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The Impact of Wind Power Generation on the Electricity Price in Germany

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Abstract

This paper provides insight into the relationship between intermittent wind power generation and electricity price behaviour in Germany. Using a GARCH model, the effect of wind electricity in-feed on level and volatility of the electricity price can be evaluated in an integrated approach. The results show that variable wind power reduces the price level but increases its volatility. With a low and volatile wholesale price, the profitability of electricity plants, conventional or renewable, is more uncertain. Consequently, the construction of new plants is at risk, which has major implications for the energy market and the security of supply. These challenges, related to the integration of renewables, require adjustments to the regulatory and the policy framework of the electricity market. This paper's results suggest that regulatory change is able to stabilise the wholesale price. It is found that the electricity price volatility has decreased in Germany after the marketing mechanism of renewable electricity was modified. This gives confidence that further adjustments to regulation and policy may foster a better integration of renewables into the power system.

JEL Code: Q42, Q48, C22.
Keywords: Renewable energy sources, intermittency, electricity price.

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1 Introduction

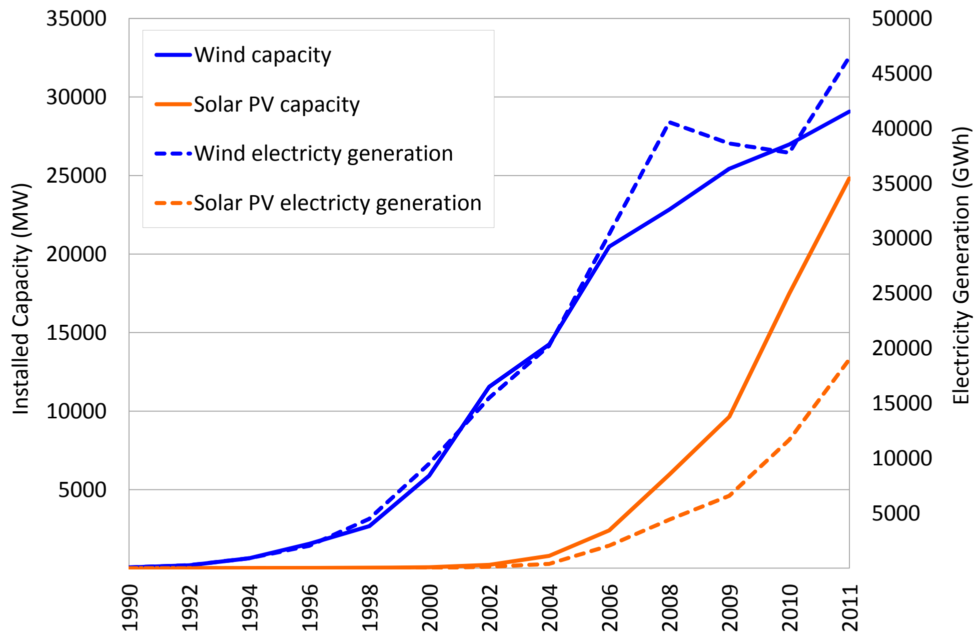
Renewable electricity has come to dominate the debate over and the development of the European electricity market. Among European countries, most wind turbines and solar panels are installed in Germany where renewable electricity has become even more important since the March 2011 decision regarding the nuclear phase-out. Figure 1 shows that Germany's wind capacity reached 29 gigawatt (GW) in 2011. Its solar photovoltaic (PV) capacity soared in the last two years: overall installed solar PV capacity reached almost 25 GW in 2011 (BMU, 2012). In 2011, wind electricity accounted for 8 per cent of gross electricity production in Germany, solar PV for 3 per cent. All renewable sources combined made up 20 per cent of gross electricity production in 2011 and are Germany's second most important source of electricity generation after lignite (BDEW, 2011). The German government plans to raise this share to 35 per cent by 2020 and to 50 per cent by 2030 (BMU and BMWi, 2011). Onshore and offshore wind will play an important role in this expansion of renewable electricity capacity.

System and market operators face two main challenges as more renewable power generation is added. First, electricity generated by wind turbines and photovoltaic panels is intermittent and hardly adjustable to electricity demand.[1] Therefore, variable electricity generation is not a perfect substitute for conventional energy sources. Figure 2 shows the variability of wind electricity generation. The horizontal line, the so-called capacity credit, gives an impression how much conventional capacity can be replaced by the existing wind power capacity, given the current power plant fleet and maintaining the security of supply (IEA, 2011).[2] The graph illustrates that the wind power generation is subject to strong variation and that only a fraction of installed wind capacity, depicted by the capacity credit line, is expected to contribute to the power mix with certainty. Second, Germany's renewable energy pol-

[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]In line with calculations from Hulle (2009), IEA (2011), and Schaber et al. (2012), the capacity credit is assumed to be 6%. A wind installation of 29075 MW in 2011 was used in the calculation for this capacity credit line (BMU, 2012).

Figure 1: Installed capacity and generated electricity in Germany



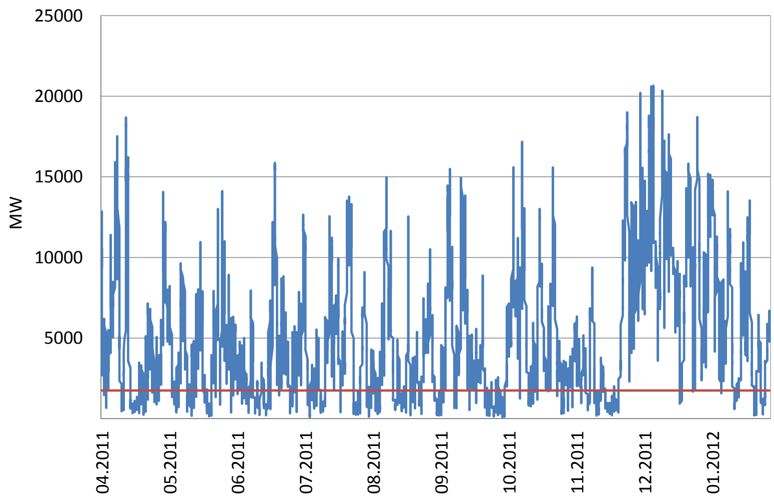
Source: BMU (2012).

icy 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 in-feed can be switched off only if grid stability is at risk (Bundesnetzagentur, 2011).[3] As storage is not yet a viable option, high levels of variable renewable electricity production can be balanced only by adjusting output from traditional power plants or by exporting excess electricity. Similarly, when too little wind or sunshine is available during times of peak demand, reserve capacity has to be dispatched at higher costs.

Grid operators are obliged to feed-in renewable electricity independent of the market price. However, the spot electricity price is not independent from renewable electricity. On the one hand, variable renewable power production is negatively correlated with the electricity price. Whenever large

[3]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.

Figure 2: Hourly wind in-feed



Note: Hourly wind in-feed in MW. The horizontal line illustrates how much electricity German wind installations (29075 MW in 2011) are expected to reliably generate during peak demand. This measure is referred to as capacity credit. In line with calculations from IEA (2011), Schaber et al. (2012) and Hulle (2009) the capacity credit is assumed to be 6%. Source: www.eeg-kwk.de.

volumes of intermittent renewable electricity are fed into the power grid, the electricity price tends to decline. As renewable installations are very capital-intensive but have almost zero operational generation cost, they are certainly dispatched to meet demand. More expensive conventional power plants are crowded out, and the electricity price declines. This dampening of the wholesale electricity price is called merit-order effect. Various assessments uncover this effect for wind electricity generation (Neubarth et al., 2006; Nicolosi, 2010; Ray et al., 2010). Due to increasing production levels, the merit-order effect can also be observed for solar PV electricity (Milstein and Tishler, 2011). On the other hand, intermittent renewable power not only influences price level, but also price volatility (Klinge Jacobsen and Zvingilaite, 2010; Cramton and Ockenfels, 2011). This is confirmed by Jónsson et al. (2010) and Woo et al. (2011) who show that wind generation tends to lower the spot price but increase its variance. The aim of this chapter is to further investigate the effects of intermittent wind power generation on the electricity price development in Germany.

The literature shows that wind power generation has a dampening effect on the electricity price but does not explicitly model the impact of wind power on the volatility of the electricity price nor elaborate on the development of this relationship over time. The present analysis 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.[4] This study makes two contributions to the literature. First, it explores the effect of wind power generation on the level and volatility of the electricity price in an integrated approach. In Germany, where renewables prospered exceptionally from feed-in tariffs, the effect on the electricity market should be particularly pronounced. Second, it investigates a regulatory change in the German marketing mechanism of renewable electricity and its impact on the relationship between wind power and the electricity price.

This study's findings suggest that wind power generation decreased the wholesale electricity price in Germany in the period from 2006 to 2011 but increased the price volatility. These results are particularly important given European and German aspirations to usher an energy system dominated by renewables. A low and volatile electricity price might alter or delay investment decisions in new capacity, renewable and conventional, required for the transformation of the energy system. To advance the energy transformation, it should therefore be in the interest of policy makers to secure a reliable and predictable electricity price. The present analysis shows that adjusting the electricity market design can stabilise the development of the electricity price to some extent. Price volatility reduced in Germany after a modification to the renewable electricity regulation.

The remainder of this chapter is structured as follows. Section 3.2 summarises the relevant literature on the interaction of wind power generation and the electricity price. Section 3.3 describes the data, Section 3.4 the employed methods. The results are presented and discussed in Section 3.5.

[4]The wind in-feed is estimated in megawatt hours (MWh) per day. Data on solar PV in-feed 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 chapter. It would be interesting to evaluate this issue at a later point in time.

Section 3.6 gives some policy recommendations and Section 3.7 concludes.

2 Literature Overview

It is widely argued that electricity from variable renewable energy sources – wind and solar PV – is hard to incorporate in the generation mix. Although the interruptive effect of variable wind electricity can already be observed today, little empirical research evaluates its current influence on the wholesale electricity price.

Most studies employ power system models to simulate the effect of increased var-RE production on the level of electricity price. In the short term, the so-called merit-order effect is quantified as the difference between a simulated electricity price with and without the renewable in-feed.[5] For Germany, Bode and Groscurth (2006) and Sensfuß (2011) find that renewable power generation lowers the electricity price. Despite being very capital-intensive, renewable installations have almost zero marginal generation cost and thus are certainly dispatched to meet demand. More expensive conventional power plants are crowded out, and the electricity price declines. This dampening of the wholesale electricity price is also shown for Denmark (Munksgaard and Morthorst, 2008) and Spain (Sáenz de Miera et al., 2008). A recent 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. The consumer price is expected to rise due to soaring costs for subsidies to renewable electricity. Both studies conclude that the volatility of electricity price will increase remarkably in the next 10 to 20 years.

Very few papers investigate the importance of intermittent renewable

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

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. 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 western Denmark. Both studies conclude that wind power in-feed 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 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 in-feed and the wholesale price.

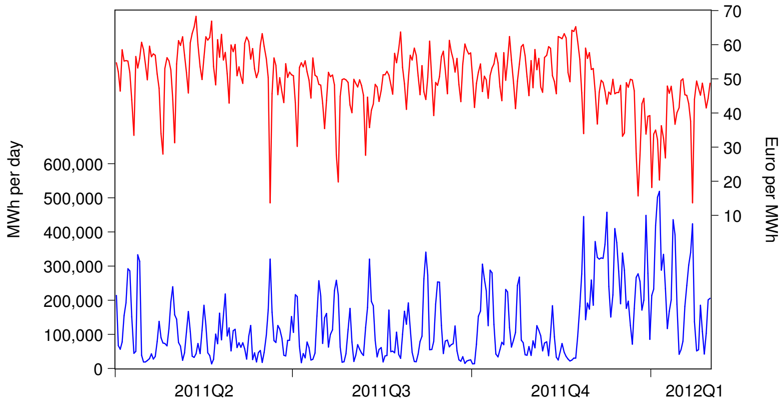
3 Data

This chapter 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. Figure 3 illustrates the negative correlation of daily wind in-feed and the spot electricity price. Whenever high wind speeds allow above-average electricity generation, one can observe a price dip. An in-depth study will reveal more insights into this relationship as well as the development of price volatility.

In the following analysis, I use the day-ahead spot electricity price, Phelix Day Base, from the European Energy Exchange (EEX) as dependent variable.[6] 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 av-

[6] The time series is downloaded from Datastream.

Figure 3: Forecasted wind in-feed and day-ahead electricity price



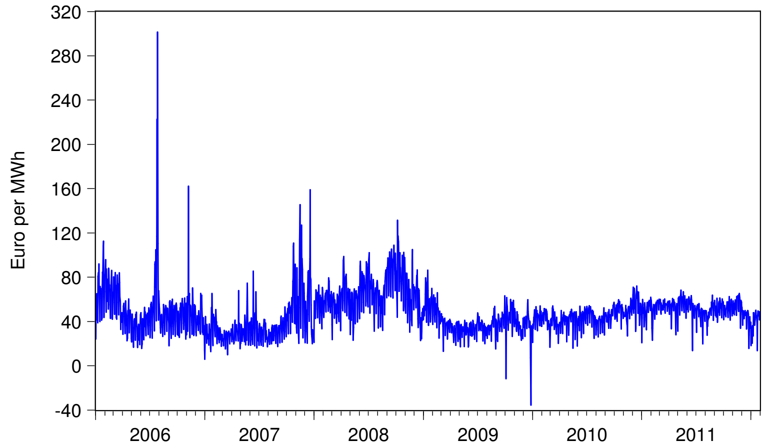
Note: Daily wind electricity generation in MWh per day (blue line) and spot electricity price Phelix Day Base (red line). Source: European Energy Exchange (EEX).

erage, weighted price over these hourly contracts. Generally, the German electricity wholesale market is dominated by over-the-counter trading, and the contracts are mostly of a long-term nature (Bundesnetzagentur, 2010). However, trading volumes on the spot market are increasing and the Phelix is an important benchmark for all other electricity market transactions (Nicolosi, 2010; Monopolkommission, 2011).[7]

The development of the electricity price, Phelix Day Base, is illustrated in Figure 4. This study covers the period from January 2006 to January 2012. As illustrated in Figure 1, 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 (Mugele et al., 2005; Gianfreda,

[7]The volume on the EEX spot market increased from 203 TWh in 2009 to 279 TWh in 2010. For comparison, the German gross electricity production was 628 TWh in 2010 (AG Energiebilanzen, 2011). Electricity is also traded on the intraday market, but this market is less liquid and mainly used to address electricity market imbalances in the short-run.

Figure 4: Electricity price development



Source: Datastream and EEX.

2010).[8] The outliers are replaced with the value of three times the standard deviation for the respective weekday.[9]

Table 1: Descriptive statistics

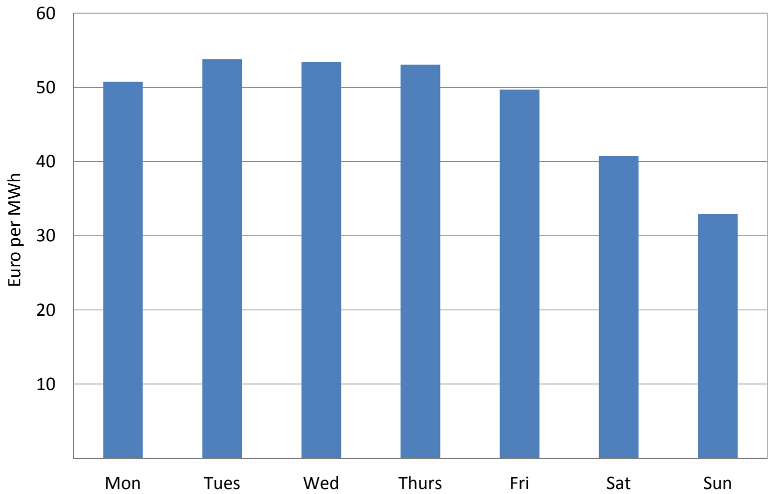
	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis
Original Price	48.06	46.07	301.54	-35.57	18.80	2.31	22.94
Deseasonalized	48.06	45.80	114.52	1.96	15.18	0.85	4.11
Log Deseasonalized	3.82	3.82	4.74	0.67	0.32	-0.70	8.09

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. Figure 5 shows that 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 seasonality is addressed by using

[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.

Figure 5: Electricity price variation within the week



Note: Average electricity price on different weekdays over the sample period.

constant step functions which consist of dummies for each seasonal cycle (Trück and Weron, 2004). Dummies for week days d_i and months m_j are included in the following function to capture seasonality:[10]

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

The results for the deseasonalisation are shown in Table 2. The coefficients for weekday dummies in Table 2 follow the same pattern as shown in Figure 5: 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

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

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)

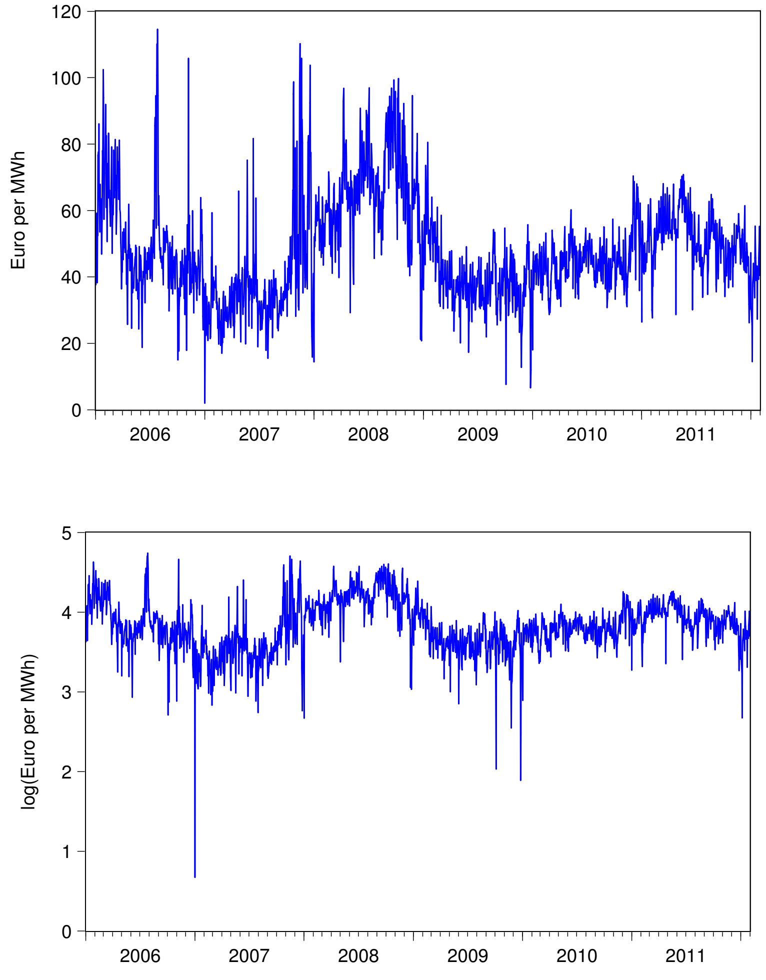
Note: OLS regression with the Phelix Day Base, corrected for outliers, as dependent variable. Monday and January are used as reference variables. p-values in parentheses.

following analysis.[11] Figure 6 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. An illustration how the in-feed of variable renewable electricity affects the existing power system can be found in Annex B, Figure 13. 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 (TSO). The TSOs then sell the predicted

[11]Estimating the logarithmic price series has the advantage that the coefficients have a straight forward interpretation. 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.

Figure 6: 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.

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 Figure 7. 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]

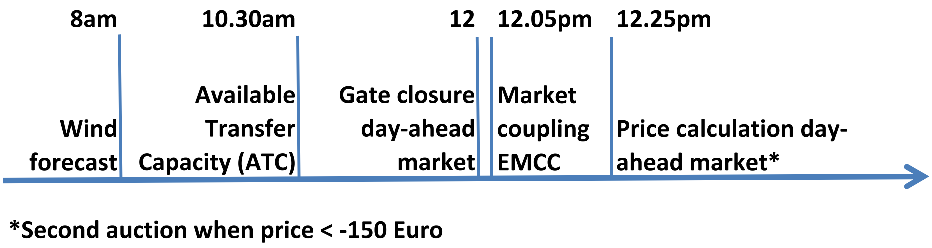
Of course, electricity price is not solely determined by wind electricity generation. Several papers indicate that the total electricity load, which reflects the demand profile, plays an important role in price behaviour. In fact, research shows that the combination of both factors is particularly important 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 termed *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.

[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 among almost all electricity users.

Figure 7: 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.

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

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

following relationship:

$$L_t = \hat{L}_t + e_t, \tag{2}$$

where L_t is the actual load, $\hat{L}_t$ 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 per cent 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 (2010) method is that the error 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 $\hat{L}_t$, its relative importance for the power system becomes clear. Figure 8 shows that the share of wind fluctuates between 0 and 40 per cent. 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.

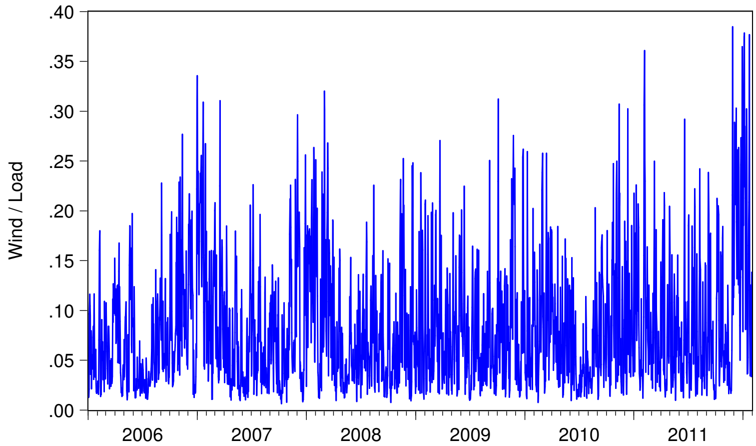
4 Model

The liberalisation of power markets turned electricity into a tradable commodity and engendered 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 that distinct features of the electricity price should be included in an empirical price model. Electricity, for example, 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 reconciled. Hence, mean reversion

[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 per cent 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 per cent 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.

Figure 8: Share of wind power generation



Note: The share is calculated as MWh of wind in-feed per MWh electricity load per day. Source: EEX and ENTSO-E.

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 among 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 improves the GARCH model.

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 reserve margins should be included to better understand price movements. Huisman (2008) also recognises the need to enrich the price model with fundamentals and uses temperature variables to detect changes in price behaviour. 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 findings from stock markets, see for example Bollerslev and Jubinski (1999) or Le and Zurbruegg (2010). Hadsell (2007) and Petrella and Sapio (2010) touch on another decisive factor for the electricity price and use a GARCH model to test whether changes in market design have an effect on price volatility.

Using a GARCH model allows to explicitly test 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 most appropriate to mimic the volatility behaviour of the electricity price. Figure 6 illustrates that volatility clustering is present which is typical in financial markets. This feature hints at autocorrelation in the data, which is emphasised 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]

As electricity is not storable, the 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. To capture mean reversion, the electricity price can be described by an Ornstein-

[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.

Uhlenbeck process (Vasiček, 1977),

$$dp_t = \kappa(\mu - p_t)dt + \sigma dw_t. \tag{3}$$

Here, p_t is the electricity price and w_t a standard Wiener process. After deviating from the mean, $\mu - p_t$, the price is corrected back to its mean. The speed of the reversion is given by κ. According to Bierbrauer et al. (2007), Equation 3 can be rewritten for the deseasonalised log price in discrete time as Gaussian AR(1) process: $y_t = c + \phi y_{t-1} + \eta_t$, where $c = \alpha \cdot \mu$, $\phi = 1 - \kappa$ and $\eta \sim iidN(0, \sigma^2)$.[22] Hence, 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:

$$y_t = \mu + \sum_{i=1}^{l} \phi_i y_{t-i} + \epsilon_t \tag{4}$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}, \tag{5}$$

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 equation of this model. Given this extension, the specification for

[22] For the deseasonalised log price, Equation 3 can be written in discrete time as $\triangle y_t = \kappa(\mu - y_t)\triangle t + sigma\triangle w_t$. Given $\triangle y_t = y_{t+1} - y_t$, the formula becomes $y_t = \kappa\mu + (1 - \kappa)y_{t-1} + \eta_t$. Check for example Dixit and Pindyck (1994) for a more detailed description of the transformation from continuous to discrete time.

the ARX-GARCHX model becomes:

$$y_t = \mu + \sum_{i=1}^{l} \phi_i y_{t-i} + \sum_{j=1}^{m} \theta_j w_{t-j} + \epsilon_t \tag{6}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{k=1}^{s} \gamma_k w_{t-k}. \tag{7}$$

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.[23] The empirical strategy of this paper is to first estimate the GARCH model with Equation 7 for the German day-ahead electricity price, extended by covariates for the wind power forecast. All specifications are first estimated including one AR(1) parameter as derived from the Ornstein-Uhlenbeck process. To capture serial correlation present in the price series, I then include the number of autoregressive lags which minimise the Bayesian information criterion (Escribano et al., 2011). I will report both specifications to show that the coefficients vary only slightly.

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 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 change can be observed in the volatility of the electricity price after the regulation was amended.

[23] As the aim of this study is not to forecast the price, checking that the actual conditional variance is positive assures stability.

5 Estimation Results

5.1 Impact of Wind Power

The results for the GARCH(1,1) estimations can be found in Table 3.[24] All standard errors are calculated using the Bollerslev and Wooldridge (1992) method which assured that the test statistics are robust to non-normality of the residual. The first column (A) shows the GARCH benchmark specification for the log level of 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 0.56 indicates that the autoregressive persistence β is not particularly strong for the electricity price. The GARCH term α reflects the impact of new shocks the conditional variance h_t, transmitted though the error term ϵ_t from Equation 4. The AR term depicts a specificity of the power market. The coefficient of 0.88 in (A) shows that the price reverts back to its long-run mean. But the speed of reversion, given by $1 - \phi_1$, is low.

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 in the specification (A*) in Table 4. The significant seventh lag mirrors the weekly seasonal component and is in line with Escribano et al. (2011). The GARCH coefficients remain fairly stable with an increase in β and, vice versa, a reduction of α. 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]

In column (B) and (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

[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-live 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.

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) and (B*), the coefficients can be interpreted as elasticities. When the wind electricity in-feed (MWh per day) increases by 1 per cent, the price decreases between 0.09 and 0.10 per cent. In the variance equation, the wind variable is significantly different from zero and positive. Hence, the fluctuating wind in-feed 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 is only significant in specification (B*) in Table 4, and illustrates that the price increases with higher electricity demand. The variance, however, is reduced in times of high demand, which might arise from higher liquidity of the electricity market.

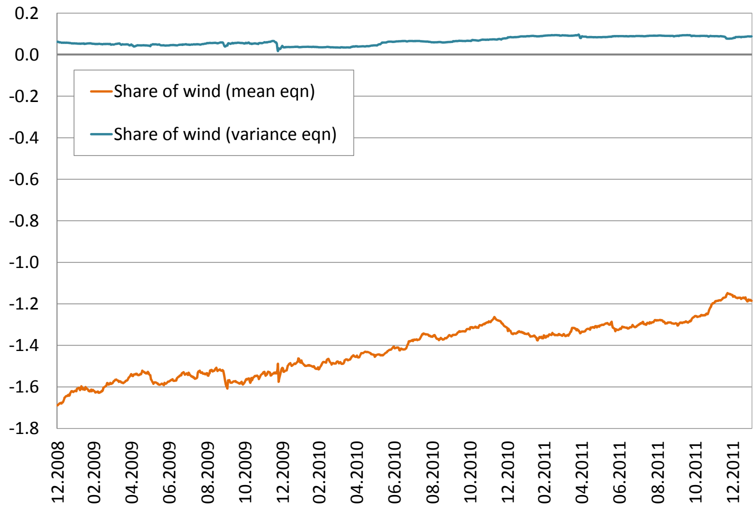
A similar picture arises in column (C) and (C*) when the share of wind is included in the GARCH model. The wind variable reflects the share of wind relative to total electricity load. The coefficient for this wind penetration measure turns out as expected: a strong wind in-feed lowers the electricity price but increases its variance. When the share of wind rises by one percentage point, the electricity price decreases by 1.32 or 1.46 per cent in specification (C) and (C*). The coefficient is higher than before because the wind variable is now expressed as a share of 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 (B) and (C), respectively (B*) and (C*), the coefficient for the GARCH term α increases slightly, accompanied by a downward adjustment of β. This suggests that a 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 autoregressive parameters are included in specifications

[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 is 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 per cent. To reach 9 per cent, wind has to rise a substantial 13 MWh or 12 per cent.

(B) and (C), respectively (B*) and (C*).

Figure 9: 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.

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).[29] Figure 9 shows how the coefficients evolve, using a three-year window. 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 orange line, becomes less negative over time. The wind in-feed can no longer decrease the price level as much. Stated differently, the merit-order effect lessens over time. Sensfuß (2011) find the same effect for Germany. A plausible explanation for the weaker merit-order effect is the increasing share of solar PV in-feed. Already, a merit-order effect from wind power can be observed for solar PV in Germany (Bundesnetzagentur, 2012). As Figure

[29]Rolling regressions with a 2 year window have been calculated as well and give a broadly similar picture. However, a longer window is preferred for the coefficients to be significant. Moreover, the picture for specification (B), including log levels for wind and load separately, looks very much the same.

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

Dependent variable: log electricity price
Sample: 1.1.2006 31.1.2012

	(A)		(B)log(Wind) log(Load)		(C)Wind/Load		(D)Wind/Load Regulation dummy	
Mean equation								
Constant	3.838	(<0.0001)	5.351	(<0.0001)	3.952	(<0.0001)	3.934	(<0.0001)
ϕ_1	0.881	(<0.0001)	0.899	(<0.0001)	0.901	(<0.0001)	0.874	(<0.0001)
log(Wind)			-0.089	(<0.0001)				
log(Load)			-0.035	(0.1945)				
Wind/Load					-1.315	(<0.0001)	-1.249	(<0.0001)
A dummy for outliers in the log price and its first lag are included in all mean equations.								
Variance equation								
ω	0.007	(<0.0001)	0.324	(<0.0001)	0.003	(0.0076)	0.011	(<0.0001)
α_1	0.243	(<0.0001)	0.273	(<0.0001)	0.267	(<0.0001)	0.250	(<0.0001)
β_1	0.557	(<0.0001)	0.541	(<0.0001)	0.555	(<0.0001)	0.300	(<0.0001)
log(Wind)			0.002	(0.0059)				
log(Load)			-0.024	(<0.0001)				
Wind/Load					0.031	(0.0155)	0.052	(<0.0001)
Regulation dummy							-0.010	(<0.0001)
Adj. R^2	0.686		0.726		0.739		0.742	
Log likelihood	829.291		1083.401		1075.098		1150.745	
AIC	-0.741		-0.966		-0.961		-1.028	
BIC	-0.723		-0.938		-0.937		-1.002	

Note: AIC stands for Akaike information criterion, BIC for Bayesian information criterion. p-values are in parentheses.

Table 4: Results AR(7)-GARCH(1,1) models with additional explanatory variables

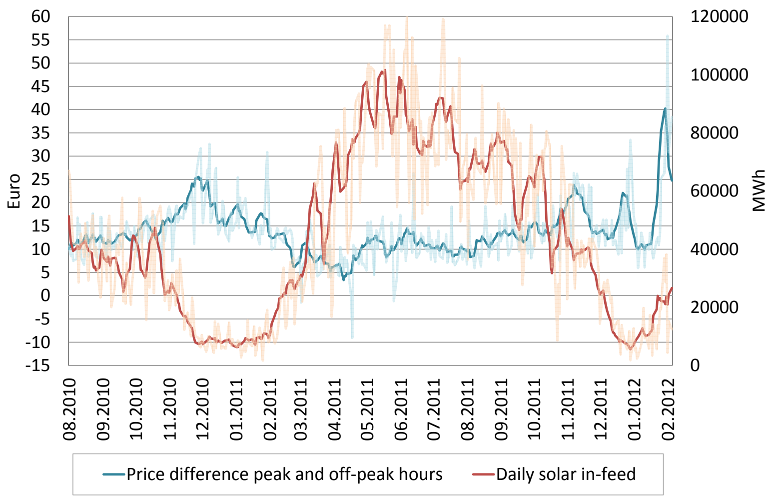
Dependent variable: log electricity price
Sample: 1.1.2006 1.31.2012

	(A*)		(B*)log(Wind) log(Load)		(C*)Wind/Load		(*D)Wind/Load Regulation dummy	
			Mean equation					
Constant	3.862	(<0.0001)	3.862	(<0.0001)	4.042	(<0.0001)	3.970	(<0.0001)
ϕ_1	0.652	(<0.0001)	0.581	(<0.0001)	0.589	(<0.0001)	0.597	(<0.0001)
ϕ_2	-0.035	(0.2539)	-0.005	(0.8668)	-0.040	(0.1968)	-0.010	(0.7238)
ϕ_3	0.096	(0.0010)	0.083	(0.0036)	0.097	(<0.0001)	0.060	(0.0313)
ϕ_4	0.008	(0.7707)	0.029	(0.3343)	-0.003	(0.9116)	-0.009	(0.7283)
ϕ_5	0.036	(0.2199)	0.024	(0.4522)	0.028	(0.3483)	0.049	(0.1744)
ϕ_6	0.104	(0.0010)	0.113	(<0.0001)	0.130	(<0.0001)	0.121	(<0.0001)
ϕ_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: An asterisk * labels the specifications that include seven autoregressive lags of the price. AIC stands for Akaike information criterion, BIC for Bayesian information criterion. p-values are in parentheses.

10 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 electivity 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.

Figure 10: Solar PV in-feed and peak prices

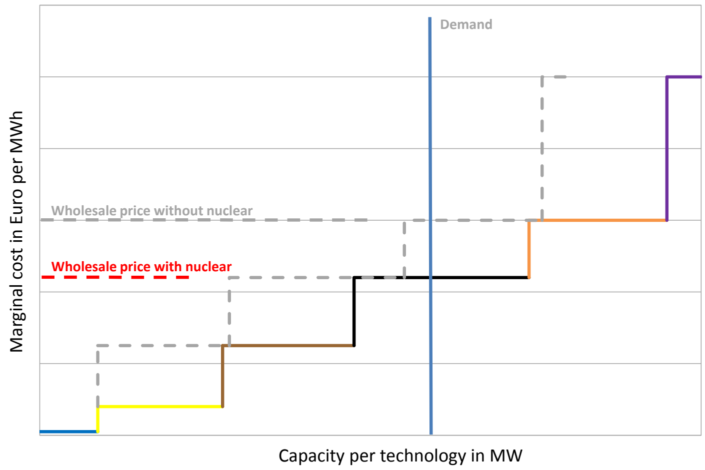


Note: The solid lines denote the 7-day moving average. The transparent lines the daily values. The difference between peak and off-peak prices shows that solar PV mainly depresses peak hour prices. In summer 2011 the off-peak price was even above the peak price on three days. Source: Bundesnetzagentur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

After April 2011, the impact of wind on the electricity price diminishes even further. This is most likely related to the nuclear phase-out in Germany. Shutting down nuclear power plants shifts the merit-order curve as illustrated by Figure 11. The price decrease, induced by wind, is less strong when the nuclear capacity is removed. This results are confirmed by findings of

Thoenes (2011).

Figure 11: 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 blue line illustrates marginal costs for electricity from wind, yellow stands for nuclear, brown for lignite, black for hard coal, orange for gas, and purple for oil. The dotted line illustrates the case without nuclear.

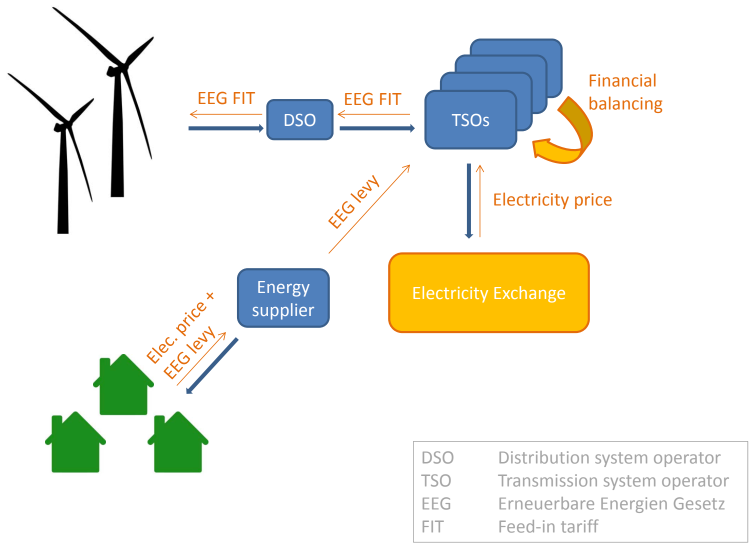
5.2 Impact of Regulatory Change

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 (see Figure 12). However, these funds are most likely insufficient to remunerate the producers of renewable electricity according to the feed-in tariff rates. Therefore, TSOs also receive the so-called EEG levy which is after all raised from the electricity users.[30] The EEG levy covers payments for feed-in tar-

[30] EEG stands for *Erneuerbare Energien Gesetz*. The EEG levy is payed by the energy suppliers who then pass the costs to consumers and industry. Some electricity users are exempt from the levy.

iffs as well as costs from forecasting, balancing, and marketing of renewable electricity.

Figure 12: Marketing mechanism after the regulatory change in 2010



Note: Illustration adapted from Buchmüller and Schnutenhaus (2009). Blue arrows show the flows of renewable electricity from the installations to the final electricity users. Orange arrows indicate monetary flows that finally remunerate the operators of renewable electricity installations. More detailed information is available at: www.bundesnetzagentur.de

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.[31] 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 (see Annex B, Figure 14 for an illustration). As the final wind in-feed 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

[31] Other renewable electricity generation, for example biomass, is less problematic in this respect.

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, they reached 595 million Euro 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 Mio 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 increase liquidity of the day-ahead and the intraday market significantly (Bundesnetzagentur, 2012). This is expected to reduce price volatility 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 market because they could socialise these expenses via the network charge (UoSC) to electricity users (Buchmüller and Schnutenhaus, 2009). According to Klessmann et al. (2008), integration of renewable electricity in Germany was opaque and inefficient before 2010. Under the new regulation, the interventions on the day-ahead market become obsolete 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. This procedure follows Antoniou and Foster (1992), Holmes and Antoniou (1995), Bomfim (2003), and Hadsell (2007). The dummy variable captures the effect on the variance after the regulatory change in 1. January 2010. The dummy is not

[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.

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 it be 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.[33]

The results from specification (D) and (D*) can be found in Table 3 and Table 4. In both cases, 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.

5.3 Impact of Market Coupling

The German market is not isolated, and electricity flows to neighbouring countries are important, especially for the integration of intermittent renewable electricity. A good example is the wind power from northern Germany which can often not be transmitted to the southern parts of the country due to capacity constraints in grid. High wind energy generation results in exports to neighbour countries, although the electricity could be used in southern Germany. To make sure that the reduction in the variance from 2010 onwards is not simply a result of the better integrated electricity market, I control for cross-border trade in the European electricity market.

The integration of the European electricity market has gained considerable importance from the creation of the European Market Coupling Company (EMCC). Since November 2009, Germany and Denmark pursuit day-ahead volume coupling on the two interconnectors between Germany and Denmark. In May 2010, the Baltic cable between Germany and Sweden joined. On 10. November 2010, the countries of the CWE region (Belgium, France, Germany, Luxembourg and the Netherlands) and the so-called

[33]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.

Table 5: 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		(E*) Wind/Load Regulation EMCC capacity	
		Mean equation		
Constant	3.863	(<0.0001)	3.775	(<0.0001)
ϕ_1	0.873	(<0.0001)	0.593	(<0.0001)
ϕ_2			0.005	(0.8501)
ϕ_3			0.058	(0.0351)
ϕ_4			-0.01	(0.6912)
ϕ_5			0.050	(0.1745)
ϕ_6			0.124	(<0.0001)
ϕ_7			0.147	(<0.0001)
Wind/Load	-1.243	(<0.0001)	-1.402	(<0.0001)
log(EMCC capacity)	0.007	(0.6425)	0.018	(0.1713)
		Variance equation		
ω	-0.017	(0.0391)	0.015	(0.6472)
α_1	0.249	(<0.0001)	0.260	(<0.0001)
β_1	0.296	(0.0001)	0.279	(<0.0002)
Wind/Load	0.051	(0.0002)	0.045	(0.0001)
Regulation dummy	-0.010	(<0.0001)	-0.008	(<0.0001)
log(EMCC capacity)	-0.001	(0.4515)	-0.001	(0.5029)
Adj. R^2	0.742		0.784	
Log likelihood	1152.265		1334.536	
AIC	-1.026		-1.187	
BIC	-0.996		-1.125	

Note: An asterisk * labels the specifications that include seven autoregressive lags of the price. 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.

Northern region (Denmark, Sweden and Norway) coupled their electricity markets.[34] The electricity flows of these countries are now jointly optimised, and electricity is exported from low-price to high-price areas, as a matter of efficiency. The necessary congestion management is carried out by the EMCC in a so-called interim tight volume coupling (Monopolkommission, 2009).[35] For this study, I use the interconnector capacities that can be used to export excess wind production.[36] The capacities are reported to the EMCC before the price setting on the day-ahead market and are therefore exogenous from the dependent variable.[37] 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) and (E*) in Table 5. The coefficients of the EMCC capacity do not turn out significant. However, the conclusions regarding the regulatory change and the wind in-feed remain valid. Therefore, previous specifications that omit the interconnector capacity seem not to be misspecified.

[34]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).

[35]The TSOs from the participating countries report the interconnector capacities one day in advance to the EMCC (see Figure 7). In addition, the EMCC receives the anonymised order books from the participating electricity exchanges after the day-ahead spot market closed at 12am. 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).

[36]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 neighbour country.

[37]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.

6 Policy Implications

This chapter shows that intermittent renewable generation already transmits volatility to the electricity price. The question is how to integrate electricity from variable sources more smoothly.

First, better geographical integration is important. Building renewable installations throughout Germany would even out the regional fluctuation and assure that wind and sunshine are captured at different sites (Klinge Jacobsen and Zvingilaite, 2010). However, optimal sites for renewable installations are limited within one country. It seems more efficient to connect renewable installations throughout Europe. Schaber et al. (2012) project that improved interconnection within Europe will reduce market effects of variable renewable electricity substantially. Hulle (2009) also emphasise that grid extensions lead to steadier wind generation levels. Better grid connection can be fostered by new cables but also by using existing capacity more efficiently. Experience in Europe has shown that modifying the market coupling regime is helpful in this regard (Hulle, 2009; Monopolkommission, 2011).

Second, flexible conventional power plants as well as electricity storage help balancing fluctuations of renewable energy. In times of high renewables in-feed, storage can collect and save excess electricity. Flexible generation units are power plants with low ramping costs, for example gas turbines. These plants operate at high variable but low fixed costs and can therefore be switched on and off to equalise low renewable power in-feed. 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 and 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). 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 mechanisms might fail to give sufficiently strong investment signals. The literature discusses various policy options, such as capacity markets, capacity payments, or reliability options, to support the construction and availability of flexible capacity. All these policy models are subject of some controversial debate (Cramton and Ockenfels, 2011). It is not clear that introducing such new policy instruments is beneficial and necessary. For the time being, ifo and FfE (2012) rather suggest using the existing structure of the balancing market to auction more long-term capacity.

Finally, this study emphasises that regulatory changes can encourage a better integration of intermittent renewable electricity in the power system. 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, on the one hand, intermittent renewables could be better integrated if gate closure on day-ahead and intraday markets would be later (Hiroux and Saguan, 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.[38] 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 minute electricity blocks (Bundesnetzagentur, 2012). Given the stochastic generation profile of wind and solar PV, this product increases flexibility for market participants. Such smaller products should probably be introduced to the day-ahead market as well. With respect to the policy framework, on the other hand, renewable support schemes should be revisited. Currently, renewable energy is not exposed to any market risk in Germany due to guaranteed feed-in tariffs. A more market-based system would give incentives to realign renewable electricity supply with demand. Support schemes that depend on the wholesale electricity price make generation most attractive during peak load. Germany already offers renewable electricity producers to choose between fixed

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

feed-in tariffs and price-dependent feed-in premiums. Since the beginning of 2012, renewable electricity producers are given a third option: they can sell their renewable electricity directly on the market without using TSO services. They forego the feed-in tariff but currently receive a similar payment to make this option attractive. This so-called *Direktvermarktung* does not yet reduce subsidy payments but creates another market-based channel to integrate renewable power. Together with a transition to feed-in premiums, this approach should be rigorously pursued. Simultaneously, balancing costs should be partly shifted to the operators of renewable installations. In Germany, these integration costs are currently passed on to energy users, in other countries, for example Spain or the UK, the operator of renewable installations has to bear these costs partly (Klessmann et al., 2008). 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 and should not be exposed to full risk (Klessmann et al., 2008). But renewable electricity generation now plays an important role in the German power system and should therefore assume more responsibility. A completely protected environment can hardly be sustained when planning to increase the renewables share to 35 per cent of gross electricity production in 2020. Market-based support could 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 Conclusions

With the aim of reducing carbon emissions and increasing energy security, renewable electricity generation is strongly supported by politicians and interest groups. This has led, especially during the last decade, to a rapid increase of renewable electricity generation in many parts of the world. In Germany, renewables now make up 20 per cent of the country's gross electricity production. The share of intermittent electricity generation from wind and solar PV has grown particularly quickly. Large amounts of stochastic wind electricity pose new challenges for the power system. Assuring a stable electricity supply and price becomes increasingly difficult. Given that Germany strives for an electricity mix with 35 per cent renewables in 2020 and 50 per cent in 2030, resilient integration of intermittent renewable electricity becomes absolutely crucial.

The presented results show 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 specifications underlining the robustness of the results. The disruptive effect of variable renewables on the wholesale price is relevant for the entire energy system. A lower and more volatile electricity price probably provides insufficient incentives to investment in new generation capacity, both in renewable as well as conventional capacity. The higher price volatility introduces uncertainty which, according to Dixit and Pindyck (1994), might lead to a delay of investments. After all, flexible generation plants become more important to back-up an increasing share of intermittent renewable electricity, but more difficult to finance. It is of the utmost importance that the electricity price continues to induce investments – in carbon-free renewables capacity and in back-up capacity needed to maintain security of supply.

This study finds evidence that a more reliable price signal can be achieved. The volatility of the German electricity price decreased after a regulatory change in 2010. Hence, the market design can to some extent smoothen the volatility of the electricity price and stabilise its level. Going from here, renewable electricity regulation should be developed further, towards a more market-orientated structure that remunerates renewable electricity during phases of high electricity prices. In Germany, the transformation of the energy system brings along many challenges. A framework that sets appropriate incentives for new investments and stabilises the wholesale price is prerequisite to meet these requirements. An efficient and more market-based integration of variable renewable electricity would unburden the consumers who currently pay most of the energy transition. This, in turn, could strengthen public support for the necessary transformations.

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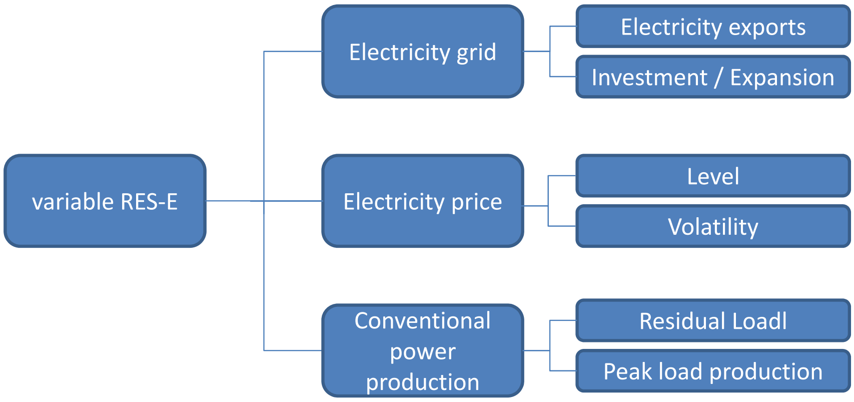
Figure 13: Variable renewable electricity and the power system

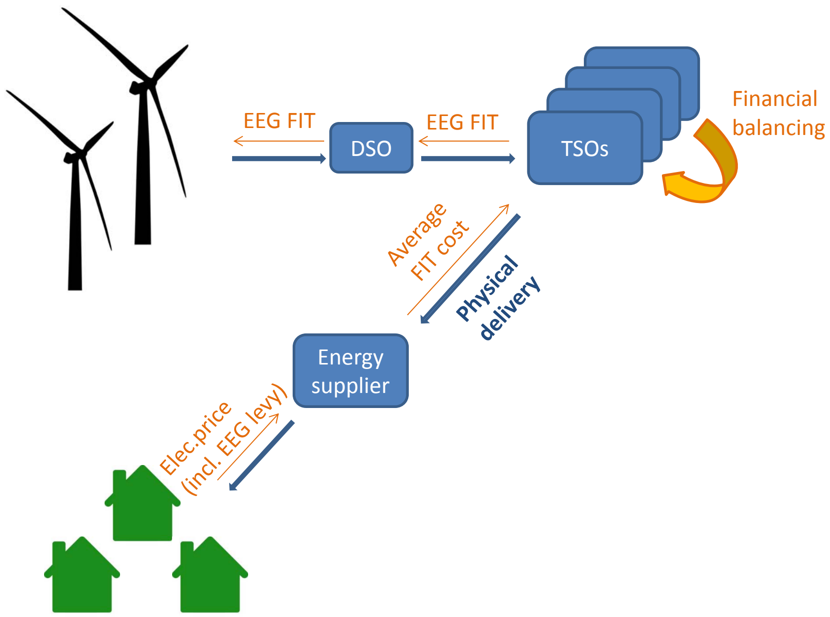


Source: Illustration adapted from Neubarth (2011).

This figure shows how variable renewable electricity influences the power system. First, the variable renewable electricity in-feed poses challenges to the grid which has to absorb the electricity at any point in time. Currently, the German transmission grid does not have enough capacity to transport the renewable electricity in-feed southwards. This problem is particularly apparent for wind power which is mainly generated in northern Germany but is needed in the south. This implies the need for massive investment in additional transmission cables. Until these cables are in place, any electricity that exceeds the demand in northern Germany is exported to neighbouring countries. Second, the impact on the level and volatility of the electricity price is studied in Chapter 3. Finally, renewable installations affect the existing power plants which need to balance the intermittent renewable electricity in-feed. Gas and coal plants in Germany have to satisfy electricity demand not met by renewables generation but have to be switched off when enough renewable electricity is generated.

B Marketing Mechanism Before 2010

Figure 14: Marketing mechanism before 2010



Note: Illustration adapted from Buchmüller and Schnutenhaus (2009). Blue arrows show the flows of renewable electricity from the installations to the final electricity users. Orange arrows indicate monetary flows that finally remunerate the operators of renewable electricity installations. Source: Illustration adapted from Buchmüller and Schnutenhaus (2009).

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