the Box–Ljung test and the ACF and PACF plots of the residuals demonstrate that the residuals of the time series are not autocorrelated (see Fig. A.10).

The model reveals that offshore and onshore wind feed-in impact intraday electricity price volatility differently. Onshore wind energy tends to increase volatility in Denmark and Germany, while offshore wind energy reduces it there. In Western Denmark, the volatility-reducing effect of offshore wind energy is stronger and more significant than in Germany. If the offshore feed-in rises by 100 MWh in Denmark, the electricity price volatility decreases by 13.2%, ceteris paribus. In Germany, rising offshore wind power generation by 1 GWh will lead to 3.2% lower electricity price volatility. For Great Britain, the opposite effects are observed. Here, onshore wind energy tends to reduce the intraday volatility, while the offshore feed-in does not significantly impact it. Overall, these results are in line with the literature [10,14,19]. These findings can primarily be attributed to a different frequency of outliers, differing legal frameworks and a different distribution of the feed-in over the day. This is laid out in more detail in the next paragraphs.

In Germany, we find the onshore wind energy to significantly increase the intraday volatility, while the coefficient for offshore wind feed-in is slightly significant and negative. A more constant offshore feed-in with less outliers mostly explains this finding.

Fig. 3 reveals that the onshore feed-in has far more outliers than the offshore feed-in. During these times, electricity prices are significantly reduced. When defining extreme outliers as 2.5 times the average feed-in of a particular year, the prices are 65% lower during these hours, on average. As these outliers mostly only occur for a few hours a day, we expect this to further raise the volatility of the electricity prices. We demonstrate this argument to be valid by following Welch's t-test[30] to test if the electricity volatility is higher during times of extreme outliers of the feed-in. The test confirms this hypothesis with a p-value of less than 0.001 for all years. On average, the volatility is 25% higher on days with extreme outliers of the feed-in. These outliers occur on around 12% of the days and have a significant importance in explaining the different impact of offshore and onshore feed-in. As the wind tends to be more strong and constant on the sea, the offshore feed-in is always

[26] A positive coefficient for the squared onshore and offshore feed-in also confirms the reducing marginal impact of wind energy feed-in.

[27] Neither the onshore nor the offshore feed-in ever reach the necessary threshold to reverse the merit-order effect in Western Denmark.

[28] Also considering the squared feed-in of onshore and offshore feed-in suggests the marginal impact to be increasing, as the coefficients are negative in both regions.

[29] We use the Arima function to fit these SARMAX models. The corresponding "*forecast*" package was developed by Hyndman et al. [54].

[30] Welch's t-test is especially recommended for hypothesis tests on data sets with differing numbers of observations and different variances. The t-value is defined as follows: $t = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{\frac{s_1}{N_1} + \frac{s_2}{N_2}}}$ [55].

Table 4
Estimation results of the SARMAX model on intra-day volatility with and without the interaction term.

	Germany		Western Denmark		Great Britain	
	With interaction term	Without interaction term	With interaction term	Without interaction term	With interaction term	Without interaction term
ϕ_1	0.96***	0.96***	0.17*	0.17*	0.93***	0.93***
ϕ_2			0.78***	0.78***		
ϕ_7	0.97***	0.97***	1.00***	1.00***	0.94***	0.94***
θ_1	−0.73***	−0.71***	0.17*	0.17*	−0.57***	−0.56***
θ_2	−0.16***	−0.18***	−0.69***	−0.69***	−0.17***	−0.19***
θ_3			−0.24***	−0.24***		
θ_7	−0.84***	−0.85***	−0.99***	−0.99***	−0.84***	−0.85***
Offshore	−0.02	−0.03*	−1.15***	−1.32***	0.01	0.01
	(0.01)	(0.01)	(0.19)	(0.18)	(0.01)	(0.01)
Onshore	0.01***	0.01***	0.13	0.20***	−0.04***	−0.03***
	(0.00)	(0.00)	(0.07)	(0.06)	(0.01)	(0.01)
Interaction	0.01***		0.38*		0.04***	
	(0.00)		(0.16)		(0.00)	
R^2	0.34	0.32	0.30	0.29	0.42	0.39
R^2 no XR[a]	0.29	0.29	0.25	0.25	0.37	0.37
Log likelihood	−366	−383	−1426	−1428	−222	−266
AIC	751	783	2873	2877	463	547
BIC	798	824	2931	2930	510	590

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.
[a] R^2 of the model without considering external regressors.

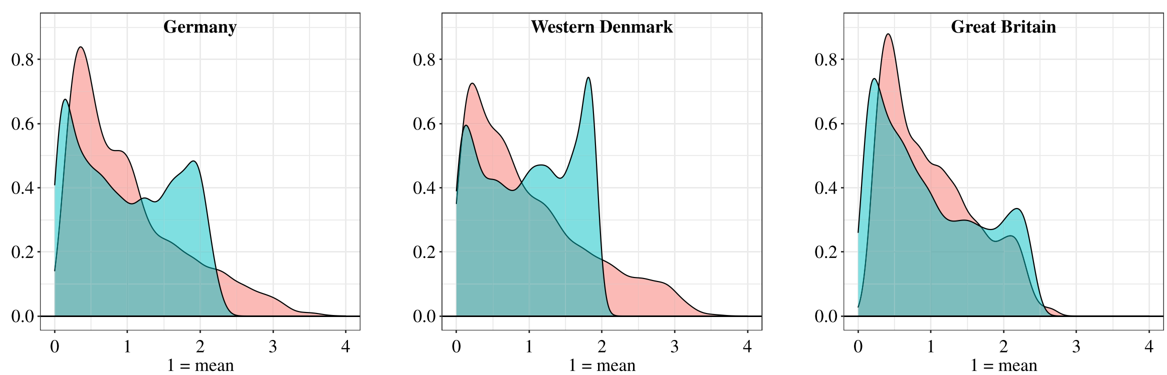

Fig. 3. Density plot of hourly offshore and onshore feed-in in 2017. The red areas represent onshore wind, the turquoise areas offshore wind. The feed-in is standardised by the respective average feed-in. Thus, a value of "1" on the x-axis represents the average feed-in in a given year, country, and technology, while a value of "2" equates to twice the average feed-in. Due to many extreme outliers in 2017, the data of 2016 is used for Great Britain.

closer to its maximum capacity and is, therefore, less prone to outliers (see Fig. 3 and [21]).[31] In addition to the lower quantity of outliers, the volatility-decreasing impact of offshore wind power is also supported by a higher feed-in during times of peak prices (see Figs. A.12 and A.13) and lower feed-in during times of the lowest prices, which lowers the intraday volatility.

Through a rolling regression (see Fig. 4), we are able to demonstrate why the coefficient for offshore wind energy is only slightly significant in Germany. It reveals that the coefficient is only significantly negative during the winter and insignificant in the summer. During the summer, solar generation is highest and known to reduce the intraday electricity price volatility [10]. From this, one could infer that the elasticity of peak electricity prices is higher when the solar feed-in is lower, and thus the volatility-decreasing impact of offshore wind energy is higher during the summer. Fig. 4 also reveals that the coefficient of the onshore feed-in does not follow any seasonal trends and is always positive, which could again demonstrate the impact of extreme outliers. Similar seasonal effects were also observed by Wen et al. [6] in New Zealand. According to their study, the merit-order effect of wind energy was most pronounced during the wet season when hydro power generation was highest. At the same time, the volatility-enhancing effect was lowest during this season of the year.

In Denmark, the impact of the onshore feed-in is significant and volatility-enhancing (see Table 4). The effect of the offshore feed-in is shown to be negative, but declining with a rising magnitude of the onshore feed-in. When weighting the coefficients by the average feed-in of each technology, our results confirm a intraday volatility-reducing effect of the total wind energy feed-in in Denmark as demonstrated by Jónsson et al. [19], Mauritzen [14] and Rintamäki et al. [10]. Again, the lower number of outliers helps explain the differences (see Fig. 3). We confirm this volatility-enhancing effect of outliers to be highly significant also in Denmark through Welch's t-test for most years.[32] As extreme outliers of the onshore feed-in were observed on approximately 13% of the days, this effect helps to explain the significant difference in the impact of two technologies. Similarly to Germany, these outliers were not observed on a single hour for the offshore feed-in.

Additionally, differing legal frameworks regarding the support of onshore and offshore feed-in in Western Denmark help explain the findings: Around 50% of the total offshore capacities were not subsidised during times of non-positive prices, which is found to have

[31] During the investigated period, outliers of the offshore wind power feed-in were not observed on a single hour.

[32] Only in 2016, the difference was not shown to be significant. For the other years, the p-value was lower than 0.001.

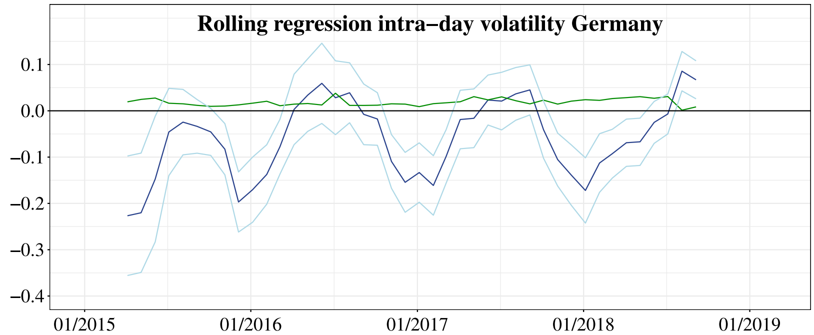

Fig. 4. Rolling regression over 120 days for the coefficients of the model on intraday volatility in Germany. The blue lines represents the coefficient of the offshore feed-in, while the green one represents the coefficient of the onshore feed-in. The faint lines represent the 95% coefficient interval.

significant consequences on the feed-in decision of affected plant operators. Only at about 9% of the times when prices were non-positive, the offshore feed-in exceeded the threshold, that is indicating that the non-subsidised plants must have also been contributing to the feed-in. As long as the prices were slightly positive (below 5€/MWh), this threshold was exceeded 90% of the time. The onshore feed-in surpassed this threshold about 80% of times during non-positive times, and 72% of times when prices were only slightly positive. Thus, this regulation most likely reduces the offshore feed-in at times of very low prices (which is mostly at night), and thereby lowers its volatility-enhancing impact. Note that non-positive prices were only observed on about 6% of the days. For onshore wind energy, none of these mechanisms are in place so far.

In Great Britain, the onshore feed-in is shown to lower intraday volatility on average, while the offshore wind feed-in is not significantly impacting it. Legal frameworks limiting the feed-in in at times of excess generation help explaining this finding. In the other regions, the volatility-enhancing effect of the onshore feed-in was attributed to its quantity and magnitude of outliers. In Great Britain, on the contrary, these outliers cannot be observed (see Fig. 3). This can be explained by differing legal provisions on the grid usage of electricity generated through wind energy. In contrast to Germany and Denmark, wind power is not granted prioritised grid usage in Great Britain and cannot exceed a certain predefined entry capacity agreement [56]. Thus, when the total onshore feed-in is about to surpass this limit, a certain number of wind plants is disconnected from the grid in order to limit its total feed-in. As a consequence, no outliers of onshore feed-in in Great Britain were observed.

Additionally, this finding is supported by a differing feed-in profile over the day. On average, the onshore feed-in is higher when prices are greater during the day and lower at night (see Figs. A.12 and A.13). Therefore, the onshore feed-in is lowering peak prices more than off-peak prices, and reducing the intraday volatility. This does not apply to the offshore wind feed-in, that has a different distribution over the day.

Overall, through this model, we could demonstrate the impact of the onshore and offshore feed-in to differ. The difference can be primarily explained through a differing hourly feed-in profile over the day and a lower magnitude of outliers. Additionally, we were able to show that the impact on the intraday volatility can be lowered through various regulatory frameworks limiting the feed-in at times of excess supply. While the lower quantity of outliers advocates the expansion of offshore capacities, the example of Great Britain proposes to establish regulations to curb the emergence of extreme outliers of the feed-in and its consequences.

Lowering intraday volatility is associated with welfare gains, as it leads to more income security of conventional plant operators and to a higher utilisation rate of power plants. Both factors foster investments in capacities and contribute to lower average costs of producers [57]. However, hourly prices often follow clear patterns which can more reliably be anticipated. Thus, in order to reduce the income uncertainty of conventional plant operators and encourage investments, estimating the volatility over longer time frames is probably even more important. Therefore, we will estimate how offshore and onshore wind energy impact weekly volatility of daily electricity prices in the next section.

3.3. Estimating the impact on weekly volatility

In the third model, we study the impact on weekly volatility of electricity prices, which we defined as the logarithmised standard deviation of daily electricity prices (see formula (4)). We decide to investigate an ARMA(1,1) model in order to study the weekly volatility.[33] This model also yields the lowest BIC values. Again, the Box–Ljung test, and the ACF and PACF plots, confirm the residuals not to be autocorrelated (see Fig. A.11).

The results convey that the magnitude of both the offshore and the onshore wind energy mostly do not have a significant impact on electricity prices (see Table A.10). These results also hold after including an interaction term, which is not significant in all regions. In a second variation of this model, we therefore investigate the impact of the volatility of the feed-in and find that it explains the weekly electricity price volatility significantly better in all countries (see Table A.11). This finding is also observed by Rintamäki et al. [10]. According to this second model, only the volatility of the onshore feed-in significantly impacts the volatility of the weekly electricity price in Germany and Denmark. The effect of offshore wind energy, however, might have been ignored due to its lower magnitude and relevance for the overall electricity market.

Therefore, we will estimate an additional model, where we only introduce the volatility of the total wind feed-in as external variable.[34] This model does not only have a higher explanatory power but also the most significant coefficient of all models (see Table 5). Therefore, we assume the volatility of the wind feed-in to best explain the weekly volatility of electricity prices. When the volatility of the wind feed-in rises by 10%, the weekly price volatility will rise by 3.4% to 4.5%, depending on the region.

This suggests the volatility measured over a larger time horizon, e.g. over one week, to be mostly impacted by shifts of the supply curve rather than the overall magnitude of the feed-in in this period. These shifts are primarily caused by fluctuations in the feed-in from

[33] Again, the Arima function from the "*forecast*" package was used to fit these models [54].

[34] The volatility of the total wind feed-in is defined as its logarithmised standard deviation of the filtered daily total wind feed-in over a week (see formula (4)).

Table 5
ARMAX(1,1) model on the weekly electricity price volatility. The volatility of the wind feed-in forms the only independent variable here.

	Germany	Western Denmark	Great Britain
ϕ_1	0.67***	0.90***	0.78***
	(0.20)	(0.06)	(0.18)
θ_1	−0.46	−0.72***	−0.51
	(0.25)	(0.09)	(0.27)
vol of wind	0.45***	0.34***	0.47***
	(0.07)	(0.09)	(0.11)
R^2	0.24	0.22	0.21
R^2 no XR[a]	0.06	0.15	0.13
Log likelihood	−112.20	−152.11	−191.19
AIC	232.41	312.21	390.39
BIC	245.50	325.58	403.72

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

[a] R^2 of the model without considering external regressors.

Table 6
ARMAX(1,1)-model investigating the impact of the magnitude of the onshore and offshore feed-in on the filtered volatility of the overall wind feed-in.

	Germany	Western Denmark	Great Britain
ϕ_1	−0.60**	0.90***	−0.54
θ_1	0.73***	−0.84***	0.54
Intercept	0.10***	0.11**	0.11***
Offshore	0.04*	−0.00	−0.03
	(0.02)	(0.09)	(0.02)
Onshore	0.02***	0.18***	0.05***
	(0.00)	(0.03)	(0.01)
Interaction	−0.01***	−0.27***	−0.02***
	(0.00)	(0.03)	(0.00)
R^2	0.53	0.42	0.28
AIC	129.30	99.36	156.92
BIC	152.21	122.76	180.24
Log likelihood	−57.65	−42.66	−71.46

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

renewable energy sources such as wind. The more prominent these shifts, the more will they increase the volatility of prices [10].[35]

Tables A.8 and A.9 demonstrate that the relative fluctuations of the offshore feed-in tend to be lower than the relative fluctuations of the onshore feed-in in Western Denmark. Moreover, there is an additional factor at play. The onshore feed-in and the offshore feed-in are not perfectly correlated. This allows for reducing the volatility of the total feed-in by increasing the share of the minor party. Thus, up to a certain point, an additional unit of offshore feed-in will lower the volatility of the total feed-in less than an additional unit of onshore feed-in. As the volatility of the offshore feed-in is not significantly higher in any country, this point will probably not be located too far below an equal share of the offshore feed-in is reached, or even higher. This hypothesis has similarities to the portfolio theory introduced by Markowitz [58]. To confirm this hypothesis, we will set up a linear regression, where the volatility of the total wind feed-in forms the dependent variable and the offshore and onshore feed-in represent the independent variables, respectively. As the wind feed-in is slightly autocorrelated, we will also include the first-order AR- and MA-process, upgrading the model to an ARMAX(1,1)-model.

The regression reveals that the weekly volatility of the total wind feed-in is significantly negatively impacted by the offshore wind feed-in in Western Denmark and Great Britain (see Table 6). Thus, a rising share of offshore feed-in will lower the weekly volatility of the total wind feed-in. At the same time, the onshore feed-in is positively affecting the volatility of the total wind feed-in. For instance, rising the onshore feed-in by 1 GWh per day, will result in 18% higher weekly volatility of the total wind feed-in, if the offshore feed-in is at its average weekly magnitude. In Germany, the coefficient for the offshore feed-in is positive, while the interaction term is negative. Thus, on days with high onshore feed-in, the offshore feed-in will have a negative impact on the volatility of the total wind feed-in. Below, its impact will be volatility-enhancing.

Following this regression, we can cautiously derive that the offshore feed-in lowers the weekly volatility of electricity prices less than the onshore feed-in does, as the volatility of the wind feed-in is the main variable in explaining the weekly volatility of electricity prices. This holds especially for Great Britain and Denmark and is also confirmed for most times through a rolling regression (see A.15). In Germany, the differing results could be potentially explained by a high correlation of the offshore feed-in with the overall wind feed-in (which is primarily generated in Northern Germany), while many onshore plants are located at locations with less correlated wind patterns, such as the German Uplands or Southern Germany [59].

In essence, this model demonstrates the importance of reducing the similarity of the different feed-in sources in order to reduce the volatility of the feed-in. Thus, up to a specific point, increasing the offshore wind power generating capacities offers a solution to lower the volatility of the feed-in and thus, of electricity prices. This is also supported by the less volatile nature of the offshore wind feed-in (see Table A.8).

As stated above, lowering the volatility over a longer time frame, such as a week, is very important to reduce income uncertainty for plant operators. Higher uncertainty leads to higher costs and discourages investments and grid expansions [57]. Generalising this argument, it advocates an allocation procedure focusing on wind power-generating plants with less correlated wind patterns and a further expansion of cross-border transmission capacities [60].

3.4. Alternative model specifications

As the obtained results depend upon the model specification and considered exogenous variables, we will check the robustness of the results by including different control variables and different specifications of our models. As both Denmark and Germany are located in the centre of Europe and their electricity grids are highly interconnected with foreign grids, we additionally introduce net electricity exports as a control variable.[36] In Western Denmark, we additionally control for the impact of wind energy generation in Germany and Eastern Denmark. We will also introduce net exports as a control variable in Great Britain. Throughout all specifications, the previously introduced and presented main results manifest themselves as stable and robust (see Tables A.12 and A.13). Further, we demonstrate the results to be robust through a rolling regression over a yearly period (see Fig. A.14).

3.5. Impact of climate change

Since the beginning of Industrialisation in the 19th century, the global average temperature has risen by 1.1–1.3 °C and is threatened to further increase with accelerating climate change [62]. In this section, we will briefly discuss the impact of climate change on wind energy and electricity prices.

According to [62] there is medium evidence for wind speeds to have declined over the past four decades globally. In the future, there

[35] This also helps explaining why the coefficients for the onshore and offshore feed-in were not or only slightly significant in the variance equation of the GARCH model (see Table A.7). In this model, the magnitude of the feed-in constitutes the external variable, which is also correlated to the volatility of the feed-in. In times of higher feed-in, the volatility also tends to be higher.

[36] Net exports are probably endogenous from electricity prices and their volatility and therefore hard to interpret [61].

is medium evidence that wind speeds will further decline in Northern Europe over this century, while the estimations differ by region and scenario. In addition, Akhtar et al. [63] expect that continued deployment of offshore wind farms in the North Sea will reduce wind speeds in this region in the future, reducing capacity factors by up to 20%. Regarding the variability of wind, IPCC [62] has medium confidence that it will increase in the extreme warming scenario in Northern Europe. For the other scenarios, results are inconclusive so far. For extreme weather events, IPCC [62] expects a slight increase in the frequency and amplitude of storms in Northern Europe.

Following the results of our models, the expected trends will also impact the effect of wind energy on electricity prices. First, lower wind speeds will reduce wind power generation dis-proportionally due to the cubic relationship between wind speeds and wind power generation [64]. This will reduce the absolute merit-order effect per unit of installed capacity. IRENA [65] show that a reduction of wind speeds in many European countries was offset by technological advancements, thus increasing the overall capacity factors despite less favourable wind conditions. It is uncertain if technical innovations can also prevail over wind speed reductions in the future. On the other hand, increasing variability and extreme weather events such as storms will also contribute towards rising volatility of power prices, due to the volatility-enhancing effects introduced previously. The cubic relationship between wind speed and wind power production further amplifies the impact of the increasing variability. Policy makers and investors need to consider these trends in the planning and investments decisions for wind parks, both offshore as well as onshore.

3.6. Impact of technological developments

The future wind feed-in patterns are also highly affected by technological developments [66]. This will also influence the impact on electricity prices [67]. While the feed-in of the existing fleet can be mostly influenced by advancements in technologies for operations and maintenance [68], new turbine models can offer new characteristics that allow for different generation potential and curves [66,69,70]. In this section, we will provide a short overview on expected trends and briefly discuss the potential impact of these developments on electricity prices.

The operation and maintenance of wind farm presents an optimisation problem around minimising the costs of maintenance while minimising foregone revenues during downtime [68]. Historically, offshore wind turbines have experienced a higher failure rates than onshore wind turbines, thus there is more improvement potential [71]. Further advancements in remote operations and maintenance are expected to reduce downtime, which will also reduce the volatility of the feed-in [68,72]. In addition, there is a vast potential to minimise downtime through predictive maintenance, yet many applications are still in a nascent stage [68,73]. Similar trends also apply to onshore wind, where automated inspections via drones are less complex than offshore [74]. In the future, it is also expected that a rising number of projects will carry out automated repairs via drones [75]. In addition to developments in maintenance, improved wind prediction models will facilitate the system integration of wind energy, offshore as well as onshore [76,77].

Over the past decades, new offshore wind turbines have grown significantly [78]. While new turbines reached a rotor diameter of 94 m in 2010, GWEC [79] expects turbines deployed in 2030 to have diameters of 275 m [78]. These larger diameters are also associated with more generation potential and higher capacity factors [79,80]. Similarly, development and deployment of floating wind turbines will allow for more steady wind generation [79,81]. Floating wind turbines can often exploit the most favourable wind conditions that are not accessible to bottom-fixed models [82]. GWEC [82] expects global floating wind installations to reach more than 10 GW by the of this decade, up from only 120 MW in 2021 [82]. On shore, turbines have grown similarly, yet at a smaller scale, increasing rotor diameters from 82 metres in 2010 to 120 metres in 2020 with capacity factors rising across the world [65,83]. In the coming years, repowering will become increasingly important for onshore wind, with almost 80 GW onshore wind farms reaching the end of their normal economic life during this decade in Europe [84]. These wind farms are often located at the sites with the best wind conditions [85]. New turbines will allow to capture higher capacity factors through the more advanced technology that can be deployed today [65].

With increasing wind deployment, the system integration becomes increasingly important [66]. New model designs that optimise for feed-in stability rather then overall generation volumes would increase the feed-in at times when wind is only moderate and help reduce both the intermittency of the feed-in as well as system integration costs [66,70,86]. Due to a higher feed-in of these turbines at times with lower wind speeds, the market value of their output is higher compared to "conventional" wind turbines [67,86]. This is relevant for onshore and offshore wind. Yet especially onshore, an increasing share of projects will be located on sites with only second-best wind conditions with lower wind speeds, increasing the need with turbines with lower cut-in speeds [87]. Optimising turbine design for feed-in at lower wind speeds also reduces the exposure to potentially declining wind speeds in Northern Europe as discussed in the previous section [62,63,88]. In addition, integrating wave energy conversion systems into offshore wind farms offers an additional solution to reduce the volatility of the feed-in from offshore wind farms [89,90]. A similar effect can be achieved through the integration of floating solar photovoltaic in offshore wind parks [91].

To reduce the rising level of curtailment of wind farms across Europe [92,93], integration with energy storage systems will increase the utilisation of wind farms [94] and will in addition allow wind farm operators to maximise the economic value of the power generation, shifting grid feed-in to times of higher prices. To date, more than 100 MW of combined wind-and-storage projects have been developed in Europe, the vast majority onshore [95].

The aforementioned developments allow for a more steady, less volatile feed-in. This will help reduce the volatility-enhancing impact of offshore and onshore wind that were discussed in previous sections. Improved wind prediction models will also reduce the volatility-enhancing impact as outlined by Weber and Woerman [76].

4. Conclusion

Through our time series models, we identified that onshore and offshore wind power *do* have differing effects on wholesale electricity prices in the investigated countries. Where results differ, offshore wind energy mostly offers more desirable results, as it mostly tends to reduce price levels or price volatility more than the onshore feed-in does [27,57]. We were also able to demonstrate that the differences can mostly be attributed to a more constant feed-in with fewer outliers and a lower correlation of the offshore feed-in to the overall wind feed-in compared to the onshore feed-in. Thus, the diversification of the feed-in sources reduced the volatility of the feed-in and of the volatility-enhancing impact itself. New wind turbine designs can also contribute towards a more constant wind feed-in in the future [70]. Additionally, our paper highlights the effect of regulations that have limited the feed-in during times of excess supply, and thereby also reduced the volatility-enhancing effect of the wind feed-in.

In Western Denmark, which has the highest share of offshore wind power generation relative to its total electricity generation in the world, the wind feed-in was shown to have a decreasing marginal impact on prices. Therefore, diversification also helped to maintain a greater merit-order effect of an additional unit of wind power feed-in in Denmark. Generalising this argument, central planners should therefore not only consider the expected wind feed-in when commissioning new sites in the future, but also the correlation of the feed-in of these new

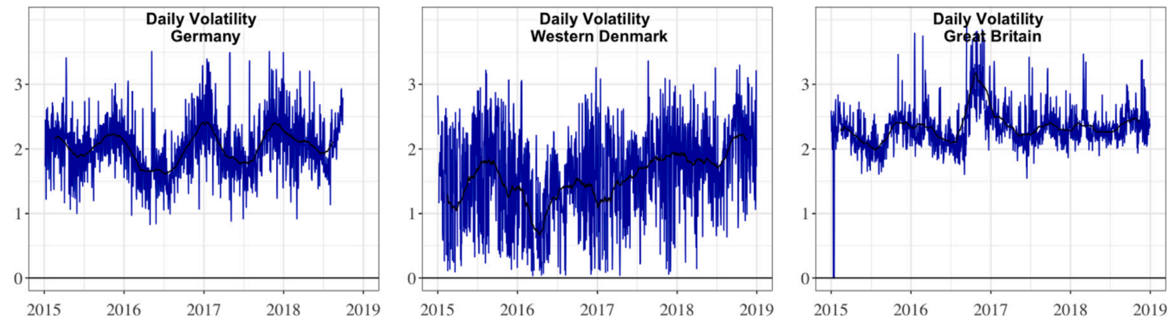

Fig. A.1. Intraday electricity price volatility of hourly prices as defined in (2). The black lines represent the 90-days rolling average.

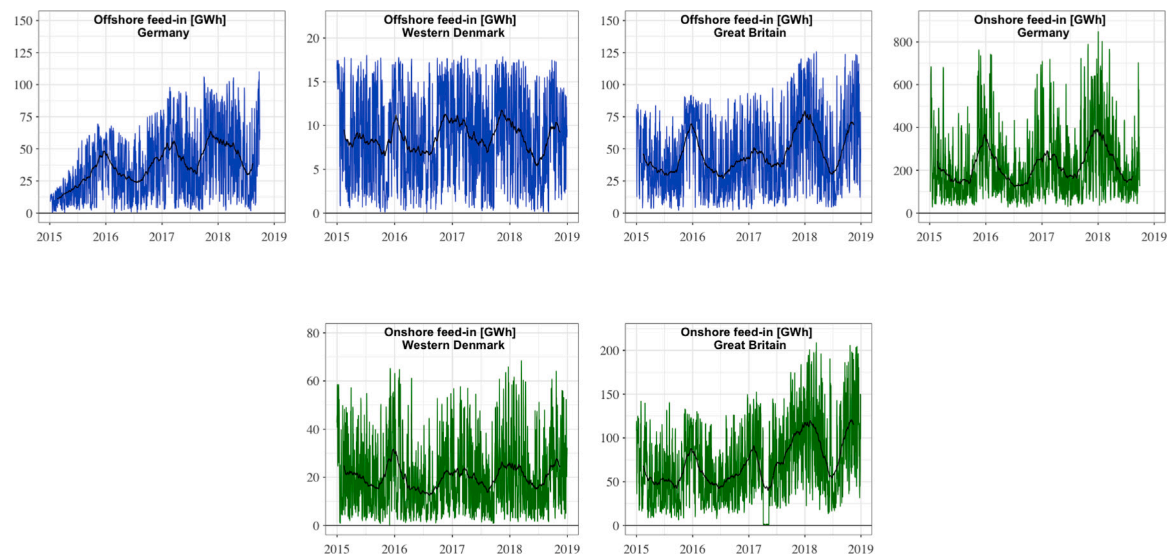

Fig. A.2. Daily offshore (above in blue) and onshore feed-in (below in green) in GWh for Germany, Western Denmark and Great Britain. The black lines represent the 90-days rolling average.

sites to the total feed-in for diversifying the feed-in structure. This can also be achieved by extending market coupling within regions with often differing weather conditions [60]. Diversified feed-in sources will not only help to reduce prices and the volatility-enhancing impact of wind power, but also achieving power supply security at lower costs [96]. With a rising share of renewables, the diversification of feed-in sources will therefore play a decisive role in reaching the most ambitious climate goals.

CRediT authorship contribution statement

Emil Hosius: Writing – original draft, Data curation, Investigation, Formal analysis, Validation, Software. **Johann V. Seebaß:** Writing – original draft, Data curation, Validation, Methodology, Software. **Benjamin Wacker:** Writing – review & editing, Validation. **Jan Chr. Schlüter:** Writing – original draft, Project administration, Supervision, Resources, Data curation, Validation, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data is freely available at ENTSO-E (2020a), ENTSO-E (2020b), ENTSO-E (2020c), and ENTSO-E (2020d). A permanent link was established at https://doi.org/10.17632/p3npk87pxw.3, an open-source online data repository hosted at Mendeley Data [97].

Appendix

See Figs. A.1–A.15.

See Tables A.1–A.13.

Table A.1
Variance Inflation Factors for the independent variables representing the onshore and offshore wind feed-in for the different models. Model 1.A is not considered as onshore wind does not form an independent variable in this model.

	Germany	Western Denmark	Great Britain
Model 1.B	1.84	3.33	2.22
Model 2	1.84	3.33	2.22
Model 3.A	2.12	2.72	2.33
Model 3.B	1.22	1.39	1.06

Table A.2
Selected filtering procedures for the variables in first two models. While all variables where filtered for trends, not all where for weekly or yearly seasonality, as they were not observable for some variables.

Variable	Weekly S.	Yearly S.	Trend
Daily electricity prices	✓	×	✓
Daily volatility of prices	×	✓	✓
Offshore and onshore feed-in	×	✓	✓
Total load	✓	✓	✓

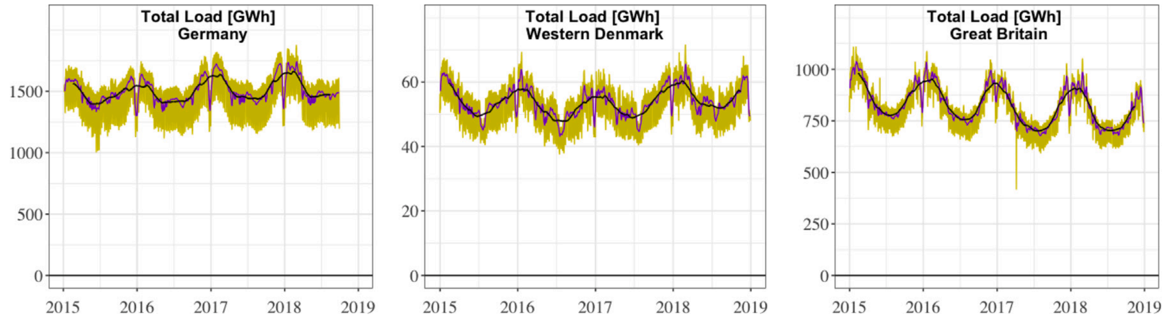

Fig. A.3. Daily electricity demand [GWh] in Germany, Western Denmark and Great Britain. While the black lines represent the 90-days rolling average, the purple lines represent the 7-days rolling average.

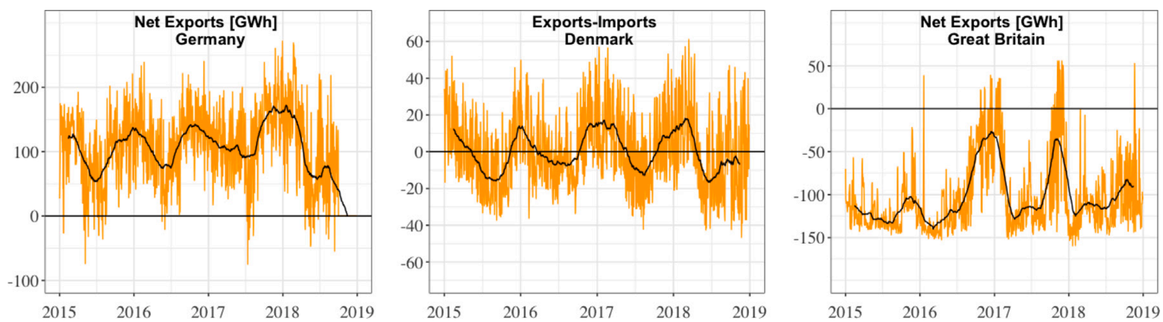

Fig. A.4. Daily electricity net exports [GWh]. A positive value indicates that more electricity has been exported than imported on this specific day. The black lines represent the 90-days rolling average.

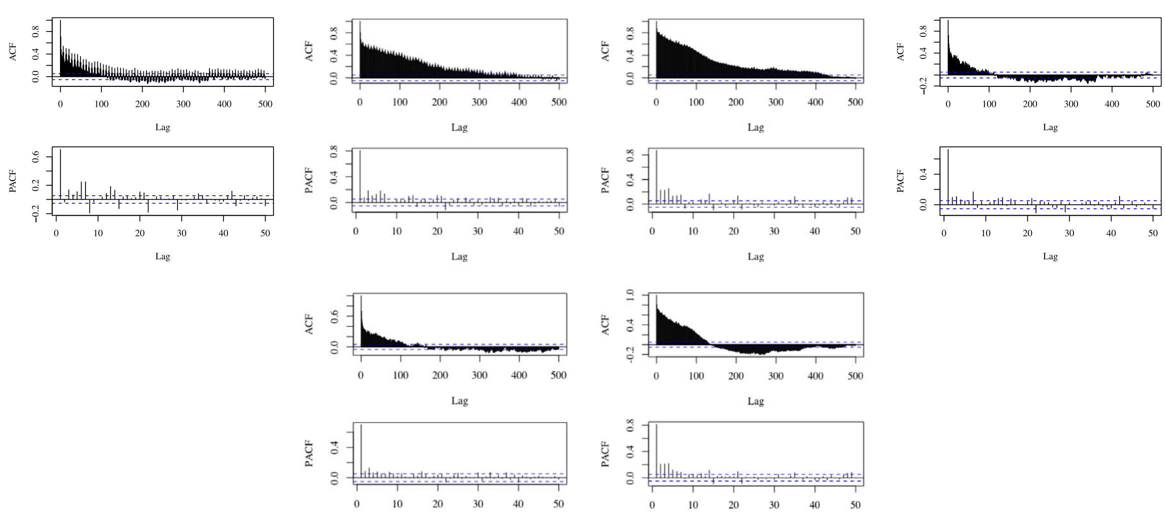

Fig. A.5. ACF and PACF plots of daily electricity prices. Germany is depicted to the left, Western Denmark in the centre, and Great Britain to the right. The plots for the original data are in the upper rows, while the ones for the filtered one are below.

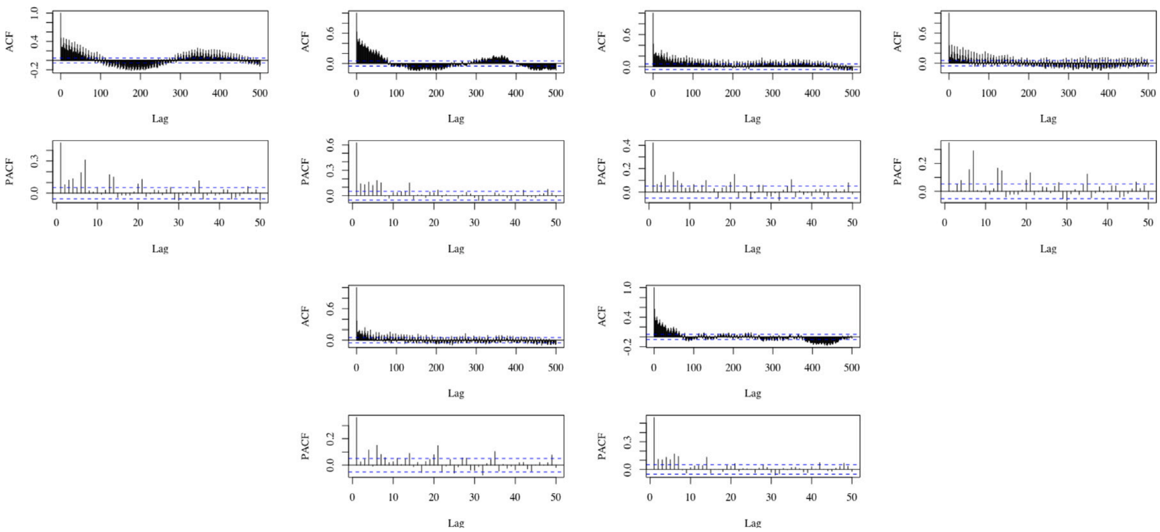

Fig. A.6. ACF and PACF plots of daily electricity price volatility. Germany is depicted to the left, Western Denmark in the centre, and Great Britain to the right. The plots for the original data are in the upper rows, while the ones for the filtered one are below.

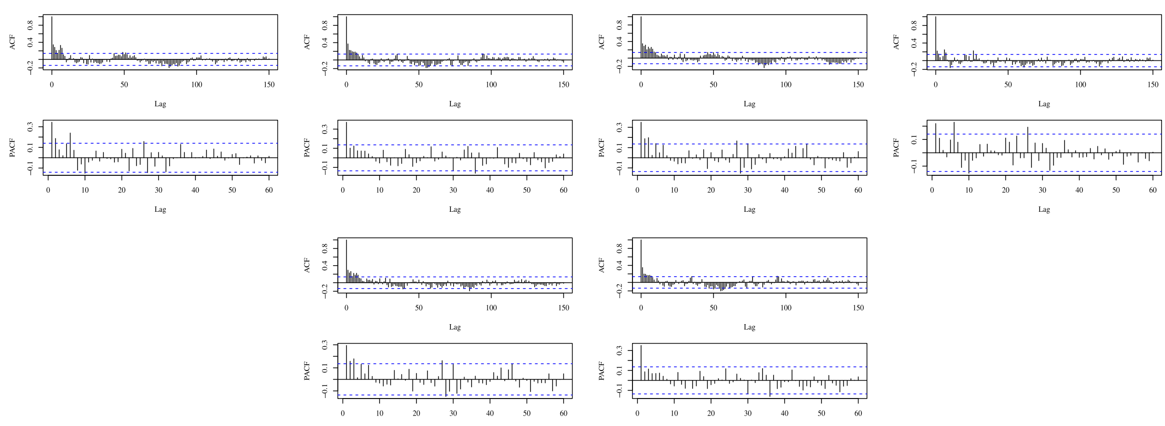

Fig. A.7. ACF and PACF plots of weekly electricity price volatility. Germany is depicted to the left, Western Denmark in the centre, and Great Britain to the right. The plots for the original data are in the upper rows, while the ones for the filtered one are below.

Table A.3
Regression estimates for filtering of dependent variables.

	Electricity price			Intraday volatility		
	GER	DK1	GB	GER	DK1	GB
Intercept	19.88***	13.31***	32.13***	1.96***	1.18***	2.31***
	(0.72)	(0.60)	(0.48)	(0.02)	(0.04)	(0.02)
Time	0.01***	0.02***	0.02***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Cosine				0.26***	0.11***	0.19***
				(0.02)	(0.03)	(0.01)
Weekend dummy	9.89***	5.79***	2.43***			
	(0.62)	(0.52)	(0.42)			
R^2	0.25	0.46	0.48	0.18	0.09	0.13
Num. obs.	1364	1461	1461	1364	1461	1446

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

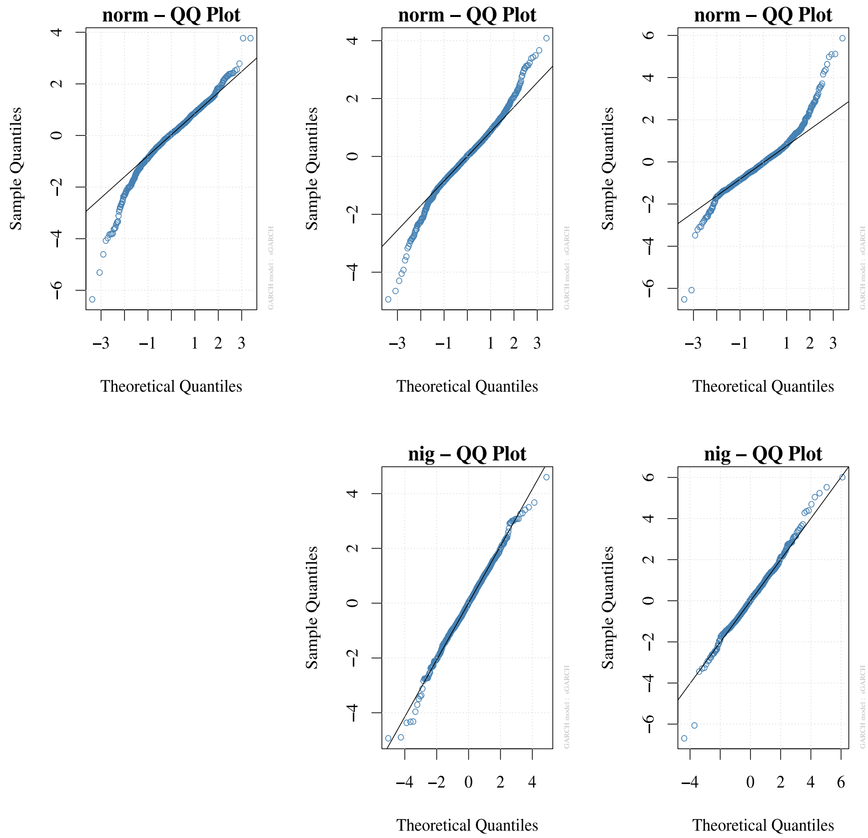

Fig. A.8. Quantile–Quantile Plots of the residuals of the AR-GARCH-models assuming normal distribution (above) and normal inverse Gaussian distribution (below). Germany is depicted to the left, Western Denmark in the centre, and Great Britain to the right.

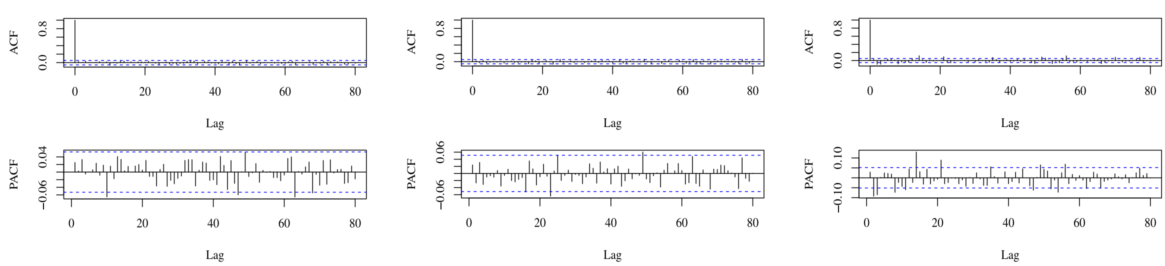

Fig. A.9. ACF and PACF plots of the residuals of the SARX(p)(P)[s,s+1]-GARCHX(1,1) model estimating daily electricity prices. Germany is depicted to the left, Western Denmark in the centre, and Great Britain to the right.

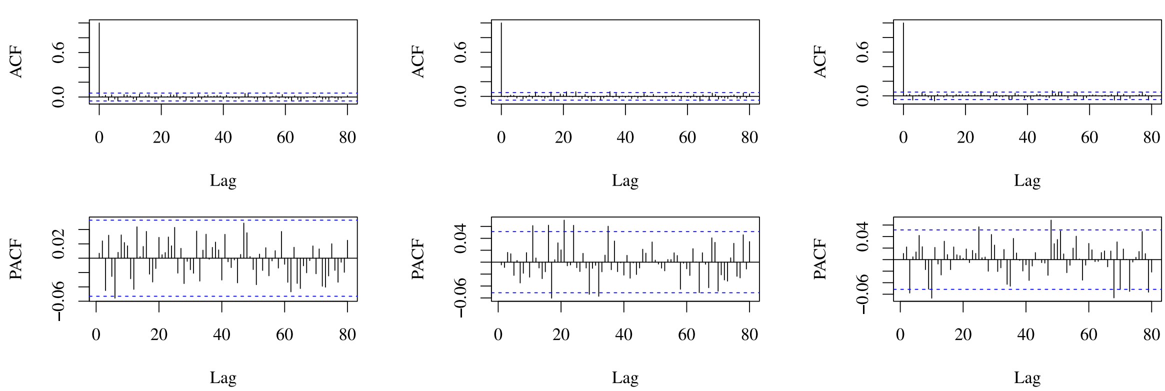

Fig. A.10. ACF and PACF plots of the residuals of the SARMAX(p,q)(1,1)[7] model estimating the intraday volatility. Germany is depicted to the left, Western Denmark in the centre, and Great Britain to the right.

Table A.4
Regression estimates for filtering of independent variables for Germany.

	Offshore	Onshore	Demand
Intercept	19,418.55***	188,167.04***	1,280,575.69***
	(1,260.37)	(7,962.88)	(5,870.54)
Time	26.50***	54.27***	59.90***
	(1.61)	(10.15)	(5.87)
Cosine	10,384.30***	94,047.44***	104,216.67***
	(894.81)	(5,653.28)	(3,269.37)
Weekend dummy			259,635.29***
			(5,081.29)
R^2	0.21	0.18	0.73
Num. obs.	1364	1364	1364

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.5
Regression estimates for filtering of independent variables for Western Denmark.

	Offshore	Onshore	Demand
Intercept	8,675.43***	19,910.42***	46,390.16***
	(261.72)	(766.49)	(238.83)
Time	0.05	0.66	0.81***
	(0.31)	(0.91)	(0.22)
Cosine	1,678.58***	5,143.34***	4,598.48***
	(184.91)	(541.53)	(132.40)
Weekend dummy			9,602.68***
			(207.23)
R^2	0.05	0.06	0.70
Num. obs.	1461	1461	1461

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.6
Regression estimates for filtering of independent variables for Great Britain.

	Offshore	Onshore	Demand
Intercept	35,946.69***	46,244.93***	819,755.71***
	(1,364.32)	(2,030.75)	(3,194.78)
Time	14.38***	35.62***	−90.80***
	(1.62)	(2.41)	(2.97)
Cosine	15,983.01***	21,511.95***	104,326.34***
	(963.90)	(1434.73)	(1,771.08)
Weekend dummy			99,627.94***
			(2,771.98)
R^2	0.20	0.23	0.80
Num. obs.	1461	1461	1461

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

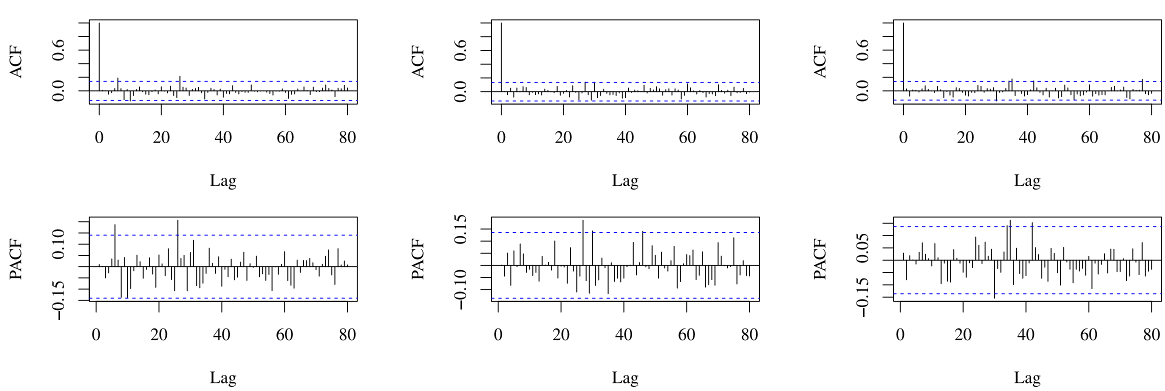

Fig. A.11. ACF and PACF plots of the residuals of the ARMAX(1,1) model estimating the weekly volatility. Germany is depicted to the left, Western Denmark in the centre, and Great Britain to the right.

Table A.7
Estimation results of the SARX-GARCHX models on daily electricity prices.

Model	Germany		Western Denmark		Great Britain	
	A	B	A	B	A	B
mean equation						
ϕ_1	0.54***	0.46***	0.55***	0.51***	0.54***	0.57***
ϕ_2	0.02	0.09***	0.04	0.10**	0.09**	0.11***
ϕ_3	0.10***	0.11***	0.11***	0.10***	0.17***	0.16***
ϕ_7	0.20***	0.23***	0.06*	0.11***	0.06*	0.07**
ϕ_8	−0.04	−0.02	0.07**	0.03	0.06*	0.01
ϕ_{14}	0.07**	0.15***	0.06*	0.07**	0.04	0.06**
ϕ_{15}	0.02	−0.09***	−0.00	−0.03	−0.01	−0.04
ϕ_{21}	0.10***	0.20***	0.06*	0.10***	0.06**	0.08***
ϕ_{22}	−0.03	−0.16***	−0.02	−0.05*	−0.04*	−0.05**
Offshore	−3.65***	−0.94***	−16.53***	−7.30***	−1.28***	−0.65***
	(0.15)	(0.15)	(0.61)	(1.08)	(0.06)	(0.08)
Demand	0.65***		10.71***		0.42***	
	(0.05)		(1.03)		(0.05)	
Onshore		−0.81***		−4.29***		−0.58***
		(0.03)		(0.40)		(0.05)
variance equation						
ω	1.39*	1.37	0.83*	4.65***	0.49***	0.57***
	(0.68)	(0.76)	(0.42)	(1.39)	(0.13)	(0.14)
α_1	0.12**	0.10**	0.11***	0.24***	0.22***	0.25***
	(0.04)	(0.03)	(0.03)	(0.05)	(0.04)	(0.05)
β_1	0.83***	0.82***	0.86***	0.54***	0.72***	0.68***
	(0.06)	(0.07)	(0.04)	(0.10)	(0.04)	(0.05)
Offshore	0.00	0.07	0.00	0.00	0.00	0.17
	(0.31)	(0.31)	(1.17)	(4.23)	(0.08)	(0.12)
Demand	0.00		0.00		0.00	
	(0.07)		(1.11)		(0.03)	
Onshore		0.03		2.42*		0.00
		(0.06)		(1.12)		(0.08)
R^2	0.73	0.83	0.69	0.71	0.77	0.77
R^2 no XR[a]	0.55	0.55	0.49	0.49	0.71	0.71
Log likelihood	−4015.10	−3740.26	−4193.74	−4177.12	−3314.47	−3286.02
AIC	5.91	5.51	5.77	5.74	4.56	4.52
BIC	5.98	5.58	5.83	5.81	4.63	4.59

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.
[a] R^2 of the model without considering external regressors.

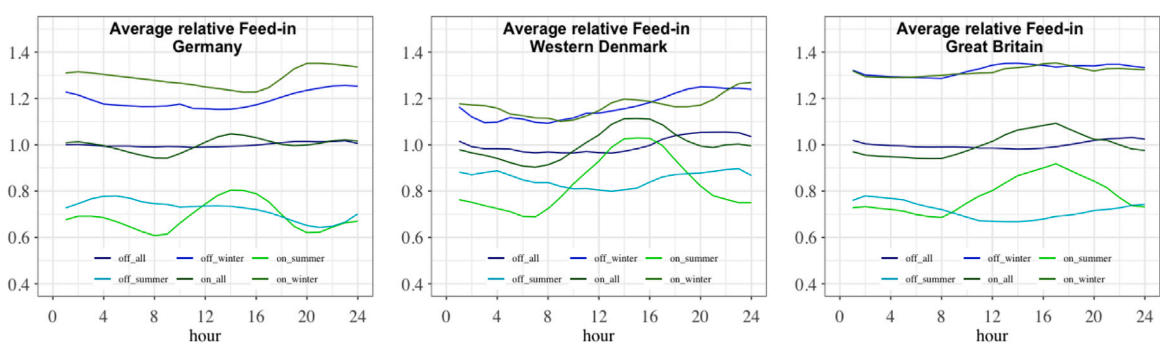

Fig. A.12. Average offshore and onshore wind feed-in per hour of the day for different seasons. 1 = Average feed-in over the year.

Table A.8
Coefficient of variation (CV) of the hourly offshore and onshore feed-in. The CV of the daily wind feed-in provides very similar results, yet proportionally lower for all regions.

	Offshore	Onshore
Germany	.77	.78
W. Denmark	.66	.83
Great Britain	.68	.66

Table A.9
Relative first difference of offshore and onshore wind energy feed-in. The relative first difference is defined as the ratio of the average first difference of the daily feed-in and the average feed-in.

	Offshore	Onshore
Germany	.43	.42
W. Denmark	.43	.54
Great Britain	.41	.38

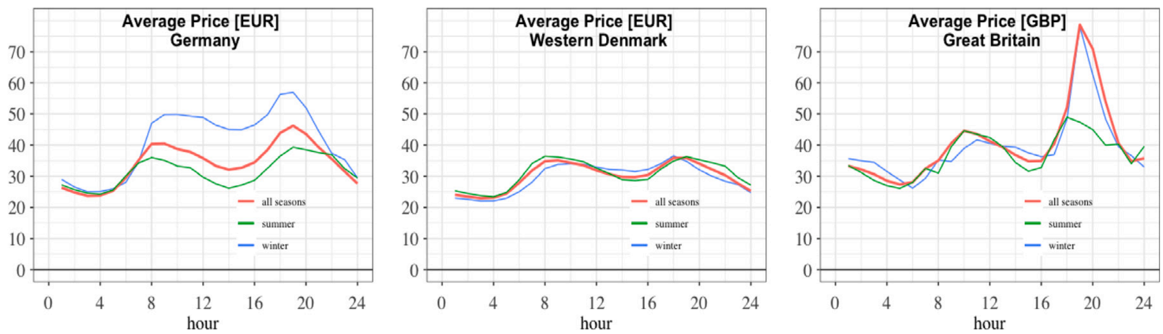

Fig. A.13. Average electricity prices per hour of the day for different seasons and the total year.

Table A.10
Estimation results ARMAX model on weekly volatility of electricity prices.

	Germany		Western Denmark		Great Britain	
ϕ_1	0.81***	0.80***	0.93***	0.93***	0.84***	0.83***
	(0.12)	(0.12)	(0.04)	(0.04)	(0.10)	(0.10)
θ_1	−0.67***	−0.66***	−0.77***	−0.77***	−0.62***	−0.62***
	(0.15)	(0.15)	(0.07)	(0.07)	(0.14)	(0.14)
Offshore	0.05*	0.05*	0.21	0.21	−0.00	−0.00
	(0.02)	(0.02)	(0.16)	(0.16)	(0.03)	(0.03)
Onshore	0.01*	0.01*	0.03	0.03	−0.02	−0.02
	(0.00)	(0.00)	(0.05)	(0.06)	(0.02)	(0.02)
Interaction		−0.00		−0.01		−0.00
		(0.00)		(0.06)		(0.01)
R^2	0.21	0.21	0.20	0.20	0.14	0.14
R^2 no XR	0.06	0.06	0.15	0.15	0.13	0.13
Log likelihood	−114.91	−114.19	−153.64	−153.63	−201.64	−201.62
AIC	239.82	240.39	317.27	319.26	413.28	415.24
BIC	256.19	260.02	333.99	339.31	429.99	435.29

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Table A.11
Estimation results ARMAX model on weekly volatility of electricity prices.

	Germany		Western Denmark		Great Britain	
ϕ_1	0.67***	0.67***	0.90***	0.90***	0.78***	0.78***
	(0.20)	(0.20)	(0.06)	(0.06)	(0.18)	(0.18)
θ_1	−0.46	−0.46	−0.72***	−0.71***	−0.51	−0.51
	(0.25)	(0.24)	(0.09)	(0.09)	(0.27)	(0.27)
Vol of wind	0.45***		0.34**		0.47***	
	(0.07)		(0.09)		(0.11)	
Vol of offshore		0.02		0.14		0.36***
		(0.09)		(0.11)		(0.11)
Vol of onshore		0.40***		0.26**		0.13
		(0.07)		(0.10)		(0.07)
R^2	0.24	0.24	0.22	0.22	0.20	0.21
R^2 no XR	0.06	0.06	0.15	0.15	0.13	0.13
Log likelihood	−112.20	−112.83	−152.11	−151.53	−191.19	−191.89
AIC	232.41	235.66	312.21	313.06	390.39	393.78
BIC	245.50	252.02	325.58	329.77	403.72	410.44

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Table A.12
Estimation results of alternative model specifications for the ARMAX-GARCHX models.

	Germany		Western Denmark		Great Britain	
	a	b	a	b	a	b
ϕ_1	0.45***	0.41***	0.49***	0.51***	0.57***	0.55***
ϕ_2	0.10***	0.10***	0.11***	0.10***	0.11***	0.11***
ϕ_3	0.11***	0.13***	0.10***	0.07*	0.16***	0.12***
ϕ_4		0.04		0.08**		0.10***
ϕ_5		0.03		0.02		0.02
ϕ_6		−0.03		−0.00		0.07**
ϕ_7	0.23***	0.36***	0.11***	0.11***	0.07**	
ϕ_8	−0.01	−0.07**	0.05*	0.03	0.02	
ϕ_{14}	0.15***		0.10***		0.06**	
ϕ_{15}	−0.09***		−0.04		−0.04	
ϕ_{21}	0.20***		0.08***		0.08***	
ϕ_{22}	−0.16***		−0.05*		−0.05*	
Offshore	−0.94***	−0.93***	−8.25***	−7.55***	−0.64***	−0.61***
	(0.15)	(0.16)	(1.12)	(1.10)	(0.08)	(0.07)
Onshore	−0.81***	−0.79***	−4.83***	−4.31***	−0.59***	−0.61***
	(0.03)	(0.03)	(0.57)	(0.41)	(0.05)	(0.05)
Net exports	−0.03		3.23***		0.07	
	(0.05)		(0.47)		(0.06)	
Wind DK2			−0.02			
			(0.02)			
Wind GER			−8.32***			
			(0.88)			
ω	1.15*	1.53*	2.06***	4.14**	0.57***	0.64***
α_1	0.10***	0.10***	0.17***	0.21***	0.24***	0.28***
β_1	0.84***	0.82***	0.73***	0.60***	0.69***	0.66***
Offshore	0.00	0.00	0.00	0.00	0.17	0.17
	(0.29)	(0.38)	(3.09)	(2.36)	(0.12)	(0.14)
Onshore	0.00	0.00	0.00	2.28	0.00	0.00
	(0.05)	(0.06)	(0.79)	(1.25)	(0.08)	(0.09)
Net exports	0.00		0.00		0.00	
	(0.08)		(0.55)		(0.04)	
Wind DK2			0.14*			
			(0.06)			
Wind GER			0.00			
			(3.86)			
R^2	0.83	0.81	0.72	0.71	0.77	0.76
Log likelihood	−3740.48	−3803.62	−4115.54	−4164.11	−3285.41	−3278.75
AIC	5.51	5.60	5.67	5.72	4.52	4.51
BIC	5.59	5.67	5.75	5.79	4.60	4.56

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

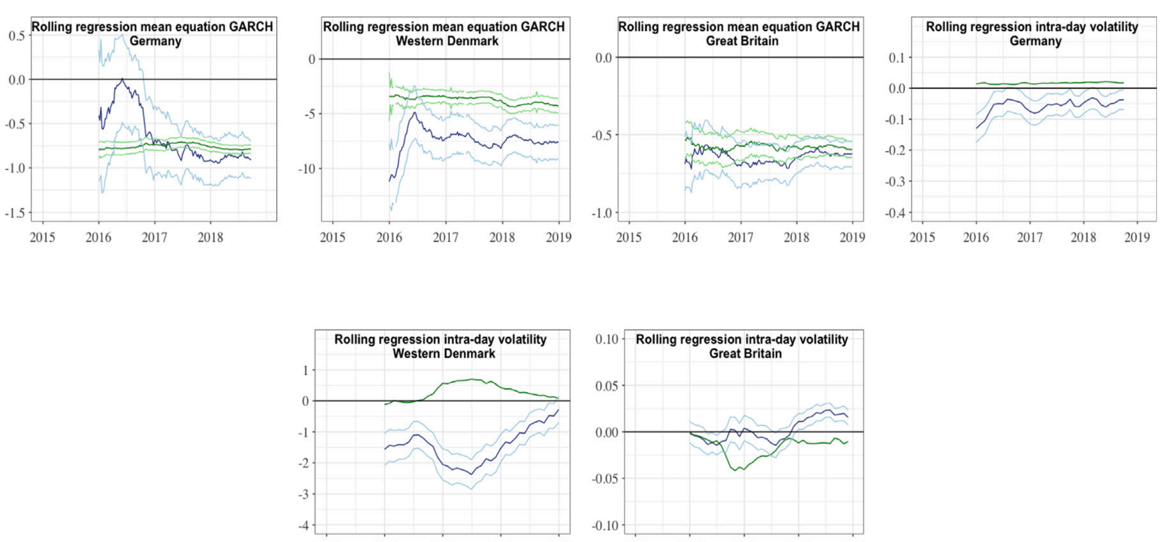

Fig. A.14. Rolling regression for the mean equation of the GARCH model (above) and the intra-day volatility (below) calculated over a moving window of 365 days. The blue lines represents the coefficient of the offshore feed-in, while the green one represents the coefficient of the onshore feed-in. The faint lines represent the 95% coefficient interval, respectively.

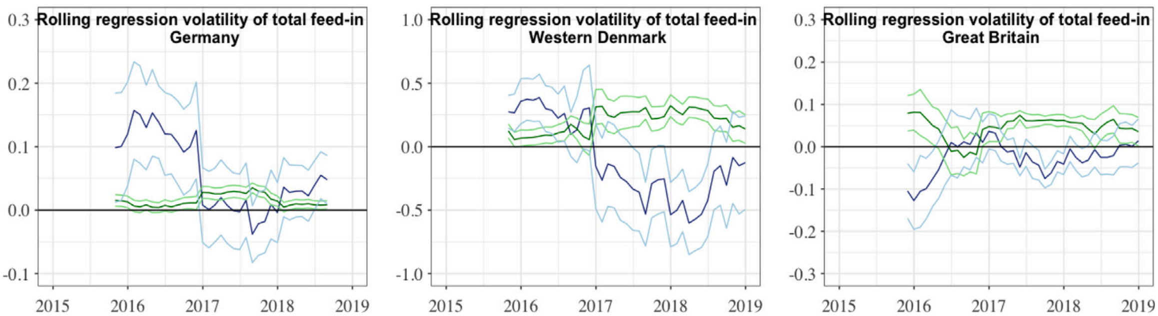

Fig. A.15. Rolling regressions on the weekly volatility of the wind feed-in over a moving window of 52 weeks (see Table 6). The blue lines represents the coefficient of the offshore feed-in, while the green one represents the coefficient of the onshore feed-in. The faint lines represent the 95% coefficient interval, respectively.

Table A.13
Estimation results of alternative model specifications for the SARMAX models.

	Germany	Western Denmark	Great Britain
ϕ_1	0.41	0.12	0.62
	(0.24)	(0.08)	(0.40)
ϕ_2	0.53*	0.82***	0.31
	(0.23)	(0.07)	(0.38)
θ_1	−0.15	0.22**	−0.19
	(0.24)	(0.07)	(0.40)
θ_2	−0.54**	−0.71***	−0.37
	(0.17)	(0.06)	(0.21)
θ_3	−0.15***	−0.24***	−0.13
	(0.04)	(0.03)	(0.08)
ϕ_7	0.96***	1.00***	0.97***
	(0.01)	(0.00)	(0.02)
θ_7	−0.84***	−0.99***	−0.91***
	(0.03)	(0.01)	(0.03)
Offshore	−0.03*	−1.54***	0.00
	(0.01)	(0.19)	(0.00)
Onshore	0.01***	−0.04	−0.01***
	(0.00)	(0.09)	(0.00)
Net exports	0.00	0.11	0.00
	(0.01)	(0.07)	(0.00)
Wind DK2		−0.00	
		(0.00)	
Wind GER		0.57***	
		(0.16)	
R^2	0.33	0.30	0.42
Log likelihood	−381.17	−1421.05	1300.37
AIC	784.35	2868.11	−2578.75
BIC	841.75	2936.83	−2520.70

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

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