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The impact of wind power generation on the electricity price in Germany☆

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ABSTRACT

This paper investigates the relationship between intermittent wind power generation and electricity price behaviour in Germany. Using a GARCH model, I evaluate the effect of wind electricity generation on the level and the volatility of the electricity price in an integrated approach. The results show that variable wind power reduces the price level but increases its volatility. This paper's results also indicate that regulatory change has stabilised the wholesale price. The electricity price volatility has decreased in Germany after a modification of the marketing mechanism of renewable electricity. This gives confidence that further adjustments to regulation and policy may foster a better integration of renewables into the power system.

1. Introduction

Renewable electricity has come to dominate the debate over and the development of the European electricity market. Amongst European countries, most wind turbines and solar panels are installed in Germany where renewable electricity has become even more important since the March 2011 decision to phase-out nuclear power. Germany's wind capacity has reached 31.3 gigawatts (GW) in 2012. Its solar photovoltaic (PV) capacity has also soared in the last years: overall installed solar PV capacity reached 32.6 GW in 2012. Renewable electricity made up 20% of gross electricity production (BMU, 2013).

System operators and market participants face two main challenges as more renewable energy capacity is added. First, electricity generated by wind turbines and photovoltaic panels is intermittent and hardly adjustable to electricity demand.[1] Therefore, variable renewable electricity generation cannot simply replace conventional energy sources. Second, Germany's renewable energy policy grants priority dispatch and fixed feed-in tariffs for renewable electricity generation. Renewable electricity can be fed into the grid whenever it is produced, regardless of energy demand, and feed-in can be switched off only if grid stability is at risk (Bundesnetzagentur, 2011).[2] High levels of variable renewable electricity production can be balanced by adjusting output from conventional power plants or by exporting excess electricity. Similarly, during times of too little wind or sunshine, sufficient dispatchable capacity has to be available to meet energy needs.

The electricity price is affected by the renewable feed-in. Additional volumes of low-cost renewable power shift the merit order curve to the right and push out the most expensive generators. This leads to a decrease of the wholesale electricity price which is called the merit-order effect.[3] The aim of this paper is to further investigate the effects of intermittent wind power generation on the electricity price development in Germany.

The literature has shown that wind power generation has a dampening effect on the electricity price but few papers have explicitly modelled the impact of wind power on the volatility of the electricity price or elaborated on the development of this relationship over time. This paper introduces daily levels of German wind power generation as explanatory variable in the mean and the variance equation of a GARCH model of the German day-ahead electricity price and thereby makes two contributions to the literature.[4] First, it explores the effect

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[1] By contrast, electricity generation from hydro or biomass sources can be managed more easily. The following conclusions hold for sources like wind and solar PV where intermittency is particularly pronounced.

[2] The operator continues to receive feed-in tariff payments even if the installation is disconnected from the grid due to capacity constraints of transmission cables.

[3] The merit order curve ranks all available generators according to their short-run marginal costs.

[4] The wind feed-in is estimated in megawatt hours (MWh) per day.

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of wind power generation on the level and volatility of the electricity price in an integrated approach. Second, it investigates the relationship over time and analyses a regulatory change in the German marketing mechanism of renewable electricity and its impact on the relationship between wind power generation and the electricity price.

The remainder of this paper is structured as follows. Section 2 summarises the relevant literature on the interaction of wind power generation and the electricity price. Section 3 describes the data, and Section 4 the employed method. The results are presented and discussed in Section 5. Section 6 gives some policy recommendations and Section 7 concludes.

2. Literature overview

Electricity from variable renewable energy sources – wind and solar PV – is difficult to incorporate in the generation mix and tends to decline the electricity price. Various studies identify this dampening effect for wind electricity generation (Di Cosmo and Malaguzzi Valeri, 2012; Neubarth et al., 2006; Nicholson et al., 2010; Nicolosi, 2010; and Ray et al., 2010). Nicholson et al. (2010) find that the merit order effect is stronger (more negative) during the day than during night. The strength of the impact depends on the generation mix and how much flexible conventional capacity is available. Graphically this can be depicted in Fig. 8 where the slope of the merit order reflects the generation mix. The steeper the slope, the stronger the merit order effect (Nicholson et al., 2010). Due to increasing production levels, the merit-order effect can also be observed for solar PV electricity (Bollerslev and Wooldridge, 1992; Grytli Tveten et al., 2013; and Milstein and Tishler, 2011).

Most studies employ power system models to simulate the effect of increased var-RE production on the level of the electricity price and calculate the merit-order effect as the difference between a simulated electricity price with and without the renewable feed-in.[5] For Germany, Bode and Groscurth (2006), Sensfuß et al. (2008) and Sensfuß (2011) confirm the presence of a merit-order effect. It is also shown for Denmark (Hu et al., 2010; Munksgaard and Morthorst, 2008), Spain (Gelabert et al., 2011; Sáenz de Miera et al., 2008) and the US (Brown, 2012). A literature overview of the merit-order effect in the European context is provided by Ray et al. (2010). Taking a more long-term perspective, Green and Vasilakos (2010) and Pöyry (2011) simulate the effects of fluctuating renewable electricity for the next two decades. Green and Vasilakos (2010) find that the British electricity price level will be significantly affected by variable wind power generation in 2020. Pöyry (2011) reports a strong merit-order effect by 2030 that decreases the wholesale electricity price. Both studies conclude that the volatility of electricity price will increase considerably in the next 10 to 20 years.

Some papers investigate the effects of increased intermittent renewable power production for the electricity price using current market data. Neubarth et al. (2006) evaluate the relationship between wind and price for Germany using an OLS regression model. Woo et al. (2011) estimate an AR(1) model for high-frequency power data from Texas, controlling for the gas price, nuclear generation and seasonal effects. Forrest and MacGill (2013) and Gelabert et al. (2011) employ econometric techniques to investigate the impact of wind on the electricity price level in the Australian and Spanish markets. Both papers find that the negative impact on price is stronger with higher levels of demand as wind then replaces load with higher variable cost. Jónsson et al. (2010) analyse hourly Danish electricity data in a non-parametric regression model, assessing the effects of wind power forecasts on the average electricity price and its distributional properties in Denmark. Both studies conclude that wind power feed-in has a significant effect on the level and volatility of the electricity price.

The present analysis builds on these findings but takes a different methodological approach. It explicitly models the influence of intermittent renewable electricity generation on the price level and the volatility in Germany by using a GARCH model. The aim is to track the development of both components over time and discover whether a regulatory change in the German electricity market had an impact on the relationship between wind power feed-in and the wholesale price.

3. Data setup

This section introduces daily data for wind electricity generation in the mean and variance equation of a GARCH model to better explain the unsteady behaviour of the electricity price.[6] Fig. 1 illustrates the negative correlation of daily wind feed-in and the German spot electricity price. When high wind speeds increase electricity generation, one can observe a price dip. The following analysis will reveal more insights about this relationship as well as the development of the price volatility.

I use the day-ahead spot electricity price, Phelix Day Base, from the European Energy Exchange (EEX) as dependent variable.[7] Electricity is traded on the day-ahead spot market for physical delivery on the next day. Separate contracts for every hour of the next day are available. Prices and volumes for all 24 contracts are determined in a single auction at noon. The Phelix Day Base is then calculated as the average, weighted price over these hourly contracts. Generally, the German electricity wholesale market is dominated by over-the-counter trading, and long-term contracts are most common (Bundesnetzagentur, 2010). However, trading volumes on the spot market are increasing and the Phelix is an important benchmark for all other electricity market transactions (Monopolkommission, 2011; Nicolosi, 2010).

The development of the electricity price, Phelix Day Base, is illustrated in Fig. 2. This study covers the period from January 2006 to January 2012. The wind installation already exceeded 20 GW during this period and played an important role in the German electricity mix. Table 1 reports extreme kurtosis and skewness for the electricity price which can either arise from extreme values or autocorrelation (Bierbrauer et al., 2007). Therefore, outliers are detected before conducting the empirical analysis. In line with the literature, I filter values that exceed three times the standard deviation of the original price series (Gianfreda, 2010; Mugele et al., 2005).[8] The outliers are replaced with the value of three times the standard deviation for the respective weekday.[9]

After smoothing outliers, the seasonal cycle is removed from the time series. Given that $p_t = y_t + s_t$, the observed price P_t comprises a stochastic part y_t and a seasonal component s_t. The average electricity price varies across the week because of changes in the electricity demand. Similarly, the price follows a yearly pattern as the different seasons influence the energy demand. Weekly and yearly seasonalities are addressed by using constant step functions which consist of dummies for each seasonal cycle (Trück and Weron, 2004). Dummies for week

[5] The merit-order effect can be observed for the wholesale price but not for the end-user price which also reflects the increasing costs to the consumer for renewables support and for investments in the electricity grid. The end-use price does therefore not necessarily decrease.

[6] Data on solar PV feed-in are only available a much shorter period from 2010 onwards. Due to data restrictions, the impact of solar PV electricity is not explicitly estimated in this study.

[7] The time series is downloaded from Datastream. As the aim of this study is to analyse the effect over a long horizon as well as the impact of the regulatory change, I therefore use daily data rather than hourly data. The effect of wind power on the electricity price can be detected even with daily data. The hourly data would show the impact in greater detail but also unnecessarily boost the dataset.

[8] The standard deviation is calculated individually for all seven weekdays to compare like with like. For example, a Monday is compared with the mean and the standard deviation of all Mondays in the sample (Bierbrauer et al., 2007).

[9] The outlier detection is repeated after the first round of outliers have been replaced, but no additional outliers are found. In an alternative run, the median is used to replace outliers. This does not lead to significant differences in the regression results.

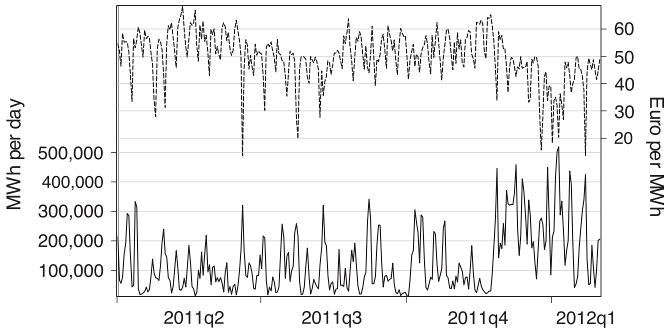

Fig. 1. Forecasted wind feed-in and day-ahead electricity price. Note: Daily wind electricity generation in MWh per day (solid line) and spot electricity price Phelix Day Base (dotted line).
Source: European Energy Exchange (EEX).

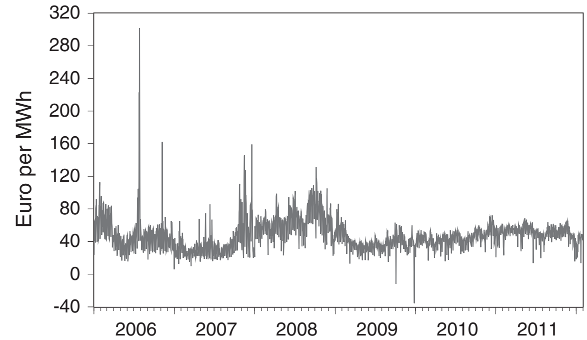

Fig. 2. Electricity price development.
Source: Datastream and EEX.

days d_i and months m_j are included in the following function to capture seasonality:[10]

$$s_t = c + \sum_{i=1}^{7} \xi_i d_i + \sum_{j=1}^{12} \nu m_j. \quad (1)$$

The results for the deseasonalisation are shown in Table 2. The coefficients for weekday dummies in Table 2 illustrate that the price remains high at the beginning of the week, declines from Friday onward, and reaches its minimum on Sundays. The dummies for months are not all significant, but a relevant electricity price reduction is observed in March, April, May, and August. In October and November, the price is significantly higher than in January. Finally, the seasonal component is deducted from the original price series and the mean of both series is aligned.

Finally, the logarithmic electricity price is calculated and employed in the following analysis.[11] Fig. 3 illustrates the original and the deseasonalised electricity price series. The descriptive statistics of both series can be found in Table 1.

The main explanatory variable is the wind electricity generation in Germany. To match the day-ahead horizon of the dependent variable, I use the predictions for daily wind power generation. These short-term forecasts are accurate and, more importantly, reflect the information available to participants in the day-ahead market. The forecasts are made and published by the four German transmission system operators (TSOs). The TSOs then sell the predicted amount of renewable electricity on the day-ahead electricity market.[12] The wind volumes are normally placed as price-independent bids to assure that they are certainly sold in the day-ahead auction. When the price falls below −150 in the daily auction, the energy exchange calls a second auction, in which the wind volumes can be auctioned with a price limit between −350 and −150 (Bundesnetzagentur, 2012). This rule was first introduced by the regulator in 2010 and revised in 2011 to avoid extreme negative prices as experienced during 2009. It was only necessary once, on 5 January 2012, to call a second auction.[13] The daily schedule of forecasting and selling wind is schematically illustrated in Fig. 4. The TSOs should have no incentive to systematically mispredict the expected renewable electricity generation: if the TSOs sell too much or too little renewable electricity on the day-ahead market, they have to balance it on the intraday market the following day (von Roon, 2011). The wind electricity generation depends on the weather development and installed capacity but is independent from the electricity price.[14]

Of course, the electricity price is not solely determined by wind electricity generation. Several papers indicate that the total electricity load, which reflects the demand profile, plays an important role in price behaviour. In fact, research shows that the combination of both factors is particularly important in this regard. Jónsson et al. (2010) show that the ratio between wind and conventional power production affects the electricity price most. They use the ratio between wind and load which is labelled *wind penetration*. Similarly, Nicolosi and Fürsch (2009)) find that the residual load, the electricity demand that needs to be met by conventional power, is a crucial parameter. The share of wind shows how much wind power contributes to meeting total electricity demand and illustrates its relative importance. The same amount of wind electricity will have a different impact on the price during a phase of high electricity demand than it will during low demand. Load data which reflects the demand for electricity should be used in the estimations in order to put the wind data into context.[15]

ENTSO-E, the Association of European Transmission Operators, publishes data on the vertical load and the total load in Germany. The vertical load reflects the net flows from the transmission to the distribution grid and therefore only a fraction of total electricity demand.[16] Therefore, a better proxy for the demand profile on a given day is the total load which also includes electricity from small and renewable sources in the distribution grid (ENTSO-E, 2012).[17] ENTSO-E does not yet

[10] Seasonal effects could also be addressed by trigonometric components (Bierbrauer et al., 2007; Lucia and Schwartz, 2002). However, such sinusoidal trends cannot be detected in the German electricity data from 2006 to 2012.

[11] Estimating the logarithmic price series has the advantage that the coefficients can be interpreted as elasticities. The augmented Dickey–Fuller test statistic is −3.57274 whereas the 1% critical value is −3.4331. The null hypothesis of a unit root is therefore rejected. The same holds for the Phillips–Perron test, employed by Knittel and Roberts (2005), with a test statistic of −17.37986 and a 1% critical value of −3.4330. Hence, it is not necessary to estimate the differences or returns.

[12] The data can be downloaded from the homepages of Tennet, Amprion, EnBW and 50Hertz. For a shorter period they are also available from www.eeg-kwk.de and the EEX Transparency Platform, www.transparency.eex.com. The data are available in hourly and 15-minute format. For this study, 15-minute MW data are averaged for each hour and then summarised to MWh per day.

[13] Personal communication with Thomas Drescher, Head of Market Operations EPEX Leipzig, in May 2012.

[14] How much renewable capacity is installed depends greatly on subsidies, namely, the German feed-in tariff (FIT) system. The FIT does not influence the wholesale electricity price traded on the energy exchange, but it influences the end-use price because the FIT costs are socialised amongst almost all electricity users.

[15] The demand for electricity should be independent from the variable wind feed-in and should therefore be an appropriate variable choice to avoid any endogeneity problems.

[16] As the wind electricity is fed into the distribution grid, it is not included in the vertical load data. However, the vertical load data are most accurate as this can be measured directly by a TSO.

[17] However, care should be taken with the quality of the total load data. TSOs can only estimate the total load, as they do not directly observe all flows in subordinated distribution grids.

Table 1
Descriptive statistics.

	Mean	Median	Max	Min	Std. dev.	Skewness	Kurtosis
Original price	48.06	46.07	301.54	−35.57	18.80	2.31	22.94
Deseasonalized	48.06	45.80	114.52	1.96	15.18	0.85	4.11
Log deseasonalized	3.82	3.82	4.74	0.67	0.32	−0.70	8.09

Table 2
Removing seasonality.

	Coefficient	p-Value
c	51.89	(<0.0001)
Tue	2.76	(0.0226)
Wed	2.59	(0.0321)
Thu	2.04	(0.0912)
Fri	−0.85	(0.4784)
Sat	−9.47	(<0.0001)
Sun	−17.49	(<0.0001)
Feb	1.07	(0.4934)
Mar	−3.80	(0.0126)
Apr	−4.54	(0.0032)
May	−6.90	(<0.0001)
Jun	−2.82	(0.0670)
Jul	−0.56	(0.7100)
Aug	−5.66	(0.0002)
Sep	2.00	(0.1913)
Oct	6.27	(<0.0001)
Nov	3.73	(0.0152)
Dec	−2.39	(0.1170)

Note: OLS regression with the Phelix Day Base, corrected for outliers, as dependent variable. Monday and January are used as reference variables. p-Values in parentheses.

provide forecasts for the total load. In line with Jónsson et al. (2010), the predicted load is constructed according to the following relationship:

$$L_t = L_t + e_t, \tag{2}$$

where L_t is the actual load, L_t is the predicted load, and $e_t \sim N(0,\sigma^2)$ a residual. By adding noise to the actual load, a load forecast is simulated. The standard deviation of the error is chosen, in line with Jónsson et al. (2010), as 2% of the average load in the sample. According to Jónsson et al. (2010) and Weber (2010), this is consistent with the errors that modern forecasting models produce.[18] The advantage of Jónsson et al.'s (Jónsson et al., 2010) method is that the errors of the simulated load forecast and the wind forecast are independent. Otherwise, both errors would be influenced by the weather forecast.[19] When the wind forecast is put in perspective with electricity demand L_t its relative importance for the power system becomes clear. Fig. 5 shows the forecasted wind power generation as the share of the total forecasted electricity demand. The share of wind fluctuates between 0 and 40%. The discussed explanatory variables, wind and load, will be included in an extended GARCH model of the electricity price. The methodology is elaborated in the next section.

4. Model

The liberalisation of power markets turned electricity into a tradable commodity and created a great deal of interest in understanding and modelling its price performance. Deng (2000), Huisman and Mahieu (2003), Lucia and Schwartz (2002), and (Knittel and Roberts (2005) pioneered this research area. These studies emphasise the distinct features of the electricity price. Electricity is not storable: supply and demand have to be matched instantly to avoid temporary imbalances. This can lead to extreme prices that usually revert quickly once supply and demand have reconciled. Hence, mean reversion is common in electricity markets and should be included in a price model (Deng, 2000; Huisman and Mahieu, 2003). Another important characteristic of electricity, reflected in its price, is seasonality. Demand varies throughout the day and during the week, as well as across the year. Therefore, models of electricity price should incorporate seasonality, as exemplified by (Knittel and Roberts, 2005) or (Lucia and Schwartz, 2002).

Given the pronounced volatility in the liberalised markets, conditional heteroscedasticity models lend themselves well to correctly explain price performance (Higgs and Worthington, 2010). These so-called GARCH models date back to Bollerslev (1986). As they appropriately capture the fluctuation and clustering of volatility, GARCH models are a widely employed method in financial and commodity markets. Knittel and Roberts (2005) were amongst the first to apply a GARCH model to the electricity price. They use an asymmetric GARCH model to capture price responses to positive and negative shocks and do indeed detect an inverse leverage effect. Other GARCH applications that have a bearing on this study are Solibakke (2002) and Mugele et al. (2005). Furthermore, Escribano et al. (2011) contribute to the literature by combining jumps and GARCH to explicitly control for price spikes. They show that taking into account mean reversion, seasonality, and jumps improve the GARCH model.

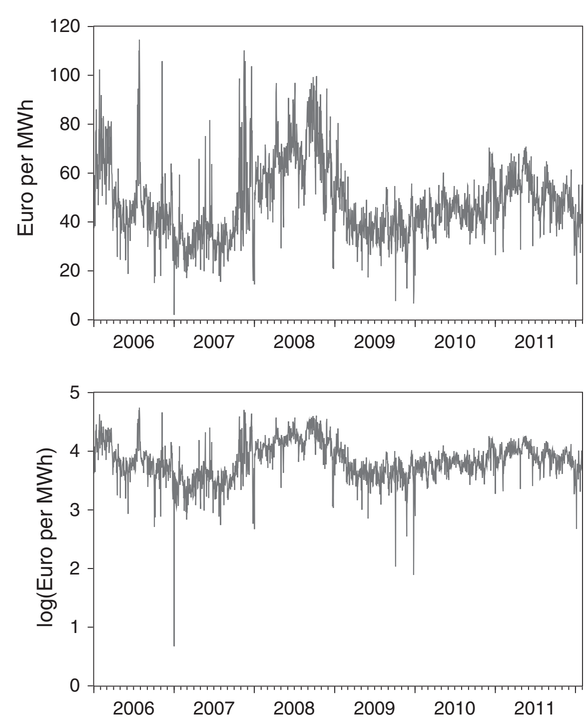

Fig. 3. Deseasonalised electricity price. Note: The upper panel shows the wholesale electricity price after outliers have been filtered and seasonal trends removed. The lower panel shows the log level of this series.

[18] ENTSO-E publishes forecasts and actual values for the vertical load for 2010 and 2011. The error has a standard deviation of 1.1% of the average load in this period. However, the vertical load data are more accurate and easier to predict than the total load. Therefore, 2% seems a reasonable assumption.

[19] The load forecast is simulated several times to test whether the regression results depend on the randomly generated noise process. This is not the case.

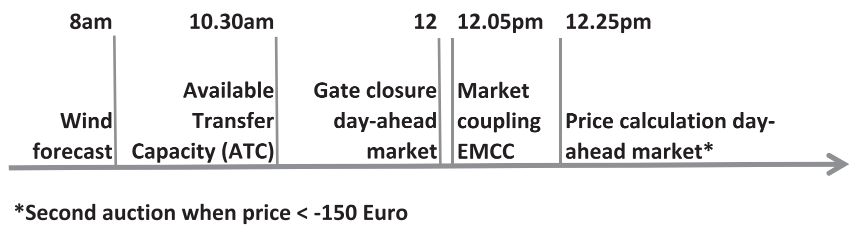

Fig. 4. Stylised scheduling in the day-ahead electricity market. Note: ATC stands for Available Transfer Capacity, EMCC for European Market Coupling Company. Information regarding the daily operations is obtained from www.marketcoupling.de and www.epexspot.com.

To better understand the performance of the electricity price, market fundamentals should be reflected in the calculations (Janczura and Weron, 2010). Mount et al. (2006) and Karakatsani and Bunn (2010) emphasise that variables for demand and available capacity should be included to better understand price movements. Huisman (2008) recognises that the price model can improve when using temperature variables. Similarly, Hadsell and Marathe (2006) and Gianfreda (2010) estimate an asymmetric GARCH model and include traded electricity volume in the variance equation. They find that the trading volume has an effect on price volatility, which is in line with other studies on stock market movements, see for example Bollerslev and Jubinski (1999) or Le and Zurbruegg (2010). Hadsell (2007) and (Petrella and Sapio (2010)) use a GARCH model to test whether changes in market design have an effect on price volatility.

Using a GARCH model allows for explicit testing of the effect of the wind power generation on the mean and volatility of the electricity price in an integrated approach. Moreover, a GARCH model seems appropriate to mimic the volatility behaviour of the electricity price. Fig. 3 illustrates that volatility clustering is present which is typical in financial markets. This feature hints at autocorrelation in the data, which is confirmed by the Q-statistic for the squared and the absolute returns (Zivot, 2009).[20] Furthermore, Engle's (1982) test for autoregressive conditional heteroscedasticity (ARCH) in the residuals confirms that ARCH effects are present.[21]

The electricity price tends to spike and then revert as soon as the divergence of supply and demand is resolved (Bierbrauer et al., 2007; Escribano et al., 2011). This mean reverting characteristic of the electricity price motivates the specification of the GARCH mean equation.

The speed of the mean reversion can be calculated from the coefficient for the autoregressive parameter. Mean reversion models have often been employed in the literature (Clewlow and Strickland, 2000; Lucia and Schwartz, 2002), but a plain mean-reverting process is found to overestimate the variance and the mean reversion driven by volatile periods (Huisman and Mahieu, 2003). Similar to Knittel and Roberts (2005), this motivates the estimation of an AR-GARCH model, including a mean reversion parameter, in the following specification:

$$y_t = \mu + \sum_{i=1}^{l} \phi_i y_{t-i} + \epsilon_t \tag{3}$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}, \tag{4}$$

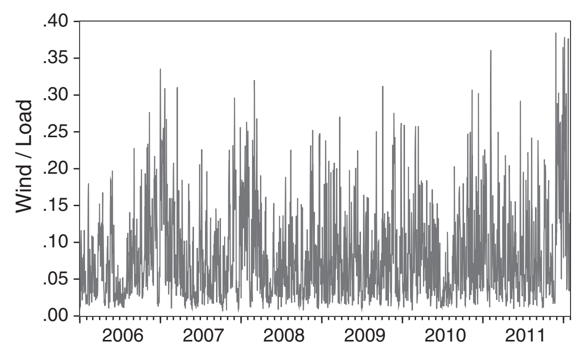

Fig. 5. Forecasted wind power generation as share of expected electricity demand. Note: The share is calculated as MWh of wind feed-in per MWh electricity load per day. Source: EEX and ENTSO-E.

where y_t is the log electricity price and h_t is its conditional variance. $\epsilon_t = \sqrt{h_t} z_t$ and $z_t \sim NID(0,1)$. ω is the long-run variance. For the model to be stationary, $\alpha_i + \beta_j < 1$ and $\alpha_i, \beta_j > 0$.

The daily data for wind generation, w_t, are included in the mean and the variance equations of this model. Given this extension, the specification for the ARX-GARCHX model becomes:

$$y_t = \mu + \sum_{i=1}^{l} \phi_i y_{t-i} + \sum_{j=1}^{m} \theta_j w_{t-j} + \epsilon_t \tag{5}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{k=1}^{s} \gamma_k w_{t-k}. \tag{6}$$

In the normal GARCH model, the coefficients in the variance equation, including the additional coefficients for γ, should be positive to ensure that the variance is always positive (Gallo and Pacini, 1998; Zivot, 2009). When a coefficient in the GARCH variance equation is negative, one can inspect the conditional variance and check whether it is always positive. In case of a negative coefficient, the variance stability of the GARCH is linked to the specific sample.[22]

The empirical strategy of this paper is to first estimate the GARCH model with Eq. 6 for the German day-ahead electricity price, extended by covariates for the wind power forecast. To capture serial correlation present in the price series, the number of autoregressive lags which minimise the Bayesian information criterion are included (Escribano et al., 2011).

[20] From an auxiliary OLS regression with the log price, autoregression is detected in the squared returns. This suggests the estimation of a GARCH model.

[21] The null hypothesis of no ARCH effects in the residuals is rejected with a highly significant test statistic of 54.720 (<0.0001) when including two significant lags of ϵ^2.

[22] As the aim of this study is not to forecast the price, it is therefore considered sufficient to check that the actual conditional variance is positive.

Table 3
Results AR(7)-GARCH(1,1) models with additional explanatory variables.

Dependent variable: log electricity price								
Sample: 1.1.2006 1.31.2012								
	(A)		(B) Log(Wind)		(C) Wind/load		(D) Wind/load	
			Log(load)				Regulation dummy	
Mean equation								
Constant	3.862	(<0.0001)	3.862	(<0.0001)	4.042	(<0.0001)	3.970	(<0.0001)
$\varnothing_1$	0.652	(<0.0001)	0.581	(<0.0001)	0.589	(<0.0001)	0.597	(<0.0001)
$\varnothing_2$	−0.035	(0.2539)	−0.005	(0.8668)	−0.040	(0.1968)	−0.010	(0.7238)
$\varnothing_3$	0.096	(0.0010)	0.083	(0.0036)	0.097	(<0.0001)	0.060	(0.0313)
$\varnothing_4$	0.008	(0.7707)	0.029	(0.3343)	−0.003	(0.9116)	−0.009	(0.7283)
$\varnothing_5$	0.036	(0.2199)	0.024	(0.4522)	0.028	(0.3483)	0.049	(0.1744)
$\varnothing_6$	0.104	(0.0010)	0.113	(<0.0001)	0.130	(<0.0001)	0.121	(<0.0001)
$\varnothing_7$	0.093	(<0.0001)	0.136	(<0.0001)	0.165	(<0.0001)	0.149	(<0.0001)
Log(wind)			−0.098	(<0.0001)				
Log(load)			0.081	(0.0185)				
Wind/load					−1.489	(<0.0001)	−1.414	(<0.0001)
A dummy for outliers in the log price and seven lags are included in all mean equations.								
Variance equation								
ω	0.003	(<0.0001)	0.281	(0.0004)	0.002	(0.0310)	0.009	(<0.0001)
α_1	0.164	(<0.0001)	0.250	(<0.0001)	0.227	(<0.0001)	0.253	(<0.0001)
β_1	0.725	(<0.0001)	0.563	(<0.0001)	0.638	(<0.0001)	0.313	(<0.0001)
Log(wind)			0.002	(0.0470)				
Log(load)			−0.021	(0.0003)				
Wind/load					0.020	(0.0631)	0.045	(<0.0001)
Regulation dummy							−0.008	(<0.0001)
Adj. R^2	0.720		0.772		0.784		0.783	
Log likelihood	948.598		1253.431		1264.987		1333.351	
AIC	−0.842		−1.115		−1.127		−1.188	
BIC	−0.792		−1.055		−1.072		−1.131	

Note: AIC stands for Akaike Information Criterion, BIC for Bayesian Information Criterion; p-values are in parentheses. The mean equation gives information about the price level where the autoregressive term $\varnothing_1$ is the price from the previous period. In a GARCH model, the variance is typically driven by two parameters, α which reflects the impact of new shocks and β which indicates whether previous shocks still persist. ω shows towards which value the variance will tend in the long-run. In specification (B), the coefficients can be interpreted as elasticities. When the wind electricity feed-in (MWh per day) increases by 1%, the price decreases 0.1%.

The aim of this study is not only to investigate the impact of wind power generation on the electricity price, but also the regulatory modification to wind electricity marketing. The German regulator amended the rules applicable to the marketing of renewable electricity in the so-called *Ausgleichsmechanismusverordnung* in January 2010. In line with Antoniou and Foster (1992), Holmes and Antoniou (1995), Bomfim (2003), and Hadsell (2007)a dummy variable is introduced to capture this regulatory change. The dummy takes the value of 1 after the change. This gives a first impression as to whether a change can be observed in the volatility of the electricity price after the change of the regulation. The dummy is not included in the mean equation as the new regulatory design only alters the way renewable electricity volumes are absorbed from the market. The overall electricity supply – whether generated from renewable or conventional power plants – remains unaffected by the regulation. Therefore, the price level should not be affected from the regulatory change and the focus lies on the price variance.[23]

5. Estimation results

5.1. Impact of wind power on the electricity price

Four different empirical specifications for the GARCH(1,1) model are presented in the following section, as summarised in Table 3. First I run a basic electricity price regression (column A), then add the wind and load variables separately (column B) as well as the combined variable, share of wind generation (column C). To test the effect of policy change, the regulation dummy is finally added in column D.

The results for the estimations can be found in Table 3.[24] All standard errors are calculated using the Bollerslev and Wooldridge (1992) method which assures that the test statistics are robust to non-normality of the residual. The Ljung–Box Q-statistic suggests that serial correlation is not well approximated by a single autoregressive term. Therefore, a more dynamic specification is estimated and further autoregressive parameters added. By minimising the Bayesian information criterion, seven lags are included. The significant seventh lag mirrors the weekly seasonal component and is in line with Escribano et al. (2011). Their sum, however, stays below 1. This shows that the conditional variance is mean-reverting and shocks only have a temporary effect on h_t (Hadsell, 2007).[25]

The first column (A) shows the GARCH benchmark specification for the electricity price. All coefficients are highly significant, the variance parameters are all positive, and their sum is smaller than one. The size of the GARCH term β with 0.73 reflects the influence (persistence) of past shocks β. The GARCH term α reflects the impact of new shocks that the conditional variance h_t, transmitted though the error term ϵ_t from Eq. 3.

In column (B) the logarithms of wind and load are included in the mean as well as the variance equation of the GARCH(1,1).[26] The negative coefficient for the wind variable shows that the day-ahead price decreases when high wind electricity generation is forecasted. This confirms findings by Jónsson et al. (2010) as well as Woo et al. (2011) and underlines the merit-order effect. In the present specification (B), the coefficients can be interpreted as elasticities. When the wind electricity

[23] This assumption was double-checked by adding the dummy variable to the mean equation. It stays insignificant and the results for the variance equation are not affected.

[24] The ARCH LM test confirms that the volatility clustering is well captured for all further specifications. Hence, no ARCH effects remain.

[25] The half-life of shocks can be calculated by $\ln(0.5) / \ln(\alpha + \beta)$, and the conditional variance reverts back to its mean after 5.91 days (Zivot, 2009).

[26] Both variables added in logarithms to normalise the size and fluctuation of the series.

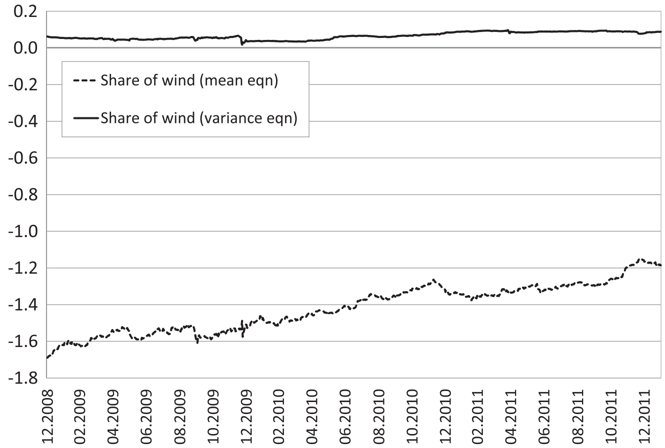

Fig. 6. Rolling regressions for specification (C) with a three year window. Note: The regressions have been estimated for a moving window of three years. The first window starts on 1.1.2006 and ends on 31.12.2008. The dates in the legend indicate the end of each three-year window. The lines show the development of the coefficients for each consecutive regression.

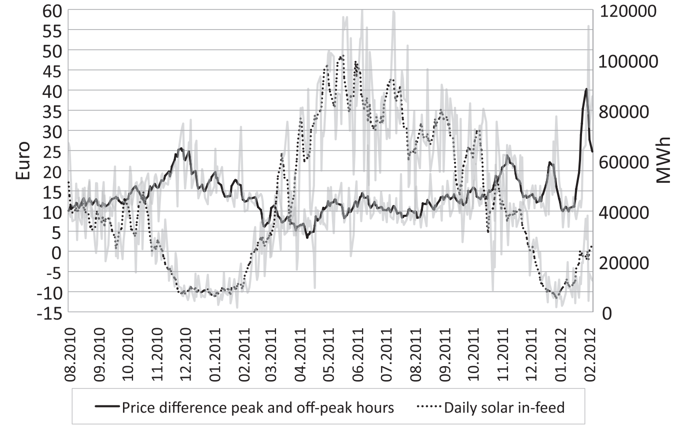

Fig. 7. Solar PV feed-in and peak prices. Note: The black lines denote the 7-day moving average. The transparent lines the daily values. The difference between peak and off-peak prices shows that solar PV mainly depresses peak hour prices. In summer 2011 the off-peak price was even above the peak price on three days.
Source: Bundesnetzagentur (2012).

feed-in (MWh per day) increases by 1%, the price decreases 0.1%. In the variance equation, the wind variable is significantly different from zero and positive. Hence, the fluctuating wind feed-in increases the volatility of the electricity price. To make sure that these results are not driven by the outliers that remain in the log electricity price, an outlier dummy is included in all mean equations.[27] The coefficient for the load variable illustrates that the price increases with higher electricity demand. This finding is in line with the literature (e.g. (Woo et al., 2011)) and confirms the expectation that price increases with demand. However, the price variance is reduced in times of high demand. This finding is counterintuitive as one would expect more price spikes with high demand as capacity limits might be reached.

The presented results are strengthened by the specification in column (C). Here, the wind variable reflects the share of wind relative to the total electricity load. The coefficient for this wind penetration measure turns out as expected: a strong wind feed-in lowers the electricity price but increases its variance. When the share of wind rises by one percentage point, the electricity price decreases by 1.46% in specification (C). The coefficient is higher than before because the wind variable is now expressed as a share of the total load. For the wind share to rise by one percentage point, the wind electricity production needs to gain quite substantially.[28] When the wind variables are added in columns (B) and (C), the coefficient for the GARCH term α increases slightly, accompanied by a downward adjustment of β. This suggests that an omitted variable bias skewed their coefficients in the previous specification (A). Generally, the fit of the model, measured by the information criteria, improves when more explanatory variables are included in specifications (B) and (C).

To arrive at a first impression of how wind power's influence on the electricity price evolved over time, rolling regressions are calculated for specification (C). Fig. 6 shows how the coefficients evolve, using a three-year window.[29] The rolling regressions illustrate, on the one hand, that the wind coefficient from the variance equation remains fairly constant. On the other hand, the coefficient for the wind share in the mean equation, depicted by the dashed line, becomes less negative over time. The wind feed-in can no longer decrease the price level as much. Stated differently, the merit-order effect reduces over time. (Sensfuß (2011) find the same effect for Germany, and Gelabert et al. (2011) for Spain. One explanation for the weaker merit-order effect is the increasing share of solar PV feed-in. Already, a merit-order effect from wind power can be observed for solar PV in Germany (Bundesnetzagentur, 2012). As Fig. 7 shows, electricity generation from solar PV depresses mainly peak power prices. Lower peak power prices reduce the daily average wholesale price used in this study. When the average price is lower on days with little wind, the calculated merit-order effect for wind will be smaller. This also explains the dip during winter 2010 when solar PV was not able to lower peak prices. Investigating this interaction in an analysis with hourly prices would be interesting but is left for further research. Another reason for the weakening merit-order effect could be the stronger electricity trade within Europe. The possibility to export excess wind electricity generation smoothes the price development (Hulle, 2009). This effect is further explained at the end of this section.

After April 2011, the impact of wind on the electricity price diminishes even further. This is most likely related to the nuclear phase-out

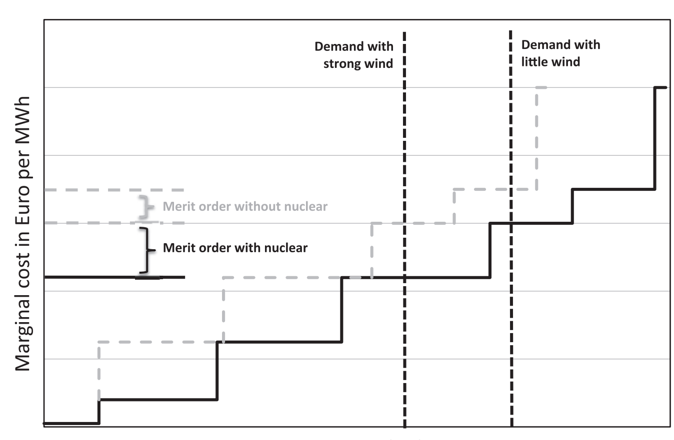

Fig. 8. Stylised merit-order curve before and after the nuclear phase-out. Note: Simplified merit order curve in line with (von Roon and Huck, 2010) and (Gruet, 2011). The dotted line illustrates the case without nuclear.

[27] The dummy captures the 1.1.2007, 1.1.2008, 4.10.2009, and 25.12.2009. When AR terms are included in the regression, the respective number of lagged dummies are included as well.

[28] This can be illustrated as follows. The mean wind forecast is 111 GWh per day, the mean load reaches 1.332 GWh. The average share therefore is 8%. To reach 9%, wind has to rise to a substantial 13 MWh or 12%.

[29] Rolling regressions with a two year window have been calculated as well and give a broadly similar picture. For the rolling regressions only one lag is included.

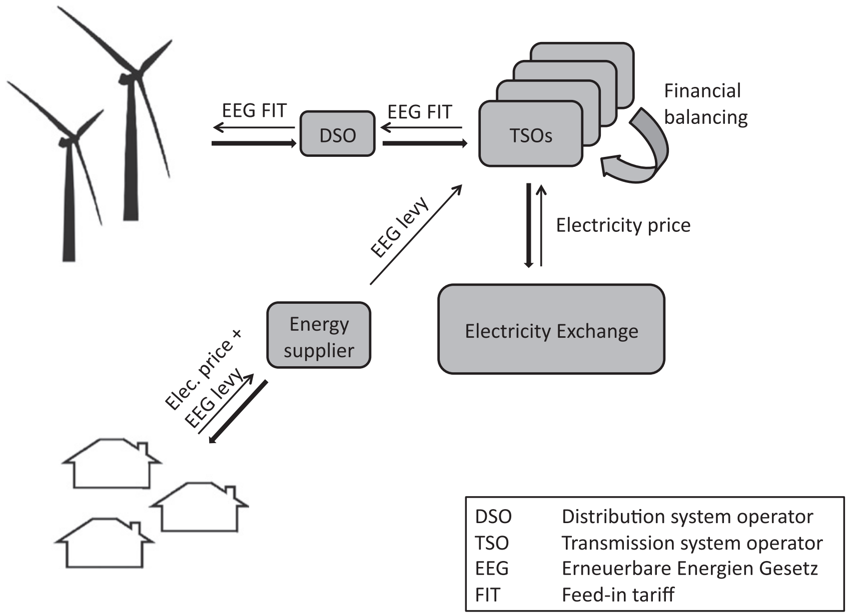

Fig. 9. Marketing mechanism after the regulatory change in 2010. Note: Illustration adapted from (Buchmüller and Schnutenhaus, 2009). Bold arrows show the flows of renewable electricity from the installations to the final electricity users. Thin arrows indicate monetary flows that finally remunerate the operators of renewable electricity installations. More detailed information is available at: www.bundesnetzagentur.de.

in Germany. Little research has been conducted on the effects on the nuclear moratorium on the merit order, except for He et al. (2013) and Thoenes (2011). Fig. 8 broadly illustrates a shift in the merit-order curve when shutting down nuclear power plants.[30] The figure visualises how the slope of the merit order influences the strength of the merit order effect. As the slope becomes flatter, the wind-induced price decrease is less strong.

5.2. Impact of a regulatory change in 2010

The empirical framework is used to evaluate modifications to the power market design and the renewables regulation. The German regulator amended the marketing of renewable electricity in the so-called *Ausgleichsmechanismusverordnung* in January 2010. All TSOs are now required to forecast the renewable power production one day in advance and to sell the total predicted amount on the day-ahead market. TSOs then receive the revenues from selling the renewable power volumes at the wholesale market price and the so-called EEG levy which is after all raised from the electricity users (see Fig. 9).[31] The EEG levy covers payments for feed-in tariffs as well as costs from forecasting, balancing, and marketing of renewable electricity.

The previous marketing mechanism was more complicated. TSOs had to predict the renewable electricity production a month in advance. These forecasts were quite inaccurate as the wind and solar PV power production is highly dependent on meteorological factors. Energy suppliers and TSOs then agreed on a fixed schedule for renewable electricity delivery on each day of the following month (Buchmüller and Schnutenhaus, 2009). These volumes had to be physically delivered from a TSO to the energy supplier. As the final wind feed-in was uncertain, the physical delivery of renewable electricity via the TSOs to the energy companies was an inefficient mechanism (Monopolkommission, 2009). When wind power generation was lower than expected, the missing electricity volumes had to be bought by the TSOs on the day-ahead or intraday market. A surplus of renewable electricity, on the contrary, had to be sold on the market (Erdmann, 2008). More sudden shortfalls had to be fixed on the balancing market. This mechanism led to substantial balancing costs for adjustments in the spot markets. In 2008, these balancing costs reached 595 mEuro for all TSOs (Bundesnetzagentur, 2012). With the new regulation, the forecasting uncertainty and interventions on the spot markets could be reduced. The related costs shrank substantially to 127 mEuro in 2010, and the electricity users were disburdened (Bundesnetzagentur, 2012).[32] Under the old regulation, the expenses for spot and balancing market interventions were hidden in the network charge (Buchmüller and Schnutenhaus, 2009). Since 2010, these costs are added to the EEG levy. This increases the transparency for electricity users who get a clearer picture of the renewable subsidy and system costs.

Transparency also increases with regard to the marketed renewable energy volumes as they have to be sold on the day-ahead market. The additional wind volumes now increase the liquidity of the day-ahead and the intraday markets significantly (Bundesnetzagentur, 2012). This is expected to reduce price volatility after 2010 as smoother prices can generally be observed in a more liquid market (Figlewski, 1981; Weber, 2010). Moreover, TSOs had no incentive under the old regulation to optimise activities on the day-ahead and the intraday markets because they could socialise these expenses via the network charge (UoSC) to electricity users (Buchmüller and Schnutenhaus, 2009). According to (Klessmann et al., 2008), the integration of renewable electricity in Germany was opaque and inefficient before 2010. Under the new regulation, the need for interventions on the day-ahead market is reduced and related disturbances are expected to reduce.

To test for the effect of the regulatory change on the price volatility, a dummy variable is included in the variance regression. The results (specification D) can be found in Table 3. The negative and significant coefficient for the dummy variable indicates a reduction of the conditional variance after the regulatory change. The effects of wind and load, discussed earlier, remain robust. Despite the negative coefficient for the dummy, the conditional variance does not become negative for the given sample. Therefore, the specification remains valid, see for example Chevallier et al. (2011).

[30] According to (Forrest and MacGill, 2013) wind should be treated like a negative demand impact in systems where wind enjoys special generation rights, e.g. priority dispatch.
[31] EEG stands for *Erneuerbare Energien Gesetz*.

[32] The overall EEG levy still continues to rise due to high liabilities from feed-in tariff payments, just the burden from the balancing costs is reduced.

5.3. Impact of increased market coupling

The German market is not isolated, and electricity flows with neighbouring countries are important, especially for the integration of intermittent renewable electricity. To make sure that the reduction in the variance from 2010 onwards is not simply a result of a better integrated, hence connected, electricity market, I control for cross-border trade in the European electricity market.

The integration of the European electricity market has greatly increased since the creation of the European Market Coupling Company (EMCC). Since November 2009, Germany and Denmark have been pursuing a day-ahead volume coupling on the two interconnectors between Germany and Denmark. In May 2010, the Baltic cable between Germany and Sweden was added. On 10 November 2010, the countries of the CWE region (Belgium, France, Germany, Luxembourg and the Netherlands) and the so-called Northern region (Denmark, Sweden and Norway) coupled their electricity markets.[33] The electricity flows of these countries are now jointly optimised and electricity is exported from low-price to high-price areas. The necessary congestion management is carried out by the EMCC in a so-called interim tight volume coupling (Monopolkommission, 2009).[34]

For this study, I use the interconnector capacities that can be used to export excess wind production.[35] The capacities are reported to the EMCC before the price setting on the day-ahead market and are therefore exogenous from the dependent variable.[36] For reasons of data availability, I use data for the interconnectors between Germany and the Northern region only (Baltic Cable, DK West and DK East).

The "north-bound" interconnector capacity is included in specification (E) in Table 4. The coefficients of the EMCC capacity do not turn out significant. However, the conclusions regarding the regulatory change and the wind feed-in remain valid. Therefore, previous specifications that omit the interconnector capacity seem not to be misspecified.

Table 4
Results AR–GARCH models with additional explanatory variables.

Dependent variable: log electricity price		
Sample: 1.1.2006 31.1.2012		
(E) Wind/load, regulation, EMCC capacity		
Mean equation		
Constant	3.775	(<0.0001)
$\varnothing_1$	0.593	(<0.0001)
$\varnothing_2$	0.005	(0.8501)
$\varnothing_3$	0.058	(0.0351)
$\varnothing_4$	−0.01	(0.6912)
$\varnothing_5$	0.050	(0.1745)
$\varnothing_6$	0.124	(<0.0001)
$\varnothing_7$	0.147	(<0.0001)
Wind/load	−1.402	(<0.0001)
log(EMCC capacity)	0.018	(0.1713)
Variance equation		
ω	0.015	(0.6472)
α_1	0.260	(<0.0001)
β_1	0.279	(<0.0002)
Wind/load	0.045	(0.0001)
Regulation dummy	−0.008	(<0.0001)
log(EMCC capacity)	−0.001	(0.5029)
Adj. R^2	0.784	
Log likelihood	1334.536	
AIC	−1.187	
BIC	−1.125	

Note: EMCC capacity is the day-ahead available transfer capacity from Germany to Sweden and Denmark. AIC stands for Akaike Information Criterion, BIC for Bayesian Information Criterion; p-values are in parentheses. A dummy for outliers in the log price and its lags are included in all mean equations.

6. Policy implications

This paper shows that intermittent renewable generation transmits volatility to the electricity price. The question is how to integrate electricity from variable sources more smoothly in the electricity market to reduce effects on the price.

On the one hand, improved interconnection of electricity markets within Europe will reduce market effects of variable renewable electricity on market prices. Better grid connection can not only be fostered by new cables but also by using existing capacity more efficiently in an improved market coupling regime (Hulle, 2009; Monopolkommission, 2011; Schaber et al., 2012).

On the other hand, a generation system with flexible conventional capacity as well as electricity storage helps balancing fluctuations of renewable energy and therefore reducing effects on the electricity price. Flexible generation operates at high variable but low fixed costs and can therefore be switched on and off to equalise low renewable power feed-in. The main difficulty of both options, storage and flexible generation capacity, is their investment cost. Providing responsive generation capacity needs to be profitable. With more renewables in the power system, conventional plants will mainly balance renewable fluctuation and therefore operate fewer full-load hours. Recovering the investment costs for flexible conventional units during these load hours will become more difficult (Klessmann et al., 2008; Klinge Jacobsen and Zvingilaite, 2010; Steggals et al., 2011; Traber and Kemfert, 2011). Periods with peak prices, which allow plant operators to generate revenues, become less certain and predictable due to the high variability of renewable electricity generation. The increased refinancing risk questions the viability of investments in flexible conventional capacity, and the market price might fail to give sufficiently strong investment signals.

This study shows that regulatory changes can encourage a better integration of intermittent renewable electricity in the power system. The price volatility reduced when the marketing mechanism for renewable electricity changed. Going forward, the regulatory and the policy framework should be further adjusted to the challenges arising from the decarbonisation of the electricity market.

Regarding the regulatory setting, intermittent renewables could be better integrated if gate closure on day-ahead and intraday markets would be later (Hiroux and Saguan, 2010; Vandezande et al., 2010). A later gate closure would reduce uncertainty on the spot markets and balancing costs because a shorter forecasting horizon makes actual wind generation more predictable.[37] Another small step towards a better integration of renewables is to offer different products on the spot markets. Since December 2011, the German intraday market offers not only hourly but 15 min electricity blocks. Given the stochastic generation profile of wind and solar PV, this product increases flexibility for market participants. The fluctuation of wind and solar PV power can be high within an hour and short-term products allow TSOs and traders to adjust their positions more accurately. Introduction of such products

[33] CWE stands for Central Western Europe. Countries connected in the CWE and the Nordic region account for approximately 55% of the European electricity generation (Böttcher, 2011).

[34] The TSOs from the participating countries report the interconnector capacities one day in advance to the EMCC (see Fig. 4). In addition, the EMCC receives the anonymised order books from the participating electricity exchanges after the day-ahead spot market closed at 12 am. The buying and selling orders, including the volumes of renewable electricity and the interconnector capacity, are optimised by the EMCC. The algorithm determines the price-independent volumes that have to be sold additionally on those markets that had too high prices. The EMCC only calculates the additional electricity quantities that are needed to equalise the price amongst participating countries. The auctioning and price setting remains in the hands of the local exchanges (Böttcher, 2011).

[35] The so-called Available Transfer Capacity (ATC) is included in the regressions. ATC is the physical interconnector capacity which is not yet allocated and is free to use. This export potential reflects the technical and physical restrictions in the neighbouring country.

[36] The electricity trade flows are an outcome variable as they are determined together with the price on the day-ahead markets. The data on the electricity trade are therefore not included in this study.

[37] The implementation may not be straight forward as all action needs to be coordinated amongst European states.

should be considered for the day-ahead market as well to match the 15 min forecasts and to reduce the need for intraday adjustments (Bundesnetzagentur, 2012). Furthermore, product coordination across the European internal market is necessary.

With respect to the policy framework, regulators need to continue revisiting and adapting renewable support schemes to technological developments. Until 2012, renewable energy has not been exposed to any market risk in Germany due to guaranteed feed-in tariffs. However, as wind technology is maturing and installed capacity is rising, a move towards a more market-based support system can be observed in Germany. Since 2012, Germany offers renewable electricity producers to choose between fixed feed-in tariffs and a feed-in premium, the so-called market premium if they market their renewable electricity directly (without using TSO services). The premium is calculated monthly as the difference between the applicable feed-in tariff and the monthly ex-post average wholesale electricity price on the energy exchange plus a management fee that differs according to technology. A wind power producer that can sell electricity at a higher price than the market average price will benefit from this support scheme. Direct marketing and the market premium do not yet reduce subsidy payments but create a more market-based channel to integrate renewable power and shift balancing costs to the operators of renewable installations. The uptake of the German market premium is high, 80% of wind installations have changed to this from of support (Klobasa et al., 2013). A more market-based system gives incentives to realign renewable electricity supply with demand (Traber and Kemfert, 2011; Vandezande et al., 2010). A recent communication from the (European Commission, 2013) calls for a move to market-orientated support, like FiT premiums, and more competition amongst developers through auctions. When exposing renewables to more market risk, the maturity of the technology and the functionality of the market need to be taken into account. Surely, intermittent installations have a limited ability to respond to price signals (Klessmann et al., 2008), but renewable electricity generation plays an important role in the German power system and should therefore assume more responsibility. Market-based support can give positive long-run incentives to exploit portfolio effects, to choose optimal installation sites, and to improve the generation forecasts (Hiroux and Saguan, 2010).

7. Conclusion

This study shows that intermittent wind power generation does not only decrease the wholesale electricity price in Germany but also increases its volatility. This conclusion holds across various econometric specifications underlining the robustness of the results. A low and volatile electricity price might alter or delay investment decisions in new capacity, renewable and conventional, required for the transformation to a low-carbon energy system. However, the results from this study show that the merit order effect, the ability of wind feed-in to depress the price, has reduced over time.

After a regulatory change in 2010, the volatility of the German electricity price has decreased. Hence, the market design can to some extent smoothen the volatility of the electricity price. As installed capacity increases and technology matures, renewable electricity regulation should be developed and adapted further, towards a more market-oriented structure that remunerates renewable electricity during phases of high electricity prices. A framework that stabilises the wholesale electricity price would also give incentives for investments in new generation capacity, both in renewable as well as conventional capacity.

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