Energy Policy 73 (2014) 196–210

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

The impact of renewable energies on EEX day-ahead electricity prices

Florentina Paraschiv*, David Erni, Ralf Pietsch

Institute for Operations Research and Computational Finance, University of St. Gallen, Bodanstr. 6, CH-9000, Switzerland

HIGHLIGHTS

- We analyze the impact of renewable energies on the day-ahead electricity prices at EEX.
- We discuss the impact of renewables on day-ahead prices.
- We show a continuous electricity price adaption process to market fundamentals.
- Renewable energies decrease market spot prices and shift the merit order curve.
- The prices for the final consumers however increased because of feed-in tariffs.

ARTICLE INFO

Article history:
Received 27 January 2014
Received in revised form
30 April 2014
Accepted 5 May 2014
Available online 2 June 2014

Keywords:
Electricity prices
Renewable energy
Negative prices
Fundamental model

ABSTRACT

In this paper, we analyze the impact of renewable energies, wind and photovoltaic, on the formation of day-ahead electricity prices at EEX. We give an overview of the policy decisions concerning the promotion of renewable energy sources in Germany and discuss their consequences on day-ahead prices. An analysis of electricity spot prices reveals that the introduction of renewable energies enhances extreme price changes. In the frame of a dynamic fundamental model, we show that there has been a continuous electricity price adaption process to market fundamentals. Furthermore, the fundamental drivers of prices differ among hours with different load profiles. Our results imply that renewable energies decrease market spot prices and have implications on the traditional fuel mix for electricity production. However, the prices for the final consumers increased overall because they must pay in addition the feed-in tariffs for the promotion of renewable energy.

© 2014 Elsevier Ltd. All rights reserved.

1. Introduction

The worldwide demand for electricity has been growing considerably since the global industrialization, starting in the middle of the 18th century. The growth of the global economy has been achieved at the expense of the environment, as most of the produced electricity is generated by fossil fuel-fired power plants that harm the environment. This process of unsustainable growth has led to significant, unforeseen, and to some extent irreversible environmental damages. In the last couple of decades, we have seen two major developments in the German electricity market. First, there has been a deregulation of the market leading to enhanced competition, and second, a shift to electricity generation from renewable energy sources was initiated by the policy. This is supposed to enable a sustainable, long lasting, and environmental friendly supply of electricity.

While Germany did not have a leading role in the deregulation of its electricity market, it stepped in as a pioneer with respect to renewable energy. With its first renewable energy law dating back to 1991, the country was an early mover in steering electricity markets into an environmentally friendly direction. As one of the most recent and significant amendments, Germany introduced the Equalization Mechanism Ordinance that became effective on 1 January 2010 and changed the rules on how to market electricity from renewable energy sources. Since then, there have been many political changes that impacted the use of renewable energy for power production. We observed a significant growth of wind and photovoltaic (PV) installations, supported by feed-in tarifs (FITs). However, over the last years, aims were shifted from the promotion of renewable energy power plants to an enhanced electricity grid, that is capable of handling the volatile electricity generated from renewables.

It was expected that the promotion of renewable energy in Germany leads to lower electricity prices, as sustainable energy supply, wind and solar, have very low or even zero marginal costs. However, as we will discuss in the literature overview, empirical

* Corresponding author.
E-mail address: florentina.paraschiv@unisg.ch (F. Paraschiv).

http://dx.doi.org/10.1016/j.enpol.2014.05.004
0301-4215/© 2014 Elsevier Ltd. All rights reserved.

support for this result is scarce. The contribution of our study is twofold: First, we offer a historical review of energy policy regulations with respect to the use of renewable energies, wind and PV, in Germany. Second, we show that the promotion of renewable energy in Germany led to lower electricity day-ahead prices and contributed to a shift in the merit order curve.

Employing a dynamic fundamental model, we investigate to which extent renewable energy reduced the level of electricity prices in Germany and, in consequence, changed the impact of traditional fuels like coal, gas, and oil over time. The sensitivities of electricity prices to fundamental variables like demand and supply, as well as to CO_2 prices were further analyzed. During the investigated sample, electricity prices were highly impacted by regulatory changes, mainly related to renewable energies. We provide evidence that there has been a substantial adaption of the electricity price process to fundamental variables over time. We have tested our model excluding and including wind and photovoltaic (PV). In this way, we show that the explanatory power of the model, by including the renewable energies, has been significantly improved. The impact of wind generation is, in this respect, stronger than the one of PV. As a consequence, renewable energy partially substitutes in production the use of traditional fuels situated at the right end of the merit order curve. We show, in addition, that for different hourly blocks during a day, market fundamentals will impact electricity prices in a different way, due to different load profiles and, thus, different production design. Wind occurs with higher frequencies during the night and thus, its impact on the electricity price formation is more noticeable then. In consequence, the extra supply from wind electricity during night hours, in the context of low demand level, determines downside spikes and even negative prices at EEX. Instead, the excess of PV-based electricity produced helps balancing the excess demand during the peak hours. For risk management purposes it is important to understand what the risk drivers of power prices during different hours of the day are. To our knowledge, this is the first comprehensive study in the literature that shows the impact of renewable energy infeed in Germany on day-ahead power prices and provides important insights concerning power production schemes.

Although it was one main goal of policy makers, the reduction of the day-ahead electricity price level in Germany did not have a direct positive effect for the individual consumers. In fact, the feed-in tariffs that consumers must additionally pay are by far not compensated by the decrease in electricity day-ahead prices due to renewables (see Frondel et al., 2010). The traditional producers are directly affected by the lower prices they get for the produced electricity. The only beneficiaries are the energy-intensive industries, that are excluded from the payment of FITs. Overall, the system shows serious drawbacks, as it did not imply so far clear positive economical and social effects. Ideally, the system needs to be designed in a sustainable way, such that power producers can earn a profit to deliver their services to the society and in the same time individual consumers can benefit from lower power prices.

The paper is organized as follows. Section 2 shows the literature overview. In Section 3, we offer an overview of regulations and political debates concerning the promotion of renewable energy sources in Germany. Section 4 links extremely large electricity price changes to high renewable infeed. In Section 5, we discuss different fundamental variables that should impact electricity prices. Section 6 describes the modeling approach. Results are discussed in Section 7. Finally, in Section 8 we conclude.

2. Literature overview

We place our paper in the context of two literature streams: the economic impact of supporting schemes on renewable energy and fundamental modeling of electricity prices.

The first literature stream we refer to concerns the economic effects of renewable energy support schemes. In a study on economic implications of different incentive schemes for promoting renewable energy, Menanteau et al. (2003) bring arguments in favor of the introduction of feed-in tariffs instead of the use of a bidding system. However, the discussion is theoretical, given that this study has been done before the implementation of incentive schemes in practice. In an empirical study on the Spanish market, de Miera et al. (2008) show that the increase in consumer power prices due to feed-in tariffs is offset by a greater price reduction effect, due to the renewable energy fed into the grid. By contrary, Frondel et al. (2010) strongly criticize the use of the feed-in mechanism in Germany and conclude that the introduction of feed-in tariffs, in fact, imposes high costs for the final electricity consumers and do not have any positive economical implications. In our paper, we update the discussion in Frondel et al. (2010) with the latest energy policy amendments in Germany. In particular, we address the need for an effective power transmission grid. In Germany, wind and solar resources are not concentrated in regions with load pockets. Therefore, transmission constraints can substantially limit renewable energy production. Building an effective grid has been the focus of energy policy makers over the last years. However, academic literature on transmission constraints is very scarce. We aim at closing this gap and shed light on the importance of an effective grid to balance electricity demand and thus, to avoid extremely large price changes.

Fundamental modeling of electricity prices is the second literature stream where we place our paper. The motivation behind fundamental models for electricity prices is that characteristic price patterns are the result of the joint behavior of fundamentals. However, the range of fundamental variables used in the literature is still rather limited. Dummies to cover seasonal effects, weather data, and the level of demand are often used as explanatory variables. Knittel and Roberts (2005) estimate an ARMAX model with temperature data on the Californian market. Torro (2007) defines an ARIMAX model with temperature, precipitation, reservoir levels, and the difference between current futures and spot prices (basis) as external variables for the Nordic market. In the general context of midterm price forecasts for Nord Pool, Fuglerud et al. (2012) study the influence of various fundamental variables like hydro and snow reservoir levels and consumption on electricity prices. Cartea and Villaplana (2008) explain US electricity spot prices by demand and capacity. Looking at the British electricity market, Bunn et al. (2013) demonstrate how the prices of gas, coal, CO_2, forecasts of demand, and reserve margin, in addition to price volatility, influence electricity price quantiles.

The studies cited above assume that market fundamentals have a constant impact in time on the electricity price formation process. Furthermore, they do not distinguish between different diurnal impacts of fuels, demand, and supply, although it is known that the load shows different patterns within one day, which implies different production design. That is, during night hours, when production is low, fuels with low marginal cost of production are used, while during the daily peak hours more efficient power plants situated to the right of the merit order curve are turned on. In Karakatsani and Bunn (2010), the authors bring evidence for electricity price adaption process to market fundamentals. Furthermore, Chen and Bunn (2010) show that for different trading periods within the day, prices can be a function of fundamentally different drivers. However, this study takes into account traditional fuels used for electricity generation in UK like gas and coal but does not analyze the impact of renewable energies. That is, however, of great importance, especially for Germany, given the promotion of renewable electricity on this market over the last years. The incentive for more wind, solar, hydro, and geothermic power production is in the focus of the

German energy policy. The input mix on the German power market has changed over the last years, as a result of the increase in the renewable energies, as shown in a recent study of Fleten et al. (2013b). Thus, there has been a partial shift from traditional production fuels and nuclear energy to renewables, in particular wind and PV. In this context, it becomes important for both producers and policy makers to analyze how the growth of renewable energy influences the spot price behavior. Huisman et al. (2013) strengthen the support for the view that an increase in wind and solar supply lowers power prices. The authors derive this conclusion based on indirect empirical evidence from hydro power. Empirical support for this result on the German electricity market is, however, scarce. In our paper, we aim at showing the shift in the merit order curve due to renewable energy in Germany and the different diurnal impact of fuels on power spot prices.

3. Promotion of renewable energy sources in Germany

The expansion of renewable energies in Germany was given by the Renewable Energy Act "the EEG".[1] The EEG was issued in 2000 and is the successor to the Electricity Feed Act ("Stromeinpreisungsgesetz", StrEG) from 1991. According to this regulation, the producers of renewable energies, wind and PV, are guaranteed a minimum compensation. The StrEG was similar to the current EEG but less efficient due to the coupling of electricity prices and ambiguous grid access (see Hirschl, 2010).

The legislation of the EEG regulates that priority shall be granted to renewable energy sources by paying feed-in tariffs (FITs). By granting this incentive, the EEG stimulated an enormous growth in renewable energy production, through apportioning the additional costs of supplying energy from renewable sources to energy supplying companies. The energy suppliers can pass the costs to the end consumer through the EEG surcharge.

In the first phase (2000–2009) of the implementation, a considerable increase in renewable energy sources was observed. Thus, a new generation of electricity supply was established. In consequence of the enormous expansion of renewable energies, especially the high volume of annual PV installations, made FITs unbearable. To manage this development, FITs had to be reduced. At the same time, due to the rise of renewable energy sources, the EEG surcharge increased.

In the second phase (2009–2011) it became clear that the electricity grid was not capable to handle the growing supply of volatile renewable energy. For example, most wind generation capacities are installed in Northern Germany, while most of the energy consumption is concentrated in the south. In case of excess supply of electricity, prices can fall down to zero or even below. This might cause modern and efficient power plants to shut down in regions where energy supply from renewables is high, in order to avoid potential grid breakdown. On the other hand, in regions where the grid is not fully developed, inefficient (oil-fired) power stations have to run in order to stabilize the electricity grid (Zirm and Auer, 2013). This would not be the case in a well-developed grid, as electricity could be sent to any area in Germany where it is actually needed. One cautionary example that emphasizes the need of expanding the power grid is the off-shore wind park "Riffgat" in the German North Sea. The construction of the wind park was recently completed and the installations could provide 120,000 households with electricity. But as the necessary grid expansion to the shore was lacking behind. Instead of providing electricity to the market, the wind park consumed 22,000 l of Diesel each month in order to maintain the installations and avoid deterioration (dpa, 2013). Since February 2014 Riffgat could finally be connected to the electricity grid and the Diesel generators could finally be switched off.

From the end of 2018 electricity will flow between Germany and Norway in both directions through a 1400 megawatt subsea cable. With this subsea cable, wind power and solar power can be exported from Germany to Norway, when there is a surplus, while Norway can export hydropower to Germany when the sun does not shine and the wind does not blow. The 1400 megawatt subsea cable interconnects the electricity markets of both countries directly for the first time. Norway and Germany thereby enhance the security of supply and contribute to more stable electricity prices, by balancing the demand in both countries. However, without an enhanced transmission grid, the surplus of hydropower imported from Norway cannot be efficiently transmitted to the south of Germany, to balance out consumption. This is another major reason for policy makers to shift the support from new installations of renewables toward enhancing the grid.

Supply and demand of electricity determine market prices which have to correspond exactly at any location and at any time (see Paraschiv, 2013). Because in Germany the supply from wind and solar is concentrated in the northern part, the grid operators have difficulties to balance out consumption, mainly concentrated in the south. In addition, limited efficient storing capacities prevent intertemporal smoothing of the demand by holding storages. These are all causes for extremely large price changes (spikes) at EEX. Hence, there is a huge need for grid expansion and more effective integration of production, expansion, and consumption, to balance demand and thus avoid extreme price spikes. This gets extremely necessary in the third phase (2012 up to date) and will cause high costs (Hirschl, 2010). However, it becomes obvious that future incentive schemes for the promotion of renewable energy in Germany should be reconsidered. Thus, future investments in wind and PV installations should not be considered in isolation, but in a consistent way with the development of an effective grid. These issues are major topics in the German political debates. An example is the "10-Punkte-Programm" of the former German Environment Minister Peter Altmaier (2012), in which he states ten points on how to improve the promotion of renewable energies in Germany. This program requires a well-integrated and fully developed grid system. Achieving this aim will involve high costs and is only attainable if feed-in tariffs are cut back to zero for intermediate terms (see BMU, 2012). In consequence, the "Photovoltaic Amendment" from June 2012 reorganized the compensation scheme: a 90% cap on photovoltaic and a volume threshold of 52 GW are compensated by the EEG.

According to the latest revision of the EEG, the new target for the share of renewable energies is 35% by 2020, compared to 23% of renewable electricity in 2012 (see Fraunhofer IWES, 2013). Major changes in the EEG include a strict reduction of FITs and volume based triggers. Additionally, energy supplying companies have now the opportunity to sell the produced renewable electricity directly into the market and receive a market premium (for details see Gawel and Purkus, 2013).

The subsidization of energy intensive industries is strongly criticized and the EU Competition Commission reviews the privilege of these consumers (see von Petersdorff, 2013). The planned cap on the EEG surcharge for private households shall be compensated by shortening the benefits for energy intensive companies. Further decisions should not only concern the review of the compensation scheme, but also consider international competition aspects.

While investor compensation for wind electricity was rather high in the past, it has been constantly decreased for PV. Thus, the guaranteed FITs of 50 ct/kWh in 2000 was gradually decreased to 29 ct/KWh in 2012, when all newly installed facilities reach the so

[1] See also "Renewable Energy Sources Act of 25 October 2008 (Federal Law Gazette I p. 2074) as last amended by the Act of 11 August 2010 (Federal Law Gazette I p. 1170)".

called grid parity, indicating production costs below end-consumer prices. However, even though photovoltaic contributes only 26% to the electricity supply from renewables, it requires still 60% of the EEG-surcharge in 2013 (see Wirth, 2013).

The reason for the reduced compensation for photovoltaic is due, on the one hand, to the fact that fixed investment costs for PV power plants decreased. On the other hand, in order to foster a sustainable development of renewable energy supply, aims were shifted from the promotion of renewable energy power plants to an enhanced electricity grid. That should be capable to handle the volatile electricity generated from renewables and bridge the distance between production intensive and consumption intensive regions.

4. Renewables and extreme events

We analyze hourly German electricity Phelix spot prices between 1 January 2010 and 28 February 2013, as displayed in Fig. 1. There are several reasons why we do not use data before 2010. The main reason is that at the beginning of 2010, the latest significant regulatory change (AusglMechV) became effective. The significant increase in the use of renewable energies during the investigated period caused large changes in the input mix at EEX (see Table 1). The change in the supply curve comes from a substantial increase in wind, PV, and biomass capacity. Another reason is that some of the data used in this paper, like photovoltaic or power plant availability, are incomplete or not available for previous time periods. Thus, photovoltaic data are consistently published by all Transmission System Operators for Electricity (TSO) zones in Germany only from January 2010.

Electricity prices have properties that differ considerably from those of financial assets or even of other commodities (see Fleten et al., 2013a). This is partly due to the inelastic short-term demand for electricity, caused by economic and business activities. Combined with the lack of efficient storage opportunities, which prevents inter-temporal smoothing of the demand, extremely large price movements (spikes) as well as various cyclical patterns of behavior occur. As shown in Fig. 1, spikes are infrequent events that occur as an effect of extreme *load fluctuations* caused, for example, by severe weather conditions, or of *supply fluctuations* in case of generation outages or transmission failures. Extreme load fluctuations occur not only because of weather, but also in the context of the so-called “holiday effect”, when low load levels are observed and therefore downside extreme price changes can be expected (see Fleten et al., 2013a). Such an example are the downside spike clusters that occurred during the week from 22 to 28 December 2012, as shown in Fig. 2. The graph shows the evolution of the hourly spot prices versus the percentage of the wind infeed in the total load. The forecasts of wind and load were

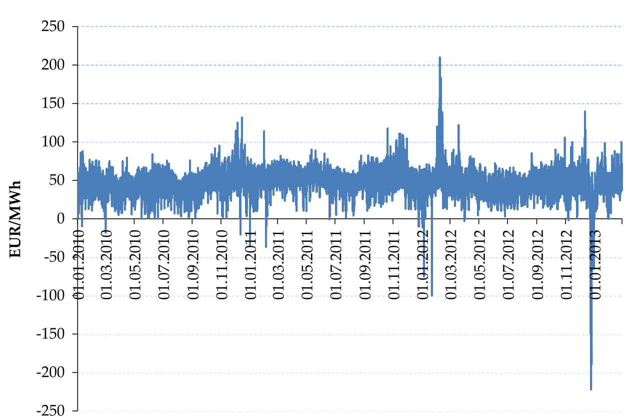

Fig. 1. Hourly EEX Phelix spot prices.

Table 1
Electricity production in Germany by source (%) (AG Energiebilanzen, 2014).

Source	2009	2010	2011	2012	2013
Coal	42.6	41.5	42.8	44	45.2
Nuclear	22.6	22.2	17.6	15.8	15.4
Natural gas	13.6	14.1	14	12.1	10.5
Oil	1.7	1.4	1.2	1.2	1
Renewable energies from which	**15.9**	**16.6**	**20.2**	**22.8**	**23.9**
Wind	6.5	6	8	8.1	8.4
Hydro power	3.2	3.3	2.9	3.5	3.2
Biomass	4.4	4.7	5.3	6.3	6.7
Photovoltaic	1.1	1.8	3.2	4.2	4.7
Waste-to-energy	0.7	0.7	0.8	0.8	0.8
Others	3.6	4.2	4.2	4.1	4

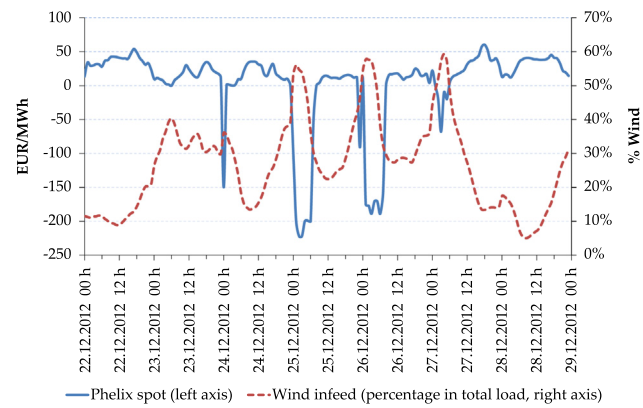

Fig. 2. EEX Phelix spot prices and percentage of the forecasted wind infeed in the electricity load.

used for the analysis since the prices were fixed already on the day before. On three days the wind infeed exceeded 50% of the total load during some night hours. These are extreme values, since the average percentage of the wind infeed in the total demand is 12.08%. This caused negative prices at EEX for the respective hours down to −222 EUR/MWh.

It is expensive to change the production of big generating units, which are further causes for spikes and even negative electricity prices. From an economic perspective, negative prices occur when the costs of shutting down and ramping up a power plant unit exceed the loss for accepting negative prices (see Keles et al., 2011). The negative prices near “0”, observed in Fig. 1, are due to the fact that energy suppliers are willing to pay a small “fee” for not shutting-down their medium-load plants (coal plants for example) for a few hours. In this way, they avoid start-up or ramping costs.

As a preliminary step, we want to see if extremely large electricity price changes occur in hours with extreme wind or PV infeed. We therefore sort out the negative prices (see Fig. 3) and extreme upwards spikes. Filtering out extreme- from normal price levels is generally a difficult task. There exist, however, some methods to implement this filtering. One of the simplest ways, and often used in the literature, is to fix a reasonable threshold and to filter out those prices beyond the threshold level (see Cartea and Figueroa, 2005). For electricity prices, often a “reasonable” threshold is predefined at 3 standard deviations (see for example Keles et al., 2011; Bannor et al., 2013). Another more complex way is to estimate regime limits in the context of regime-switching models (Fleten et al., 2013a) or to work with quantile regression models (see Bunn et al., 2013). However, in this section we do not define a model for electricity prices, but we only aim at a descriptive analysis of price spikes at EEX. We therefore pre-define upward

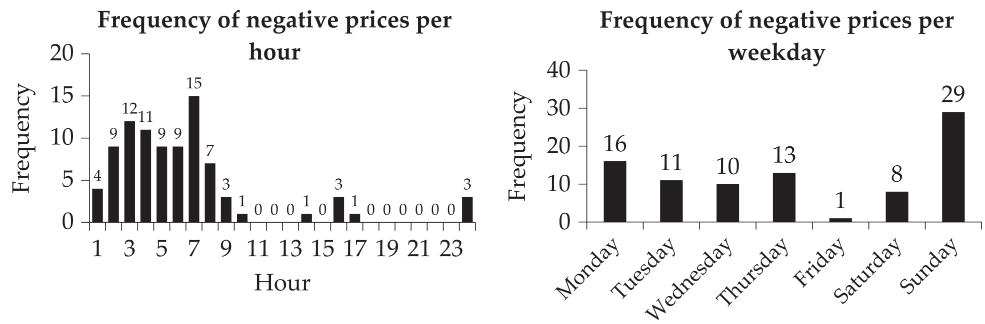

Fig. 3. Distribution of negative prices.

price spikes as price levels above 3 sigma events. In this way, we look at the prices above 70 EUR/MWh, which seem a reasonable choice, if we look at Fig. 1. Concerning the downward spikes we focus on the negative prices, as they pose a particular challenge for electricity producers, as explained above. We look, thus, at 108 positive spikes and 88 negative prices, which constitute 0.71% of all price observations. Interestingly, almost all upward spikes occur during weekdays (excluding holidays), when demand for electricity is usually higher than on the weekends. Contrary, negative prices occur only 31 times during weekdays but 57 times during the weekend, or on a holiday. Furthermore, we find that upward spikes solely occur during day hours, whereas about 65% of the observed negative prices occur during night hours.

We further examine if hours with extreme price changes coincide with high or low levels of wind and PV infeed. We found no clear evidence that high levels of PV lead to extreme price changes. Our analysis shows that during hours with upward spikes, an hourly average of 3137 MWh wind infeed is observed, while for hours with negative prices, 15,689 MWh. To better interpret these results, Table 2 shows the distribution of wind infeed over the investigated time period. We observe that the average wind infeed in hours with negative prices lies above the 90% quantile. So we can clearly link extreme wind infeed to negative prices.

Under the EEG regime, the Transmission System Operators (TSOs) are obliged to accept the delivery of power from independent producers of wind- and PV-based electricity into their own grid and must thereby pay feed-in tariffs. If the wind infeed is very high and the load is very low, then base-load power plants like coal or nuclear are forced to shut down. Especially for nuclear power plants the shutting-down and starting-up costs are high: an authorization from the state is required to restart. Therefore, these power plants are willing to accept to pay a much higher “fee” of up to 120 Euro/MWh or more to handle the excess of electricity produced, and thus, negative prices occur (Keles et al., 2011). However, we cannot clearly link renewables infeed to upwards spikes.

5. Fundamental variables driving electricity prices

As mentioned in the previous section, we analyze hourly German electricity spot prices between 1 January 2010 and 28 February 2013 (source EEX). The day-ahead auction for hourly delivery in the German and Austrian TSO zones takes place every day at 12:00 noon (including weekends and holidays). Market participants can anonymously submit their bids with a minimum volume of 0.1 megawatt (MW) for individual hours and blocks, and a tick size of EUR 0.01 per MWh. After all bids have been collected, the market clearing price, which applies to all transactions, is determined and published after 12:40 pm. The delivery takes place during the respective hour of the following day (Erni, 2012).

This section describes and motivates the choice of fundamental factors to explain the dynamics of electricity spot prices in the long- and short-term. We have chosen to categorize the variables into demand and supply side factors.

Table 2
Distribution of actual wind in MWh, overall hours between 1 January 2010 and 28 February 2013.

Stat	Wind
Average	4841
Max	24,021
90% Quantile	10,887
Min	92

5.1. Demand

As the electricity grid needs to be balanced at any point in time, demand equals supply. The Vertical Net Load (VNL) published by all four Transmission System Operators (TSOs) is an approximation for the electricity demand in Germany. It represents the sum of all power which is transferred from the high voltage transmission grid to the next lower level, which is the distribution grid. However, VNL does not include wind and PV energy, since renewable electricity is not fed in the high voltage transmission grid, but directly into the medium voltage transmission grid. Consequently, in order to approximate the total demand for electricity in the German market, we compute it in the following way:

$$\text{Demand}_t = \text{Vertical Net Load}_t + \text{Total Wind Infeed}_t + \text{Total PV Infeed}_t \tag{1}$$

However, as we model day-ahead spot prices, we are not interested in the actual demand of a specific day t, but in a forecast of demand for $(t+1)$. Demand forecast is not consistently published by the TSOs in Germany. Unfortunately, only one of the four TSO zones in Germany (TransnetBW) publishes demand forecast figures, and often also these data are incompletely and not comprehensively provided (see European Energy Exchange, http://www.eex.com). Therefore, we need to model the expected/predicted total demand in a separate model, for each hour of the day, and use it in the following models as an input variable. Therefore, we consider the demand defined in Eq. (1) as a vector of the stacked demands for each hour of the day $t=1,\ldots,T$.

Similar to Viehmann (2011), Nowicka-Zagrajek and Weron (2002), Taylor et al. (2006), and Weron (2006) we apply an Autoregressive Moving Average model with exogenous regressors (ARMAX) to forecast the expected electricity demand on the German market. Additionally, we allow for conditional variance by introducing a GARCH(1,1) structure. The choice of our model is based on some preliminary tests applied on the demand data. The autocorrelation function (ACF) and the partial autocorrelation function (PACF) show clear evidence for autocorrelation, while the Lagrange multiplier test shows clear evidence for GARCH

Table 3
MAPE for the demand model tested in-sample (1 January 2010–31 August 2012) and out-of-sample (1 September 2012–28 February 2013).

In-sample				Out-of-sample			
	MAPE		MAPE		MAPE		MAPE
Hour 1	0.042	Hour 13	0.044	Hour 1	0.066	Hour 13	0.035
Hour 2	0.046	Hour 14	0.046	Hour 2	0.065	Hour 14	0.038
Hour 3	0.046	Hour 15	0.045	Hour 3	0.064	Hour 15	0.034
Hour 4	0.044	Hour 16	0.046	Hour 4	0.063	Hour 16	0.034
Hour 5	0.043	Hour 17	0.043	Hour 5	0.063	Hour 17	0.033
Hour 6	0.041	Hour 18	0.031	Hour 6	0.057	Hour 18	0.047
Hour 7	0.044	Hour 19	0.030	Hour 7	0.050	Hour 19	0.050
Hour 8	0.044	Hour 20	0.031	Hour 8	0.046	Hour 20	0.051
Hour 9	0.042	Hour 21	0.032	Hour 9	0.043	Hour 21	0.056
Hour 10	0.037	Hour 22	0.035	Hour 10	0.035	Hour 22	0.060
Hour 11	0.039	Hour 23	0.037	Hour 11	0.032	Hour 23	0.067
Hour 12	0.039	Hour 24	0.038	Hour 12	0.031	Hour 24	0.073

effects in the squared demand.[2] We employ the following specification for daily observations of the demand in hour i at day $t=1, \ldots, T$:

$$\text{Demand}_{i,t} = \alpha_i + \varrho_i \text{Demand}_{i,t-1} + \beta_i' x_{i,t} + \varphi_i \varepsilon_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

where $\varepsilon_{i,t} = \sqrt{\sigma_{i,t}^2} u_{i,t}$, $u_{i,t} \sim N(0,1)$ and a conditional variance process that reads

$$\sigma_{i,t}^2 = \omega_i + \phi_i \varepsilon_{i,t-1} + \psi_i \sigma_{i,t-1}^2 \quad (3)$$

In Eq. (2), the vector $x_{i,t}$ represents exogenous variables. We account for an intraday seasonality pattern of electricity prices by modeling separately each hour of the day. In order to account for other seasonality patterns, we introduce dummy variables with values 1 or 0 for four out of five weekdays and 11 out of 12 months. The remaining exogenous variables are formed by climatic data retrieved from the German Weather Service. As we are interested in modeling an electricity demand forecast, we utilize climatic data from weather stations with high population densities and geographically diverse regions. We retrieved data from a total of four stations, namely from Hamburg Airport, Berlin-Tegel (Airport), Dusseldorf and Munich Airport. We believe that these cover the market area sufficiently well. The following climatic factors are used as exogenous variables: sunshine duration, mean degree of cloud cover, maximum air temperature, mean relative humidity and cooling degree days. For the estimation we use the level of the climatic variables. For more information about the composition of these data, see Appendix A.

Table 3 depicts the Mean Absolute Percentage Error (MAPE) of the estimated demand models per hour of the day, for the in- and out-of-sample period. The in-sample period is 1 January 2010–31 August 2012. The out-of-sample period is 1 September 2012–28 February 2013.[3] We eliminate weekends and German national holidays.[4] We find that the average MAPE over all 24 h is 0.040, with a minimum value of 0.030 and a maximum value of 0.046. For the out-of-sample period MAPE estimation results are robust. The average MAPE in the out-of-sample period is 0.050, which is one percent point higher than in the in-sample period. The minimum is located at 0.031 and the maximum at 0.073. We additionally check for serial correlation and heteroscedasticity in the standardized residuals $u_{i,t}$ in Eq. (3), after estimating the model. We apply the Ljung-Box Q-test and the Engle's ARCH test, respectively. We show in-sample results in Appendix B.[5] For most hours, the Ljung-Box Q-test shows no serial correlation in the standardized residuals. The Engle's ARCH test results show homoscedastic standardized residuals for most hours. Overall we conclude a good performance of the model in explaining electricity demand.

5.2. Supply

The concept of the Merit-Order Curve is a vital part of understanding the electricity spot price building mechanism. It can be interpreted as the sorted marginal cost curve of electricity production. With the help of the Merit-Order Curve, one can easily determine the given demand for electricity at any point in time, its market clearing price, and the types of power plants used to supply it (von Roon and Huck, 2010). In case of off-peak hours, base-load must-run facilities (nuclear and lignite-fired power plants) are mainly used in production. Contrary, during phases of high demand, power plants with high flexibility and high marginal costs of production such as gas- and oil-fired power plants are additionally used.

Renewable energy sources such as wind and photovoltaic power plants have an additional impact on the Merit-Order Curve. Electricity supply from renewable energy sources reveals not only one of the lowest marginal costs of production, but has also a guaranteed feed-in-tariff regulated by German legislation. In addition, it is assumed that the electricity demand is inelastic in the short-term (Sensfu et al., 2008). Therefore, since the electricity generated by renewable energy sources is directly fed into the (medium voltage) grid, the remaining demand is reduced, which leads to lower prices.

On the supply side we take into account the following fundamental variables: prices for coal, gas, oil, CO_2 emission allowances, and the renewable energies wind and photovoltaic. Additionally, we take into account the expected power plant availability. The EEX Transparency Platform, which is a joint venture of the EEX and the transmission system operators, publishes data on installed and available capacities. Although these publications are voluntary, participating companies have tripled in 2010 and by the end of the year represented 89% of all relevant companies.[6] Thus, the numbers provided can be considered a reasonable approximation for the entire market. We use ex-ante expected power plant availability as an explanatory variable for our models.

In Table 4 we give an overview of the data sources behind the explanatory variables. Table 5 defines whether the respective variables are available with daily or hourly granularity. In case of daily granularity, the same value is used for all 24 h of the day. In Table 6 we show descriptive statistics of the level of model variables used in the analysis.

5.2.1. Renewable energies: wind and photovoltaic

Among renewable energy sources, *wind energy* attracts the most attention in Germany. On a global scale, wind energy exhibited the second largest growth rates in Europe, after the United Kingdom and Denmark (Fraunhofer IWES, 2013). In 2013 electricity from wind power plants alone contributed 8.4% to the total production in Germany (compared to 8.7% in UK and 28% in Denmark). Wind infeed tends to be higher in early morning hours

[2] Results are available upon request.

[3] The out-of-sample period is not strictly out-of-sample, as we use ex-post climatic data as input variables. But as weather forecasts for the next 24 h appear to be very accurate, we believe that this approach is a reasonable approximation.

[4] We systematically remove weekends and holidays from the spot electricity prices and the explanatory variables. One reason is the seasonality: during weekends and holidays demand for electricity is consistently lower than during weekdays. Additionally, some of the fundamental variables used as input for the spot model are not traded during weekends/holidays.

[5] Out-of-sample results are robust. For convenience, we show in Appendix B only the in-sample results. The out-of-sample test results are available upon request.

[6] See European Energy Exchange AG (2011a).

Table 4
Overview of fundamental variables used in the analysis. Note: For Oil, the price of this contract is typically used as a reference for derivatives contracts and thus most relevant for trading. For Coal, Gas, and Carbon, the prices result from a daily auction which does not exist for oil.

Variable, units	**Description**	**Data source**
Lag spot price, EUR/MWh	Market clearing price for the same hour of the last relevant delivery day	European Energy Exchange: http://www.eex.com
Average lag spot price, EUR/MWh	Average market clearing price across all 24 h of the last relevant delivery day	European Energy Exchange: http://www.eex.com
Spot price volatility, EUR/MWh	Standard deviation of market clearing prices for the same hour on the last five relevant delivery days	European Energy Exchange: http://www.eex.com
Coal price, EUR/12,000 t	Latest available price (daily auctioned) of the front-month Amsterdam–Rotterdam–Antwerp (ARA) futures contract before the electricity price auction takes place	European Energy Exchange: http://www.eex.com
Gas price, EUR/MWh	Last price of the NCG Day Ahead Natural Gas Spot Price on the day before the electricity price auction takes place	Bloomberg, Ticker: GTHDAHD Index
Oil price, EUR/bbl	Last price of the active ICE Brent Crude futures contract on the day before the electricity price auction takes place	Bloomberg, Ticker: COA Comdty
Price for EUA, EUR 0.01/EUA 1000 t CO_2	Latest available price of the EEX Carbon Index (Carbix), daily auctioned at 10:30 am	European Energy Exchange: http://www.eex.com
Expected wind and PV infeed, MWh	Sum of expected infeed of wind electricity into the grid, published by German transmission system operators in the late afternoon following the electricity price auction	Transmission system operators: http://www.50Hertz.com, http://www.amprion.de, http://www.transnetbw.de, http://www.tennettso.de
Expected power plant availability, MWh	ex ante expected power plant availability for electricity production (voluntary publication) on the delivery day (daily granularity), daily published at 10:00 am	European Energy Exchange & transmission system operators: ftp://infoproducts.eex.com
Expected demand, MWh	Demand forecast for the relevant hour on the delivery day as modeled in Section 5.1	Own data, German Weather Service:http://www.dwd.de
Lag demand, MWh	Sum of total vertical system load and actual wind infeed for the same hour on the last relevant delivery day	Transmission system operators: http://www.50Hertz.com, http://www.amprion.de, http://www.transnetbw.de, http://www.tennettso.de

Table 5
Data granularity of fundamental variables.

Variable	**Daily**	**Hourly**
Lagged spot price		×
Average lag spot price		×
Spot price volatility		×
Coal price	×	
Gas price	×	
Oil price	×	
Price for EU emission allowances	×	
Expected wind and PV infeed		×
Expected power plant availability	×	
Expected demand		×
Lag demand		×

and during afternoon hours (see Erni, 2012). Leuthold et al. (2008) compare costs of wind power with other energy sources, and report generation costs of about 4.00 EUR/MWh. Once installed, wind power plants produce at much lower costs than for instance nuclear power plants (10 EUR/MWh), lignite (15 EUR/MWh), or gas fired plants (40 EUR/MWh). From an ecological perspective, another benefit of wind energy is that it is produced nearly carbon free (see Traber and Kemfert, 2011).

Photovoltaic energy infeed is another important component in the German renewable energy mix. After wind- and biomass-energy, photovoltaic energy fed in 28 TWh in 2012, which made up 4.7% of the German gross demand for electricity (BDEW, 2013). There has been a noticeable increase in the photovoltaic infeed since 2010, as shown in Fig. 4.

5.2.2. *Coal*

Coal-fired power plants still play the most important role, with a share of approximately 46%, in the German electricity production in 2011 (Federal Ministry of Economics and Technology, 2013). Electricity production with coal can be classified into two groups. The most prominent type of coal is lignite, which accounts for 27.2% of the German electricity production and is mainly used to cover base load. On the other hand, hard coal-fired power plants account for 19% of the German electricity production and cover phases of medium electricity demand.

5.2.3. *Gas*

Gas is the second most important source in the German energy-mix. With a share of 20.4% of the primary energy demand in Germany, gas has a significant contribution to the German energy supply (Federal Ministry of Economics and Technology, 2013). Due to their high operational flexibility and short ramp-up times, gas power plants are price-setting during peak hours, when demand for electricity is high (Sensfu et al., 2008). The comparably low investment costs, the expansion of the continental gas pipeline system, and the development of more efficient technologies, increased the importance of gas in electricity production over the last decades.

5.2.4. *Oil*

Although oil has a huge share in the primary energy production, it is rarely used directly for electricity production in Germany. Burger et al. (2007) note that the negligible role of oil is mainly due to environmental legislation. Oil-fired power plants are almost exclusively utilized as Cold Reserve (Zirm and Auer, 2013). Analogous to Erni (2012), we decide to consider oil price as an exogenous input variable, because it has a significant impact on transportation costs of imported coal.

5.2.5. *CO_2 allowances*

Especially CO_2 intensive power plants such as coal-fired power plants (but also gas-fired power plants) are influenced by the price level of CO_2 allowances. During phases of high CO_2 allowance prices, a phenomenon called fuel switch can be observed. It is a change in the Merit-Order Curve in which, for example, the marginal production costs of gas-fired power plants get lower than those of coal-fired power plants. This phenomenon is discussed in Kovacevic and Paraschiv (2013).

Table 6
Descriptive statistics for the level of the input variables between 1 January 2010 and 28 February 2013. Data granularity is consistent with Table 5.

Statistics	Phelix spot	Demand forecast	Expected PPA	Coal	Gas	Oil	CO_2	PV forecast	Wind forecast
Mean	46	42,448	54,764	76	22	76	11	3674	5043
Median	46	42,801	55,249	74	23	76	12	1985	3691
Maximum	210	57,625	63,981	99	38	91	17	21,862	24,690
Minimum	−222	24,818	40,016	52	11	59	3	0	229
Std. dev.	16	7633	5008	10	4	8	4	4227	4228
Skewness	−2	0	0	0	−1	0	0	1	2
Kurtosis	30	2	2	2	3	2	2	4	5
Jarque-Bera	83,7967	1406	42	22	120	59	112	4699	18,027
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	27,720	27,720	1155	1155	1155	1155	1155	13,860	27,720

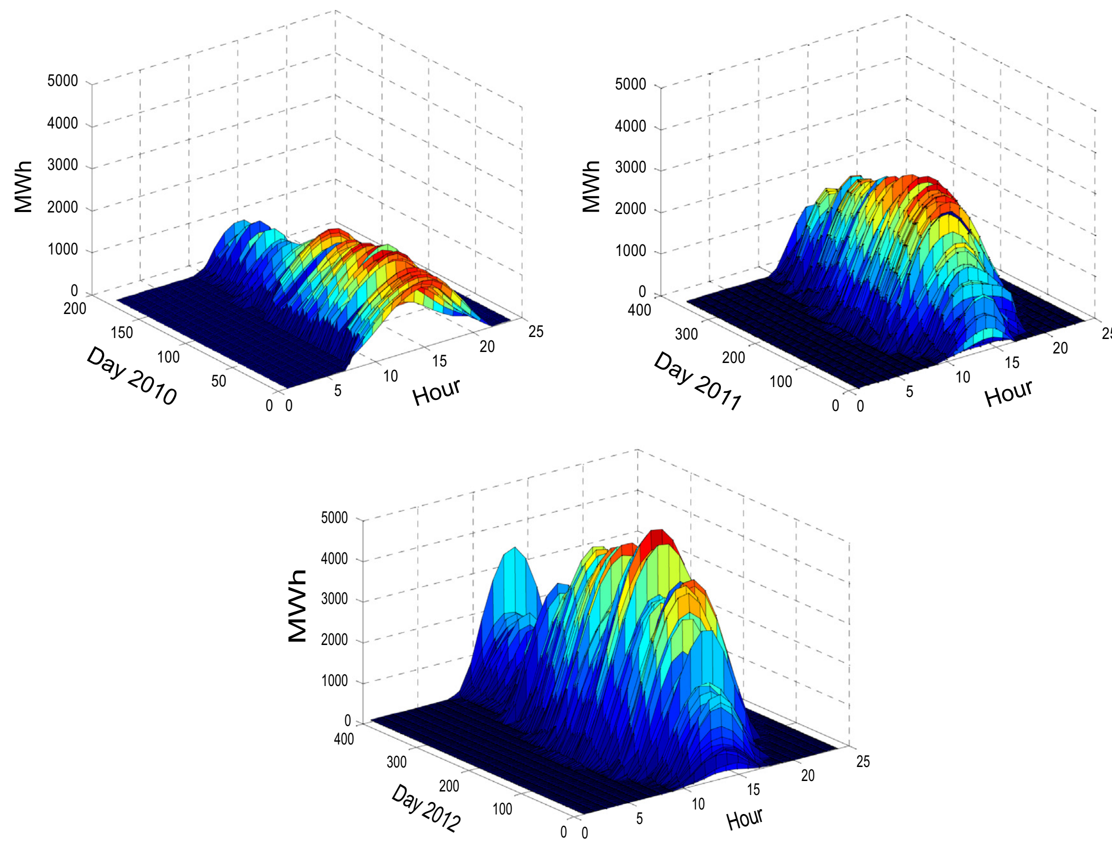

Fig. 4. Photovoltaic infeed. Data retrieved from Amprion.

6. Dynamic fundamental model for electricity prices

In this section, we propose a dynamic fundamental model for electricity prices and test their time-varying sensitivities with respect to the market fundamentals described above. During the time period investigated, as discussed in the previous sections, feed-in tariffs for renewables supported a substantial increase in their use for power production. The goals of the energy policy in Germany are, on a long-term, a reduction of consumer power prices, in parallel to a reduction of the CO_2 emissions. We investigate to which extent the use of wind and PV energy contributed to a decrease in electricity prices over time. Furthermore, we want to assess how the sensitivity of electricity prices to traditional input fuels like gas, oil, or coal, and to CO_2 prices changed after 2010, given the increasing role of renewable energies. Our hypothesis is that time-varying volatility observed usually in electricity prices (see Erni, 2012) reflects an *adaption* of price formation, i.e. the changing sensitivities of prices to various fundamentals (Karakatsani and Bunn, 2010). Such a price structure can evolve for example in the context of an increase in the PV infeed during the peak hours, that will partially replace the gas and oil traditionally used to supplement the production in hours with excess demand. In consequence, we expect that the impact of gas and oil on electricity prices will diminish with the increase in the PV infeed. Further time-varying sensitivities to fundamentals can be due to agent's learning or to energy policy regulator's announcements. We assume, in addition, that for different trading periods within a day, market fundamentals will impact electricity prices in a different way, due to different production design (see Chen and Bunn, 2010). Thus, we will estimate the model for each hour of the day, to validate this assumption.

6.1. Model formulation

We assess the inter-temporal changes in the relation of hourly day-ahead electricity prices and market fundamentals described in Section 5 in the context of a time-varying regression model. Stability tests (following Brown et al., 1975; Karakatsani and

Bunn, 2010) show strong evidence for time-varying parameters. By deriving individual models for each hour of the day, the daily seasonality pattern is taken into account. In this way we can distinguish between peak and off-peak hours, corresponding to different load levels, where power plants with different marginal costs of production operate. The weekly and yearly seasonality is incorporated in our demand variable.

Additionally to the variables discussed in Section 5, we include the lagged electricity market clearing price for the same hour of the last relevant delivery day, and the average spot price of all 24 h of the last delivery day. This helps to reduce autocorrelation in our data and, furthermore, incorporates historic price and risk signals, which usually influence agents' price expectations and risk aversion. As discussed in Bunn et al. (2013), the sensitivity of spot power prices to the lagged prices (adaptive behavior) is expected to be positive. Thus, adaptive behavior will consist of reinforcing previously successful offers and thus high prices will tend to be followed by high prices. Furthermore, if there is an element of repeated gaming in power markets, signaling among market agents will perpetuate that and thus, a positive sensitivity to lagged prices is expected (see Bunn et al., 2013).

As an additional indicator for historic price instability and risk, we add to the list of explanatory variables the spot price volatility. This is computed as the standard deviation of market clearing prices for the same hour over the last five relevant delivery days.

We formulate a state space model that allows for changing regression coefficients over time and estimate it with the Kalman Filter and maximum likelihood. The model formulation reads

$$y_{i,t} = z'_{i,t}\gamma_{it} + v_{i,t} \tag{4}$$

$$\gamma_{i,t} = \gamma_{i,t-1} + w_{i,t} \tag{5}$$

where for $i \in \{1, \ldots, 24\}$

$v_{i,t} \sim \mathcal{N}(0, R_i)$

$\gamma_{i,t} = (\gamma_{i,1,t}, \gamma_{i,2,t}, \ldots, \gamma_{i,k,t})'$

$w_{i,t} = (w_{i,1,t}, w_{i,2,t}, \ldots, w_{i,k,t})'$

$w_{i,t} \sim \mathcal{N}(0, Q_i)$

$E(v_{i,t} w_{i,t}) = 0$

$Q_i = diag\{\sigma^2_{w_{i,1}}, \ldots, \sigma^2_{w_{i,k}}\}$

The size of the exogenous variables vector $z_{i,t}$ is given by $k=11$. The elements of $z_{i,t}$ are listed in the first column of Table 4. The measurement noise variance R_i and transition noise covariance matrix Q_i are assumed to be constant over time.

Eq. (4) represents the measurement equation of the state space model. It relates the known quantity $z_{i,t}$ (vector of exogenous, fundamental variables) to the variable $y_{i,t}$, which represents the day-ahead electricity price for hour i. Eq. (5) is known as the transition equation and describes the dynamics of our time-dependent regression coefficients. In the above state-space formulation, the regression coefficients are not unknown constants, but latent, stochastic variables that follow random walks, estimated by Kalman Filter (Kalman, 1960). The intuition behind the random walk assumption is that the coefficients react to new information (see for example Karakatsani and Bunn, 2010; Kim and Nelson, 1989). Such an evolving price structure is likely to emerge in general due to agents' learning, regulator's announcements, mergers and acquisitions in the electricity industry, or stressed events in electricity markets. The choice of a random walk is justified by the many regulations and renewable-related institutional policies which marked our investigated time period.

Throughout the estimation algorithm, as we run from $t=1$ to $t=T$, we distinguish between two possible states of knowledge, namely the *a priory state*, when the electricity price is known up to $t-1$: $\hat{\gamma}_t^- = E(\gamma_t | y_{t-1})$, and the *posterior state*, when observations up to t are available: $\hat{\gamma}_t = E(\gamma_t | y_t)$. The predicted day-ahead electricity spot price $y_{i,t}$ is projected applying the a priori estimated regression coefficient of this stage to the observed exogenous variables. For a detailed derivation of the Kalman Filter and for the derivation of the likelihood function, see Karakatsani and Bunn (2010) and Song and Wong (2003).

As electricity prices feature pronounced spike characteristics as well as high volatilities, researchers often apply a log transformation in order to obtain series with more stable variances which is a desired feature when using certain quantitative models (Weron, 2006). However, for interpretability reasons, we analyze the level of all model variables, and not the log prices. A similar approach was used by Karakatsani and Bunn (2010) and Fleten et al. (2013b). As explained in Karakatsani and Bunn (2010), when investigating the variability of electricity prices, efforts to stabilize the variance of the original series are not in the researcher's interest, as they conceal detailed statistical properties and also lead to multiplicative error effects.

7. Estimation results

In Figs. 5 and 6 we display the evolution of the time-dependent coefficients for each of the explanatory variables. Results are displayed and discussed for 3 h with different load profiles: hours 3, 12 and 18. We thus chose one night hour, when generally demand is low and because of a surplus of wind electricity produced, often negative prices occur at EEX. In addition, we are interested to analyze the shift in the merit order curve during the noon-peak or the evening peak hours, 12 and 18, when the demand is high and additional power plants situated to the right of the merit order curve are turned on. In general, the time-varying coefficients reveal a substantial, systemic component in spot electricity prices.[7] They exhibit different patterns for hours with different load profiles, both in terms of magnitude and, in some cases, of sign. It is known that the load level varies over the day, which implies different production schemes. Specifically, results can be summarized as follows:

- *Learning*: The sign of the coefficient of the lagged spot price for a specific hour is negative most of the time. This reverts the level of electricity prices for that hour, in the next day. However, the aggregate price signal from the previous day, namely the coefficient of the lagged average spot price, has a positive impact on the next day price. This result is in line with the discussion in Bunn et al. (2013): the authors expect a positive elasticity of power spot prices to lagged prices. As mentioned in Section 6.1, market agents tend to reinforce previously successful offers in the market, keeping the level of the prices high. Furthermore, signaling between market agents will keep prices moving in the same direction, which motivates a positive coefficient for lagged prices. Depending on the load level for different hours of the day, we observe different reactions to lagged price signals. For hours 3 and 18, with low/moderate load, the impact of the lagged average spot price level decreases slightly. This is due to the fact that bidding became progressively more sophisticated, relying upon other fundamental drivers (see also Karakatsani and Bunn, 2010). However, for the peak hour 12, the impact of lagged price signals increased, especially after 2011.
- *Price volatility*: As proxy for the price volatility we computed the standard deviation of the past hourly prices over the last

[7] The marginal effect of each variable is partial, conditional on constant effects of all other variables (ceteris paribus analysis).

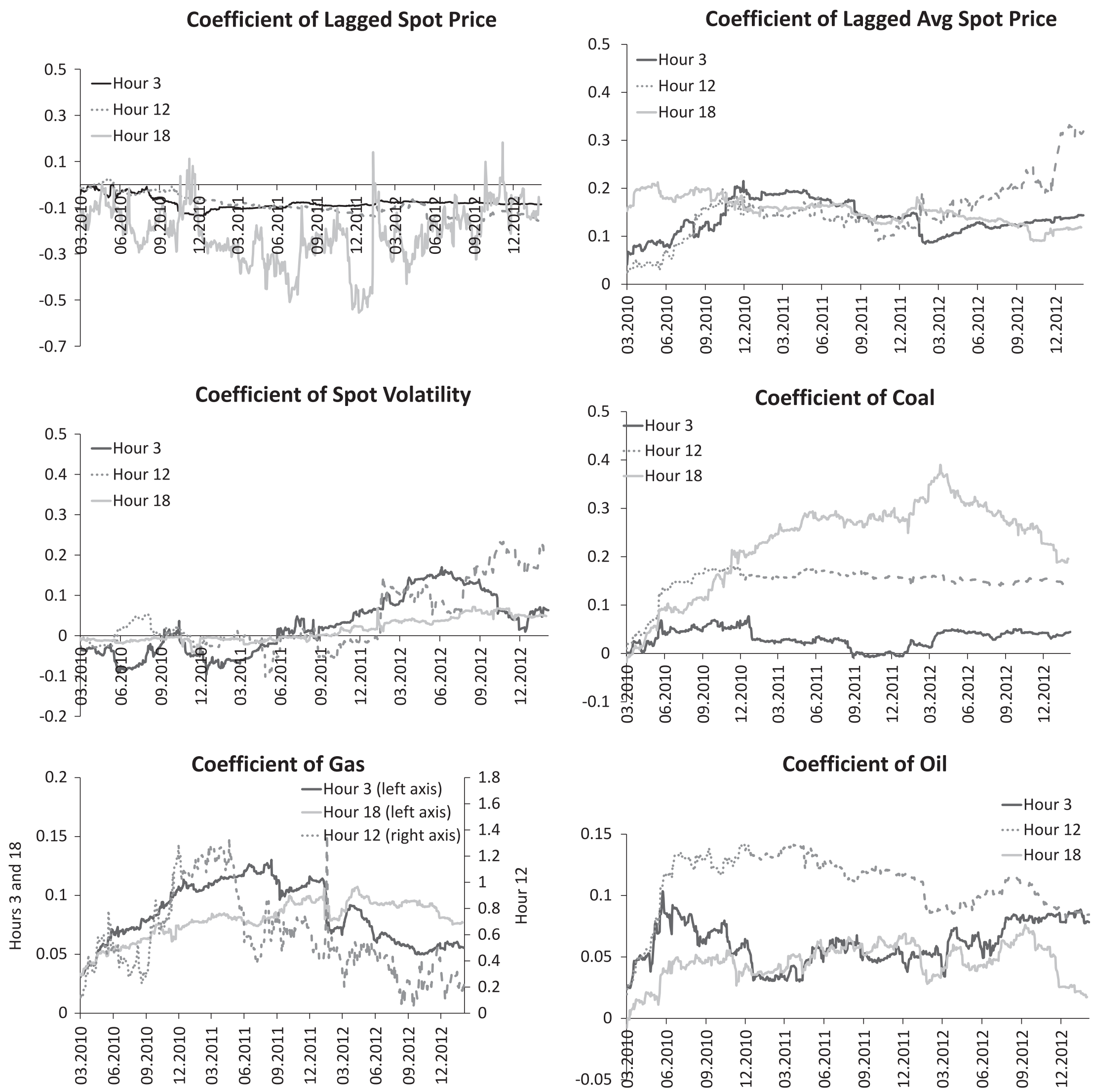

Fig. 5. Evolution of time-varying coefficients #1.

five working days. The impact of price volatility on electricity prices can be interpreted as a risk compensation in the market. The coefficient of historic price volatility increased over time and became even positive after 2012. An increase in the price volatility in the market can explained by the higher infeed of the volatile renewable energies. This shows that the hedging of price risk via the spot market became more expensive over time. Similar results were found by Karakatsani and Bunn (2010).

- *Responses to fuel prices*: When production capacities based on coal, gas, and oil prices are in use, depends strongly on the hourly load profile.

  Coal: We observe higher marginal effects of electricity prices to coal for hours with higher demand: 12 and 18. For the evening hour 18, when the production is mainly coal based, coefficients are the highest. Another observation is that the time-varying coefficients of coal have a more noticeable variation for hours 3 and 18. Generally speaking, coal still plays an important role for the electricity price formation process, since it is still the most relevant fuel in Germany (as shown in Table 1). Therefore, we observe less price adaption of electricity with respect to coal than to gas.

  Gas and oil: During hours of high demand, power plants at the right of the Merit-Order Curve run in addition to coal-fired power plants. Therefore, it is interesting to study the adaption of electricity spot prices to gas and oil prices, particularly for hour 12. We clearly observe a much higher marginal effects, in both cases, for hour 12, compared to the other 2 h (refer for gas to the secondary axis). We further see that there has been a continuous electricity spot price adaption process to these two fuel prices over time. In particular, the coefficient of gas prices was quite variable, without a consistent pattern across periods. We observe, however, a decrease of coefficient for gas after the middle of 2011. This can be explained by the increase in the PV infeed (see Fig. 6) especially at noon, when the sun is very intense. Our results reflect, in this respect, the substitution effect in electricity production between traditional fuels and renewable energies.
- *Demand and supply*: It is apparent that there is no substantial price adaption to demand and power plant availability (PPA). That is because we estimated our model for each hour of the day, and it is known that the load for electricity is, at least in the short run, inelastic (see Blochlinger, 2008). In other words, there is an easily predictable load and PPA scheme for different hours.
- *Renewable energies*: The infeed from renewable energies decreases electricity prices, which is shown by the negative sign of wind and PV coefficients. We can clearly observe a

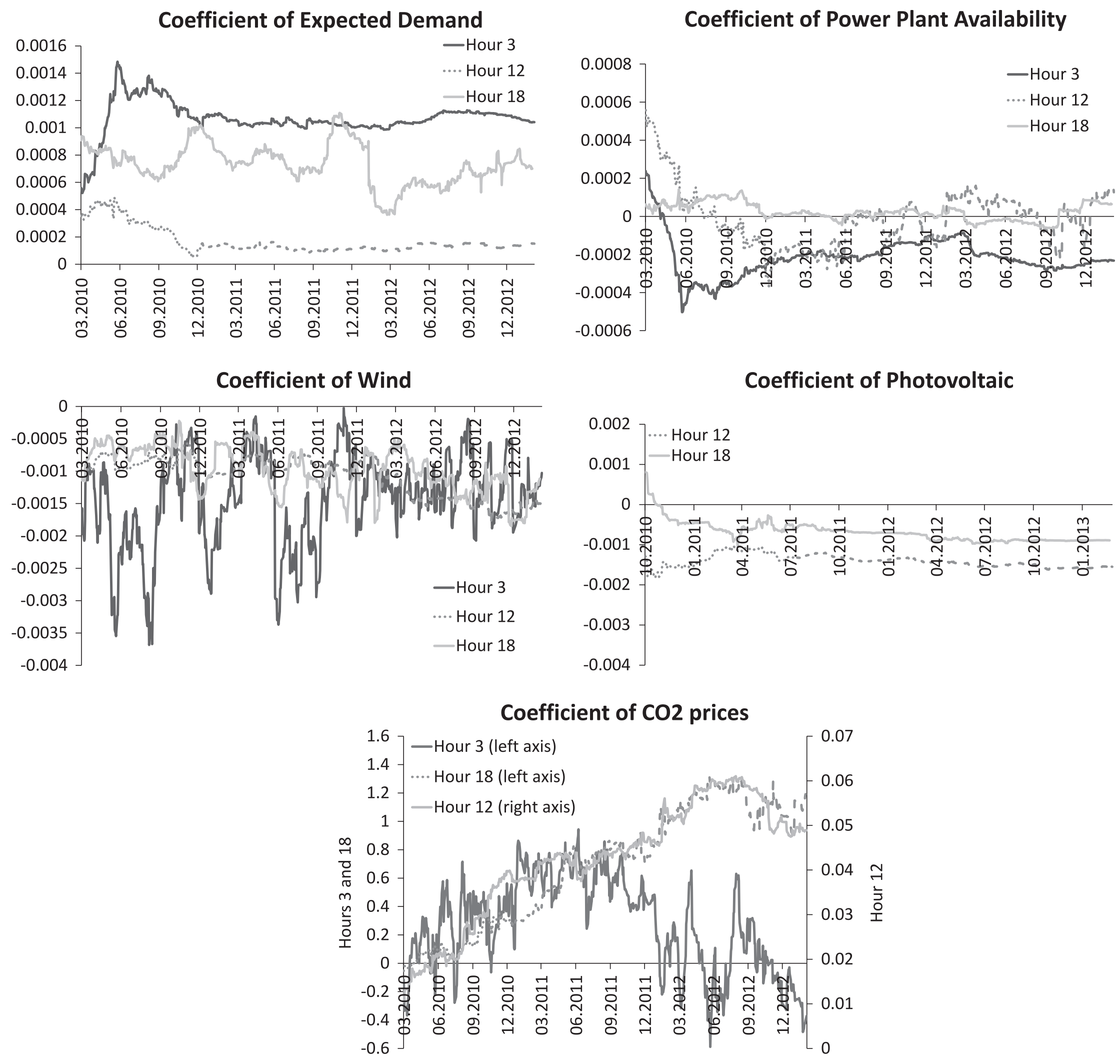

Fig. 6. Evolution of time-varying coefficients #2.

highly variable price adaption process to wind infeed, particularly for the night hours. As it has been explained, negative prices occurred mainly during the night hours, and were caused to a large extent by the high wind infeed. This occurs because of the excess of electricity produced versus low demand during night hours. We observe a relatively constant coefficient magnitude of electricity prices to PV infeed over time, but higher over noon, given the high sunshine intensity.

- *CO_2 emission certificates*: We observe a continuous price adaption process to CO_2 prices. The marginal effect is clearly higher for night and evening hours (see the left axis), when actual production is mainly coal based. Coal power plants pollute more than gas and oil, which can explain the higher adaption of electricity prices to CO_2 emission certificates.

In order to test for the impact of renewable energies on electricity prices, we re-estimated our model formulated in Eqs. (4) and (5), for the following four versions: (1) Exclude wind and PV from the list of explanatory variables; (2) Add just the PV; (3) Add just the wind; (4) Include all variables. For each case, we recomputed the goodness of fit, as shown in Fig. 7, for each hour of the day and for hourly blocks, as shown in Tables 7 and 8. We observe that for the first model version, when we exclude the renewable energies from the list of explanatory variables, the R^2 has an average of about 35% over all hours (see the first bar in Fig. 7, for each hour). The mean average percentage errors (MAPE) are larger for the night hours, but this is not surprising, given the large negative spikes observed historically for these hours. If we include just the PV, the R^2 does not change for most hours, however it helps to improve the explanatory power of the model with up to 5% for the high-noon peak hours (see the second bar in Fig. 7, for each hour), and it further reduces the errors (MAE and MAPE). As expected, due to the high frequency of PV fed into the grid during the high-noon hours, this variable contributes to the price formation at EEX during this interval. By adding just the wind, but excluding the PV, the explanatory power of the model increases by up to 50%. This increase becomes more obvious during the evening and night hours, when usually high wind frequencies are fed into the grid (see the third bar in Fig. 7, for each hour). Thus, from the second and third model versions we conclude that overall there is a higher impact of the wind on the price formation at EEX, than of the PV. However, the two renewables impact the prices in different ways, dependent on the time of the day. In a fourth model version we finally add both renewables to the list of variables (see the last bar in Fig. 7, for each hour). Up to 80% of the total variation is explained by the model. Overall, we conclude a high marginal explanatory power and fairly low MAE and MAPE of the model when including both wind and PV. This also leads to a better understanding of the risk drivers of the electricity spot price at EEX.

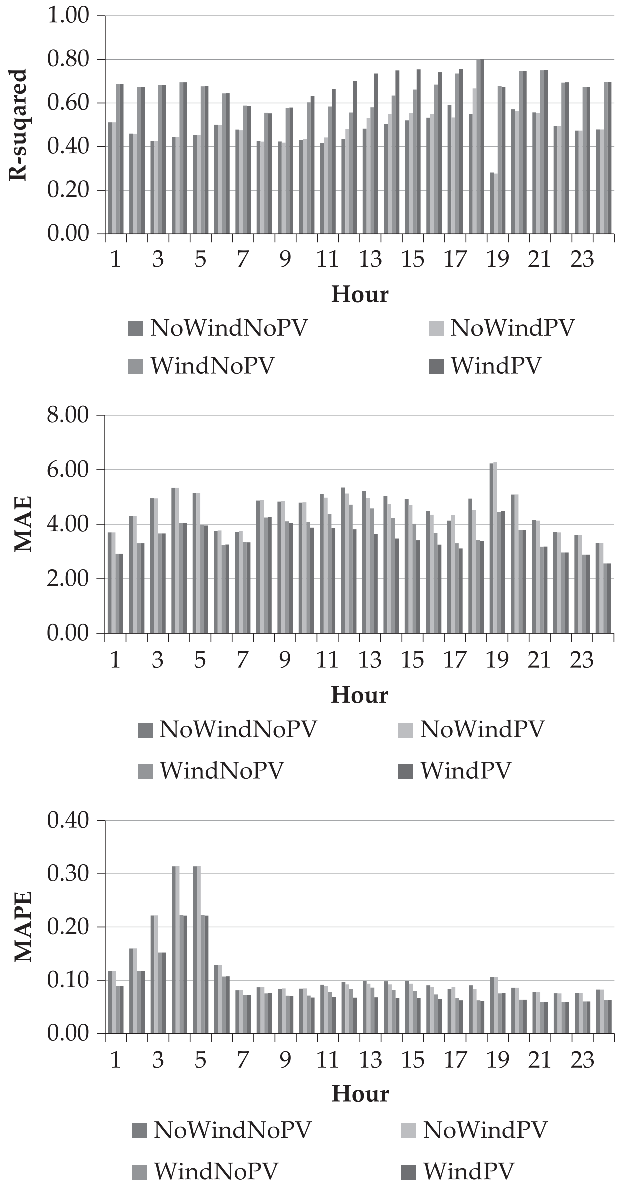

Fig. 7. The goodness of fit for the corresponding four model versions: (1) Exclude wind and PV from the list of explanatory variables. (2) Add just the PV. (3) Add just the wind. (4) Include all variables.

Serial correlation is removed from residuals, as shown by the Durbin Watson statistics. Furthermore, Lagrange Multiplier tests for ARCH effects indicated no serial correlation in the squared forecast errors of the time-varying model. The p value of the test statistics was 0.47, assuming 5 lags of squared residuals. The elimination of GARCH effects implies that the adaptive nature of the price structure is a possible source for the observed autoregressive structure in the volatility of electricity prices (see Karakatsani and Bunn, 2010; Fleten et al., 2013a). As shown in Karakatsani and Bunn (2010), allowing for the time-varying responses of prices to fundamentals can yield more precise volatility estimates than an explicit GARCH specification. For robustness, the performance of our dynamic model was compared to a simple GARCH(1,1) model, where we included the same fundamentals in the mean equation, this time with constant coefficients. We concluded a significantly higher performance of the time-varying regression model.[8]

[8] Results are available upon request.

Overall our results show that renewable energies, especially wind, have a high impact on the formation of electricity spot prices during the investigated period.

8. Conclusion

We found that the sensitivities of day-ahead electricity spot prices to the fundamental variables coal, gas, oil, and renewable energies, vary over time. Generally speaking, we observe a continuous price adaption process of electricity prices to market fundamentals. This is due to agents' learning, regulatory announcements, or stressed events in electricity markets. In addition, the supply for electricity consists of different producers with different fuels, causing time variation in the correlation between electricity prices and fuels depending where demand crosses the supply curve. Furthermore, we conclude that the adaptive nature of the price structure is a possible source for the observed autoregressive structure in the volatility of electricity prices. Overall, our results show the importance of linking electricity spot prices to their fundamentals and suggest that purely stochastic models can be a too simplistic assumption in this case.

We show that the increase in the infeed from renewable energies, wind and PV, led to a partial decrease in electricity day-ahead prices in Germany. This effect is noticeable for afternoon, evening and night hours in case of wind, and for noon peak hours, in case of PV. Furthermore, the inclusion of renewable energies improves considerably the explanatory power of the model. Additionally, renewable energies substitute the use in production of traditional fuels situated to the right of the merit order curve. In particular, the sensitivity of electricity prices to gas decreases over time. This fact becomes more visible for peak hours, due to the increase in the PV infeed.

The promotion of renewable energies in Germany stimulated their fast development and led to a partial decrease of prices at the day-ahead market, due to the merit order effect. This had different implications for traditional electricity producers and private consumers. The latter must carry higher electricity prices, since ultimately they finance the EEG surcharge. However, this financial burden is by far not compensated by the lower day-ahead market prices. Only the energy-intensive industry, which is excluded from the EEG surcharge, benefits from the decrease in the day-ahead prices. Further increases in the electricity prices for private consumers can be avoided if the feed-in tariffs are cut back once certain capacity targets for renewables are achieved and the industry consumers also contribute to the surcharge payments.

Traditional produces suffer from the generally lower price level that decreases their margins, particularly during night hours, when the strong wind infeed reduces prices considerably or causes even negative prices. We found that the sensitivity of spot prices with respect to coal remained high, while after 2011 we found decreasing sensitivity to gas. This is consistent with the fact that the production of gas-fired plants, which are at the end of the merit order curve, is replaced by renewables. This result illustrates also a change in the risk drivers of electricity spot prices at EEX. It further implies that the design of the incentive scheme for renewable energies led first to a substitution of fuels with lower CO_2 emissions.

The roll-out of renewable energies requires storage capacities for electricity as well as flexible production facilities such as gas-fired plants or pump storages to bridge the time with insufficient wind and PV infeed. The current market design does not compensate the provision of reserve capacity adequately. Additionally, the excess supply from renewables in Northern Germany must be efficiently distributed to regions with excess demand, which requires enhancements of the electricity grid. Future incentive schemes for the promotion of renewable energies should take these aspects into account, since the matters of production, storage, and transportation cannot be treated separately.

Table 7
Goodness of fit, for morning, high noon and afternoon hourly blocks, comparison among various model versions: (1) Exclude wind and PV from the list of explanatory variables. (2) Add just the PV. (3) Add just the wind. (4) Include all variables.

Hourly blocks Version	**Morning 7–10** NoWindNoPV	NoWindPV	WindNoPV	WindPV
Observations	739.250	739.250	739.250	739.250
R^2	0.440	0.438	0.581	0.588
Adjusted R^2	0.394	0.391	0.547	0.553
MAE	4.554	4.575	3.945	3.882
MAPE	0.084	0.084	0.072	0.071
D/W	2.043	2.038	2.047	2.060
LLF	−2398.250	−2400.831	−2284.486	−2276.825
Hourly blocks Version	**High noon 11–14** NoWindNoPV	NoWindPV	WindNoPV	WindPV
Observations	741.500	741.500	741.500	741.500
R^2	0.459	0.501	0.589	0.713
Adjusted R^2	0.415	0.460	0.555	0.689
MAE	5.183	4.951	4.473	3.702
MAPE	0.096	0.092	0.082	0.068
D/W	1.972	1.919	1.946	1.954
LLF	−2475.307	−2444.539	−2355.222	−2230.804
Hourly blocks Version	**Afternoon 15–18** NoWindNoPV	NoWindPV	WindNoPV	WindPV
Observations	739.250	739.250	739.250	739.250
R^2	0.548	0.576	0.720	0.763
Adjusted R^2	0.512	0.541	0.697	0.743
MAE	4.622	4.477	3.607	3.289
MAPE	0.091	0.088	0.070	0.064
D/W	2.002	1.953	1.929	1.968
LLF	−2367.954	−2359.506	−2200.477	−2142.819

Table 8
Goodness of fit for evening and night hourly blocks, comparison among various model versions: (1) Exclude wind and PV from the list of explanatory variables. (2) Add just the PV. (3) Add just the wind. (4) Include all variables.

Hourly blocks	**Evening 19–24**		**Night 1–6**	
Version	NoWindNoPV	WindNoPV	NoWindNoPV	WindNoPV
Observations	739.000	739.000	738.500	738.500
R^2	0.476	0.706	0.466	0.677
Adjusted R^2	0.434	0.682	0.423	0.650
MAE	4.352	3.305	4.536	3.522
MAPE	0.084	0.063	0.415	0.233
D/W	2.091	2.052	1.960	1.958
LLF	−2317.262	−2120.312	−2403.872	−2179.582

Acknowledgment

We would like to thank very much Prof. Karl Frauendorfer for his continuous support and for his very valuable input that helped to enrich the content of this paper.

Appendix A. Climatic factors used to forecast the demand

The following climatic factors are used as exogenous variables in the models:

Sunshine duration: This variable denotes the average sunshine duration in hours, measured 24 times across the day.

Mean degree of cloud cover: This measure is defined as the degree to which the sky is covered by clouds. Again, it is measured 24 times across the day.

Maximum air temperature: This variable measures the average temperature in centigrade two meters above ground based on 24 measurements across the day.

Mean relative humidity: Relative humidity expressed in percent and computed as the average of 24 measurements across the day.

Cooling degree days: The concept of cooling degree days (CCD) and its counterpart heating degree days (HDD) is a widely used measure that indicates the need for cooling or heating based on outdoor temperatures. These measures are, among others, relevant quantities for temperature futures trading. CCDs are defined as

$$CDD_t = \max(T_t - c, 0) \tag{A.1}$$

where T_t denotes the mean daily temperature and c the so-called comfort level. This comfort level is generally set to 18.3 °C and hence indicates the need for cooling and heating respectively. Due to very high (negative) correlations of close to (-1), Minimum Air Temperature (as opposed to Maximum Air Temperature) and HDDs (as opposed to CDDs) have been omitted in the models, as they hardly add any explanatory power.

Appendix B. Demand model diagnostics

In-sample results of Ljung-Box Q-test and Engle's Engle's ARCH test performed on standardized residuals after the estimation of demand models are given in Tables B1 and B2.

Table B1
In-sample results of Ljung-Box *Q*-test performed on standardized residuals after the estimation of demand models. Test statistics with values higher than the respective critical values reject the null hypothesis of no serial correlation. Weekends, holidays, and bridge days are excluded.

Lag	1	5	10	15	20
Critical values					
0.99-Significance	6.63	15.09	23.21	30.58	37.57
0.95-Significance	3.84	11.07	18.31	25.00	31.41
Test statistics					
Hour 01	0.44	5.44	6.79	9.32	21.22
Hour 02	0.03	3.78	8.96	10.80	20.69
Hour 03	1.19	3.53	11.99	15.07	21.59
Hour 04	1.09	5.05	14.24	17.77	24.72
Hour 05	1.12	5.43	12.36	16.11	25.45
Hour 06	4.22	15.04	19.36	24.50	36.03
Hour 07	6.44	21.41	28.64	29.90	35.55
Hour 08	3.80	12.04	19.39	21.12	27.37
Hour 09	1.63	12.30	21.63	23.64	25.46
Hour 10	7.91	32.92	49.44	60.36	64.58
Hour 11	1.50	16.50	24.87	32.36	34.75
Hour 12	0.18	18.08	26.60	40.08	44.01
Hour 13	0.59	24.59	37.30	54.62	64.88
Hour 14	0.74	26.75	39.99	61.53	70.95
Hour 15	0.31	12.28	16.69	27.93	34.14
Hour 16	4.88	24.90	30.41	37.92	45.63
Hour 17	0.26	6.29	10.43	13.68	15.53
Hour 18	0.03	12.95	17.95	21.83	24.67
Hour 19	0.27	15.92	20.32	26.81	32.62
Hour 20	0.03	1.92	5.96	8.63	13.47
Hour 21	0.22	17.10	18.04	21.20	29.10
Hour 22	7.11	22.52	26.77	27.91	31.95
Hour 23	20.42	49.33	57.83	62.99	65.26
Hour 24	7.29	16.85	20.96	23.97	28.47

Table B2
In-sample results of Engle's ARCH test performed on standardized residuals after the estimation of demand models. Test statistics with values higher than the respective critical values reject the null hypothesis of homoscedasticity. Weekends, holidays, and bridge days are excluded.

Lag	1	5	10	15	20
Critical values					
0.99-Significance	6.63	15.09	23.21	30.58	37.57
0.95-Significance	3.84	11.07	18.31	25.00	31.41
Test statistics					
Hour 01	0.05	0.67	1.38	2.27	40.67
Hour 02	0.10	1.22	9.63	11.51	25.89
Hour 03	0.05	1.59	26.55	30.68	38.60
Hour 04	0.05	1.77	25.45	29.35	37.71
Hour 05	0.05	1.64	13.08	15.08	25.46
Hour 06	0.09	1.60	2.54	3.92	14.75
Hour 07	0.00	2.03	6.26	8.25	23.95
Hour 08	0.14	2.36	10.12	10.49	15.95
Hour 09	0.14	0.79	2.92	3.32	4.03
Hour 10	0.00	1.68	7.57	8.18	9.45
Hour 11	0.02	3.09	9.22	10.72	13.39
Hour 12	0.30	4.27	6.17	7.48	9.09
Hour 13	0.20	5.37	6.46	9.13	9.19
Hour 14	0.13	3.05	4.57	6.51	7.21
Hour 15	0.03	0.77	1.65	2.92	3.64
Hour 16	0.01	1.12	1.93	2.68	3.07
Hour 17	1.80	2.05	2.32	3.20	3.79
Hour 18	2.10	2.42	2.91	3.65	4.30
Hour 19	2.99	3.73	4.03	5.02	6.00
Hour 20	3.04	4.07	4.57	5.70	6.92
Hour 21	2.04	2.45	2.84	3.82	5.11
Hour 22	0.00	1.68	3.11	3.96	5.85
Hour 23	0.09	0.94	3.76	4.56	5.91
Hour 24	0.02	1.01	1.46	1.85	2.54

References

AG Energiebilanzen, 2014. Bruttostromerzeugung in Deutschland von 1990 bis 2013 nach Energieträgern. Downloaded on 30/04/2014 from ⟨http://www.ag-energiebilanzen.de/⟩.

BDEW, 2013. Erneuerbare Energien und das EEG: Zahlen, Fakten, Grafiken. BDEW, Berlin.

BMU, 2012. Mit neuer Energie. Berlin, Bundesministerium für Umwelt, Naturschutz und Reaktorsicherheit.

Blochlinger, L., 2008. Power Prices – A Regime-Switching Spot/Forward Price Model with Kim Filter Estimation (Ph.D. thesis), University of St. Gallen. Available at: ⟨http://www1.unisg.ch/www/edis.nsf/SysLkpByIdentifier/3442/$FILE/dis3442.pdf⟩.

Brown, R.L., Durbin, J., Evans, J.M., 1975. Techniques for testing for the constancy of regression relationships over time. J. R. Stat. Soc. B 37 (2), 149–192.

Burger, M., Graeber, B., Schindlmayr, G., 2007. Managing Energy Risk. An Integrated View on Power and Other Energy Markets. Wiley & Sons, West Sussex.

Bunn, D., Andresen, A., Chen, D., Westgaard, S., 2013. Analysis and Forecasting of Electricity Price Risks with Quantile Factor Models. Working Paper.

Bannor, K., Kiesel, R., Nazarova, A., Scherer, M.-A., 2013. Model Risk and Power Plant Valuation. Available at SSRN: ⟨http://ssrn.com/abstract=2259615⟩ or http://dx.doi.org/10.2139/ssrn.2259615.

Cartea, A., Figueroa, M.-G., 2005. Pricing in electricity markets: a mean reverting jump diffusion model with seasonality. Appl. Math. Financ. 12, 313–335.

Cartea, A., Villaplana, P., 2008. Spot price modeling and the valuation of electricity forward contracts: the role of demand and capacity. J. Bank. Financ. 32, 2502–2519.

Chen, D., Bunn, D.W., 2010. Analysis of the nonlinear response of electricity prices to fundamental and strategic factors. IEEE Trans. Power Syst. 25 (2), 595–606.

dpa, 2013. Ein Windpark, der Strom Verbraucht und Diesel Frisst. Frankfurter Allgemeine Zeitung, 14, 10 August.

European Energy Exchange ⟨http://www.eex.com⟩.

Erni, D., 2012. Day-Ahead Electricity Spot Prices. Fundamental Modelling and the Role of Expected Wind Electricity Infeed at the European Energy Exchange. Dissertation of the University of St. Gallen.

European Energy Exchange AG, 2011. Annual Report 2010. European Energy Exchange AG, Leipzig.

Federal Ministry of Economics and Technology, 2013. Energie in Deutschland – Trends und Hintergründe zur Energieversorgung. Federal Ministry of Economics and Technology, Berlin.

Fleten, S.-E., Paraschiv, F., Schürle, M., 2013a. Spot-Forward Simulation of Electricity Prices with Regime Shifts. Working Paper. University of St. Gallen. Available at: ⟨https://www.alexandria.unisg.ch/Publikationen/225270⟩.

Fleten, S.-E., Huisman, R., Kilic, M., Pennings, E., Westgaard, S., 2013b. Electricity Futures Prices: Time Varying Sensitivity to Fundamentals. Working Paper.

Fraunhofer, IWES, 2013. Windenergie Report Deutschland 2012. Fraunhofer Verlag, Stuttgart.

Frondel, M., Ritter, N., Schmidt, C.-M., Vance, C., 2010. Economic impacts from the promotion of renewable energy technologies: the German experience. Energy Policy 38, 4048–4056.

Fuglerud, M., Vedahl, K.L., Fleten, S.-E., 2012. Equilibrium Simulation of the Nordic Electricity Spot Price. European Energy Market (EEM). ISBN: 978-1-4673-0834-2, http://dx.doi.org/10.1109/EEM.2012.6254696, 1–10.

Gawel, E., Purkus, A., 2013. Promoting the Market and System Integration of Renewable Energies through Premium. A Case Study of the German Market Premium. UFZ, Leipzig.

Hirschl, B., 2010. Zehn Jahre EEG - Entwicklung und Zukunft. ETAgreen, 48–50.

Huisman, R., Stradnic, V., Westgaard, S., 2013. Renewable Energy and Electricity Prices: Indirect Empirical Evidence from Hydro Power. Documents de Treball de l'IEB, 2013/24.

Kalman, R.E., 1960. A new approach to linear filtering and prediction problems. Trans. ASME – J. Basic Eng. 82 (Series D), 35–45.

Karakatsani, N.V., Bunn, D.W., 2010. Fundamental and behavioural drivers of electricity price volatility. Stud. Nonlinear Dyn. Econ. 14 (4), Article 4.

Keles, D., Genoese, M., Most, D., Fichtner, W., 2011. Comparison of extended mean-reversion and time series models for electricity spot price simulation considering negative prices. Energy Econ. 34, 1012–1032.

Kim, C.J., Nelson, C.R., 1989. The time-varying parameter model for modeling changing conditional variance: the case of the Lucas hypothesis. J. Bus. Econ. Stat. 7 (4), 433–440.

Knittel, C.R., Roberts, M., 2005. An empirical examination of restructured electricity prices. Energy Econ. 27 (5), 791–817.

Kovacevic, R., Paraschiv, F., 2014. Medium-term planning for thermal electricity production. OR Spectrum, 1-37. doi:10.1007/s00291-013-0340-9.

Leuthold, F., Weigt, H., von Hirschhausen, C., 2008. Efficient pricing for European electricity networks – the theory of nodal pricing applied to feeding-in wind in Germany. Util. Policy 16, 284–291.

Menanteau, P., Finon, D., Lamy, M.-L., 2003. Prices versus quantities: choosing policies for promoting the development of renewable energy. Energy Policy 31, 799–812.

de Miera, G.-S., del Rio Gonzalez, P., Vizcanio, I., 2008. Analysing the impact of renewable electricity support schemes on power prices: the case of wind electricity in Spain. Energy Policy 36, 3345–3359.

Nowicka-Zagrajek, J., Weron, R., 2002. Modeling Electricity Loads in California: ARMA Models with Hyperbolic Noise. HSC Research Report 02/02, Wroclaw University of Technology, Wroclaw (Poland), May 2002.

Paraschiv, F., 2013. Price dynamics in electricity markets. In: Kovacevic, R.M., Pflug, G.Ch., Vespucci, M.T. (Eds.), Risk Management in Energy Production and Trading, 57-111, ISBN 978-1-4614-9034-0.

von Petersdorff, W., 2013. Hohe Energiekosten in Deutschland – Die Stromabrechnung. FAZ, 13. Available at: ⟨http://www.faz.net/aktuell/wirtschaft/wirtschaftspolitik/hohe-energiekosten-in-deutschland-die-stromabrechnung-12240420.html⟩.

von Roon, S., Huck, M., 2010. Merit Order des Kraftwerkparks. Munich. Available at: ⟨http://www.bayern-innovativ.de/ib/site/documents/media/82ac1235-665c-20e6-3c3e-92a0e10a29a7.pdf/Merit_Order.pdf⟩.

Sensfu, F., Ragwitz, M., Genoese, M., 2008. The merit-order effect: a detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. Energy Policy 36, 3086–3094.

Song, H., Wong, K.K.F., 2003. Tourism demand modeling: a time-varying parameter approach. J. Travel Res. 42, 57–64.

Taylor, J.W., de Menezes, L.M., Mc Sharry, P.E., 2006. A comparison of univariate methods for forecasting electricity demand up to a day ahead. Int. J. Forecast. 22, 1–16.

Torro, H., 2007. Forecasting Weekly Electricity Prices at Nord Pool. Working Paper, University of Valencia, No. 88.2007. Available at: ⟨http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.117.5239&rep=rep1&type=pdf⟩.

Traber, T., Kemfert, C., 2011. Gone with the wind? Electricity market prices and incentives to invest in thermal power plants under increasing wind energy supply. Energy Econ. 33, 249–256.

Viehmann, J., 2011. Risk premiums in the German day-ahead electricity market. Energy Policy 39, 386–394.

Weron, R., 2006. Modeling and forecasting electricity loads and prices. A statistical approach. Wiley & Sons, West Sussex.

Wirth, H., 2013. Aktuelle Fakten zur Photovoltaik in Deutschland. Fraunhofer ISE, Freiburg.

Zirm, J., Auer, M., 2013. Energiewende erweckt alte Ölkraftwerke zum Leben. Die Presse. Available at: ⟨http://diepresse.com/home/wirtschaft/international/1338965/Energiewende-erweckt-alte-Olkraftwerke-zum-Leben⟩.