RUHR
ECONOMIC PAPERS

Andreas Gerster

Negative Price Spikes at Power Markets – The Role of Energy Policy

Ruhr Graduate School in Economics
rwi
#636

Imprint

Ruhr Economic Papers

Published by

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

RWI - Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

Editors

Editorial Office

Ruhr Economic Papers #636

Responsible Editor: Manuel Frondel

ISSN 1864-4872 (online) – ISBN 978-3-86788-740-3

Ruhr Economic Papers #636

Andreas Gerster

Negative Price Spikes at Power Markets – The Role of Energy Policy

Bibliografische Informationen der Deutschen Nationalbibliothek

Die Deutsche Bibliothek verzeichnet diese Publikation in der deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über: *http://dnb.d-nb.de* abrufbar.

Das RWI wird vom Bund und vom Land Nordrhein-Westfalen gefördert.

http://dx.doi.org/10.4419/86788740
ISSN 1864-4872 (online)
ISBN 978-3-86788-740-3

Andreas Gerster[1]

Negative Price Spikes at Power Markets – The Role of Energy Policy

Abstract

In Germany, substantial drops in wholesale power prices have become a regular phenomenon. While such price drops have far-reaching implications for the functioning of the power market, their underlying determinants remain poorly understood. To fill this gap, we propose a Markov regime-switching model to investigate low-price events at the European Power Exchange. Our analysis focuses on the role of energy policies that promote renewable energies and have led to significant reductions of nuclear capacities after the Fukushima accident. We find that high electricity infeed from renewable sources increases negative price spike probabilities, while the decommissioning of nuclear plants under the Nuclear Moratorium has an opposing effect. Simulations of market outcomes under different energy policies indicate that reaching ambitious renewable energy targets increases the frequency of low-price events and compromises the financial viability of conventional generation units, while a nuclear phase-out or an increase in storage capacities mitigates these effects.

JEL Classification: C32, L94, Q40, Q41

Keywords: Renewable energies; nuclear phase-out; day-ahead prices; regime-switching models; price spikes

September 2016

1 Andreas Gerster, RGS Econ and RWI. – The author thanks Mark Andor, Colin Vance and, in particular, Manuel Frondel for very helpful comments. – All correspondence to: Andreas Gerster, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: andreas.gerster@rwi-essen.de

1. Introduction

On September 1, 2008, negative bids were allowed for the first time at the day-ahead market of the European Power Exchange (EPEX). Since then, negative price spikes – sometimes quite large – have become a regular phenomenon. For example, on October 4, 2009, the day-ahead price plunged to -500 EUR per megawatt-hour (MWh) in the trading hour between 2 and 3 a.m., a huge drop given that average price levels during that trading hour amounted to about 38 EUR per MWh in 2009.

In addition to the typically low demand levels in the evenings, particularly on weekends, a key reason for this phenomenon is the rapid growth of electricity supply from renewable technologies in Germany. Between 2000, when Germany introduced the Renewable Energy Sources Act to support investments in renewable energy technologies, and 2015, the share of "green" electricity in Germany's electricity production almost quadrupled, increasing from almost 7 to some 33%. The support regime established by the Renewable Energy Sources Act grants a technology-specific feed-in tariff per kilowatt-hour (kWh) of renewable electricity that is far above the utilities' production cost of conventionally generated electricity. Furthermore, irrespective of the level of demand, utilities are obliged to preferentially accept the feed-in of renewable electricity onto the grid. When demand is low, this regime is one of a confluence of factors, including the absence of sufficient storage possibilities for electricity as well as costly and long ramp-up times of baseload power plants, that impel producers to accept even negative prices, reflecting the high opportunity costs of a production stop in conventional plants (Andor et al., 2010; Nicolosi, 2010).

Besides the strong support for renewable energies, another defining feature of Germany's energy policy in recent years has been the Nuclear Moratorium in response to the catastrophe in Japan's Fukushima. The moratorium, which was issued by the German government on March 15, 2011, eventually led to the permanent shut-down of 8 out of a total stock of 17 nuclear power plants and, hence, an immediate capacity reduction of 8,409 Megawatt (MW) (BNetzA, 2016). The remaining nuclear capacities are legally stipulated to be permanently shut down by 2022. This contrasts with Germany's ambitions to steadily increase the share of renewables in gross electricity consumption to 35% by 2020 and 80% by 2050 (BRD, 2010).

Drawing on day-ahead prices from the EPEX spanning from November 1, 2009, until October 31, 2012, and using Markov regime-switching models to separate times of both negative and low prices from a normal price regime, this article econometrically investigates the effects of both Germany's substantial expansion of renewable energy technologies in electricity production and its Nuclear Moratorium of 2011 on day-ahead prices. By specifying a model that endogenously distinguishes a low-price regime with low or even negative prices from a base regime capturing mean price levels, we analyze the impact of both policies on the frequency of low-price events. Furthermore, to investigate the impact of different policy scenarios on the financial viability of conventional plants, we simulate spot prices and compare them to variable cost of modern lignite- and hard coal-fired power plants with 2010 technology.

Given the efforts to foster the development of renewable energies all over the world, it is crucial to understand the interplay between increasing shares of renewables and the occurrence of price drops, as the latter may have substantial implications for the functioning of the power sector. Negative prices, in particular, can result in welfare losses if they are caused by renewable energy technologies that do not respond to prices signals because of fixed feed-in tariffs (Andor and Voss, 2016). Moreover, even modest price drops can cause "hidden system cost" (Mount et al., 2012) by endangering the profitability of conventional power plants that are needed to maintain reliability of electricity supply when intermittent renewable energy sources are absent. The financial burden of price drops is particularly large for inflexible baseload power plants, because reducing production levels implies large cost, originating from both ramping cost and opportunity cost due to missed trading opportunities in subsequent hours.

The present study builds on the literature of electricity spot price models that often presume multiple price regimes to account for positive price spikes. As an early contribution to this literature, Ethier and Mount (1998) propose a model for electricity prices that captures positive price spikes by applying Hamilton's (1994) Markov regime-switching framework. Building on the same model framework by expanding it to distinguish between mean-reversion in the absence of a price spike and after a spike, Huisman and Mahieu (2003) introduce an additional regime, whereas Huisman and Jong (2003) and Weron et al. (2004) propose to model independent regimes. To take advantage of fundamental data for modeling time-varying switching probabilities, Mount et al. (2006) introduce a model that employs data on capacity utilization, while Huisman (2008) as well as Kosater and Mosler (2006) employ temperature data.

Several empirical studies support the adequacy of regime-switching models for modeling electricity prices, such as Higgs and Worthington (2008) for the Australian electricity market, Jong (2006) for eight distinct electricity markets and Bierbrauer et al. (2007) for day-ahead prices at the EEX. As identified by Janczura and Weron (2010), one of the main drawbacks of existing Markov regime-switching models is implausible classifications of observations into regimes. To avoid such misclassifications, these authors propose modeling the spike regime by a shifted log-normal distribution, which prevents prices below or above a certain threshold value from being classified as a spike.

By proposing a Markov regime-switching model that captures price drops instead of positive price spikes, we are able to investigate the determinants of price drops and to simulate the impact of different policy scenarios on the profitability of conventional generation technologies. Our estimation results indicate that governmental regulations concerning renewable energies and nuclear capacities influence the occurrence of price drops. More specifically, we find that high electricity infeed from renewable sources increases the probabilities for price drops, while the reduction of nuclear capacities after the Nuclear Moratorium decreased them. Using the estimated Markov regime-switching models to simulate price trajectories, we demonstrate that reaching an 80% share of renewables decreases the profitability of conventional power plants substantially, with prices falling below variable cost in as many as 47 and 77% of the trading hours for modern lignite- and hard coal-fired power plants, respectively. Further simulations indicate that a nuclear phase-out or the construction of additional storage capacities for load-shifting can mitigate the occurrence of low-price events and thus ease the integration of renewables.

The remainder of the article is structured as follows. Section 2 describes the data, while Section 3 introduces the econometric model. Section 4 presents the estimation results, evaluates the model and discusses results from policy simulations. Section 5 summarizes and concludes.

2. Data

In this section, we present data on day-ahead prices for electricity, as well as on important influencing factors, such as load, fuel prices, the infeed of renewable energy technologies and available nuclear power capacities. We obtain hourly day-ahead prices for the market zone comprising Germany and Austria from the EPEX.[1]

At the EPEX, all 24 hourly day-ahead prices for electricity are simultaneously determined the day before delivery. Therefore, they constitute panel data of cross-sectional prices for each of the trading hours that vary from day to day (Huisman et al., 2007). Although estimating a panel data model could potentially increase forecasting precision by exploiting the auto-correlation of

[1] Cf. `http://www.epexspot.com/en/`.

Table 1: Summary Statistics

Data	n	Min	Max	Mean	Std. dev.	Skewness	Kurtosis
Day-ahead price hour 1	1,096	-119.9	57.3	38.4	10.0	-4.1	58.9
Day-ahead price hour 2	1,096	-120.0	54.0	34.8	11.0	-3.3	38.5
Day-ahead price hour 3	1,096	-120.0	52.1	31.8	12.2	-3.0	28.6
Day-ahead price hour 4	1,096	-149.9	51.1	29.4	13.4	-4.1	47.3
Day-ahead price hour 5	1,096	-120.0	52.1	29.9	12.1	-2.8	28.9
Day-ahead price hour 6	1,096	-120.0	53.5	33.6	11.6	-2.8	30.4
Day-ahead price hour 7	1,096	-200.0	73.3	40.0	16.1	-4.4	53.1
Day-ahead price hour 8	1,096	-199.9	183.5	48.8	18.7	-2.2	34.0
Day-ahead price hour 21	1,096	10.8	136.0	52.7	10.1	0.7	7.4
Day-ahead price hour 22	1,096	17.9	94.9	48.3	8.1	0.3	4.2
Day-ahead price hour 23	1,096	16.1	79.7	47.9	7.2	-0.1	4.0
Day-ahead price hour 24	1,096	-36.8	60.4	41.9	8.1	-2.0	17.5
Day-ahead price off-peak	1,096	-80.6	68.0	39.8	9.6	-2.3	25.4
Load hour 7	1,096	31,650	67,297	51,435	8,166	-0.5	2.2
Wind prognosis hour 7	1,096	288	23,610	4,695	3,849	1.6	6.0
Avail. nuclear capacity	1,096	4,297	18,360	13,098	3,197	0.0	2.0
Coal price (API 2)	1,096	50	101	76	12	-0.4	2.3

Notes: Day-ahead prices are in EUR/MWh, electricity load, wind power forecasts and available nuclear capacities in MW and daily coal prices (API 2 index) in EUR per metric ton.

hourly electricity prices, Markov regime-switching models are unavailable for panel data. For this reason, we model day-ahead prices separately for each trading hour.

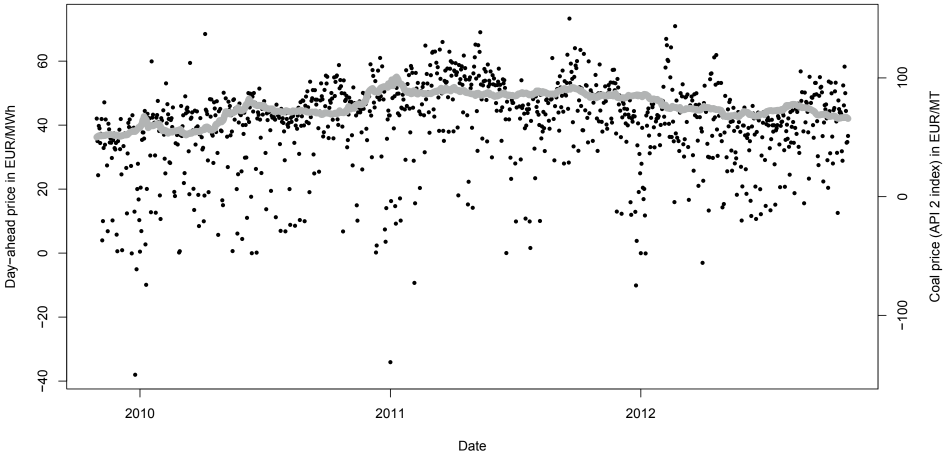
The analysis is restricted to the trading hours during the off-peak period between 8 p.m. and 8 a.m., which is when negative price spikes occur, and to an off-peak index as their arithmetic average. To avoid any effects from unbalanced seasonality, the time period under investigation comprises three complete years, spanning from November 1, 2009, until October 31, 2012.

The descriptive statistics in Table 1 demonstrate that day-ahead prices in the hours from 23 p.m. to 7 a.m. (i.e. in the trading hours 24 to 7) have homogeneous characteristics, displaying negative price spikes, negative skewness and excess kurtosis. In contrast, during trading hours 21 to 23 and 8 positive, rather than negative, price spikes occur, leading to positively skewed price distributions in some of these trading hours.

Day-ahead prices for trading hour 7 are depicted in Figure 1, indicating that prices in the range of 40 - 50 EUR per MWh occur most often, low positive prices occur on a regular basis, whereas pronounced negative prices are scarce. Furthermore, a periodic yearly seasonality cannot be observed. Comparing day-ahead prices to coal prices shows that they have very similar trends, which is due to the fact that in Germany hard coal-fired power plants are the price-setting power plants in most low- and medium-load situations (BKartA, 2011, p.167).[2]

[2]Data on the coal prices (API 2 index) was obtained using Thomson Reuters Datastream. As the API 2 index is not given for weekends, we calculated such values as the average of the respective Fridays and Mondays.

Figure 1: Day-Ahead Prices (Trading Hour 7) in EUR per MWh and Coal Prices in EUR per Metric Ton



Notes: Day-ahead prices in trading hour 7 are represented by black points, while daily coal prices (API 2 index) are given by the grey line. Day-ahead prices below -40 EUR per MWh are not displayed.

Considering hourly load levels, which we obtain from the European Network of Transmission System Operators (ENTSO-E) website, we find that they vary quite substantially, ranging from 32,000 to 67,000 MW during trading hour 7, for example (Table 1).[3] Differences in load originate mainly from seasonal patterns as well as from different levels of economic activity during holidays and workdays.

The first part of Figure 2 visualizes available capacities of German nuclear power plants and the impact of the Nuclear Moratorium in Germany after the Fukushima accident.[4] On March 15, 2011, the German government announced mandatory security checks for eight nuclear power plants, which led to a shutdown of 8,409 MW of capacity in the subsequent days (BNetzA, 2016). Within a short period of time, this decision caused substantial variation in available nuclear capacities, falling from 17,000 MW on March 15, 2011, to some 4,300 MW on May 30, 2011.

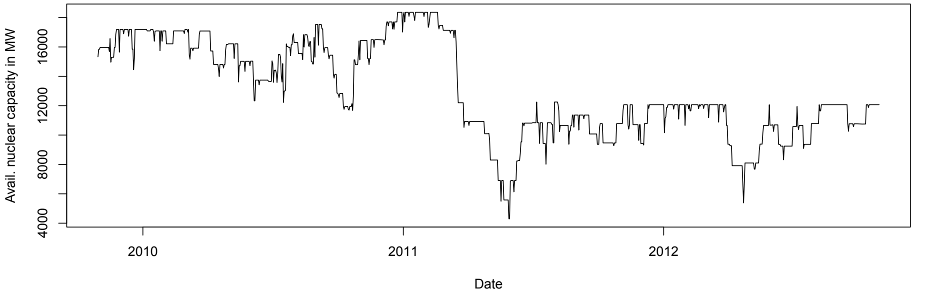
With regard to renewable energy technologies, we exclusively focus on wind power and neglect solar power, which is not relevant for the off-peak hours considered here. Data on day-ahead forecasts of wind power is available from the transmission system operators (TSOs) in Germany.[5]

[3] Cf. `https://www.entsoe.eu/resources/data-portal/consumption`.

[4] Cf. `http://www.transparency.eex.com/de/`.

[5] `http://www.50hertz.com/de/152.htm`, `http://www.amprion.net/bilanzkreis-eeg#`, `http://www.transpower.de/site/Transparenz/veroeffentlichungen/netzkennzahlen/`, `http://transnet-bw.de/`

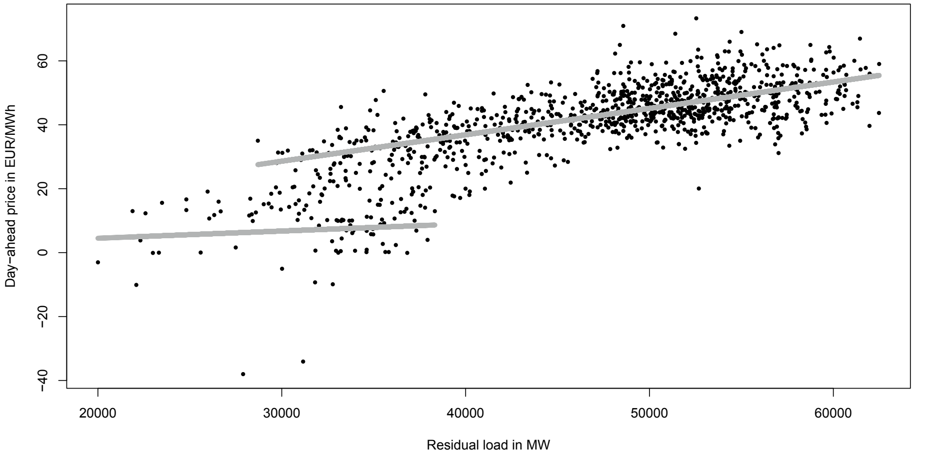
Figure 2: Available Nuclear Capacities in MW (Trading Hour 7)



As Table 1 illustrates for trading hour 7, wind power is extremely volatile, with a standard deviation of roughly 3,800 MW and values ranging from 300 to 24,000 MW.

To capture the amount of load that is satisfied by the price-elastic part of electricity supply, we calculate residual load as the difference between load and wind power levels. Figure 3 shows that low residual load levels are typically associated with low day-ahead prices, a relationship that is not linear. When residual load falls below 40,000 MW, day-ahead prices in the range of 0 and 20 EUR per MWh become much more frequent and negative prices may occur, indicating that the price behavior changes when low residual load levels are reached. In short, Figure 3 provides some first intuition on the kind of regime switches that are predominant in the data.

Figure 3: Residual Load in MW and Day-Ahead Prices in EUR per MWh (Trading Hour 7)



Notes: Prices below -40 EUR per MWh are not displayed. The lines visualize possible residual load-price relationships in different regimes.

3. The econometric model and estimation

Following the model framework proposed by Hamilton (1994), the time series of day-ahead prices p_t is modeled as a Markov regime-switching process. Its basic building blocks are stochastic processes for each regime and a latent state variable s_t that evolves according to a Markov chain. To account for fundamental information that determines the spiking behavior, the switching probabilities between the states are modeled as a function of explanatory variables, as for example described by Diebold et al. (1994). We distinguish the mean-reversion after a spike from normal mean-reversion by modeling two independent regimes, a base and a low-price regime, which are denoted by the superscripts b and l, respectively.

More specifically, for the base regime we follow Knittel and Roberts (2005) and model the differences of day-ahead prices from their mean by an AR(1) process:

$$(p_t^b - \mu_t) = \phi(p_{t-1}^b - \mu_{t-1}) + \epsilon_t,$$

where μ_t denotes the time-varying mean of prices, $\epsilon_t \sim N(0, \sigma^b)$ is a normally distributed error term with a standard deviation of σ^b and the AR parameter ϕ is assumed to be smaller than one in absolute value. The mean is specified as a linear function of residual load, coal prices and available nuclear capacities: $\mu_t = \alpha + \beta\, resload_t + \gamma\, coal_t + \delta\, nuclear_t$.

This specification reflects the mean-reverting nature of day-ahead prices and captures the trend and seasonality patterns inherent in the explanatory variables. For example, its time-changing mean allows modeling weekly periodicity in the data that stems from changing demand patterns over the week. Moreover, it can also capture situations where increased residual load levels lead to price changes, which occur, for example, when less efficient power plants of the same fuel type become price-setting.

In contrast, the low-price regime captures deviations from the mean that are more pronounced. For that purpose, we model that regime by:

$$(p_t^l - \mu_t) = \tau - LN_t,$$

where LN_t denotes a lognormally distributed random variable with $ln(LN_t) \sim N(\mu^l, \sigma^l)$, and τ is a threshold parameter that determines an upper limit for price deviations that can occur in that regime. The use of shifted lognormal distributions has been suggested by Weron (2009), as they capture leptocurtic behavior while avoiding implausible spike classifications.

We add further flexibility to the model by not predetermining τ to a certain quantile of prices but rather by treating it as an additional parameter to be estimated. This is in line with the reasoning of Zachmann (2013), who argues that distinct price regimes may reflect different types of price-setting power plants. Determining τ endogenously allows identification of the regime switch that is predominant in the data.

The states s_t are assumed to follow a Markov chain with time-varying switching probabilities $P^{ij}(z_t) = P(s_t = j|s_{t-1} = i, z_t)$, where z_t denotes the variables influencing the switching behavior. The probability to stay in the base regime in period t is modeled by the following logistic function:

$$P^{bb}(resload_t, nuclear_t) = \frac{exp(a^b + b^b resload_t + c^b nuclear_t)}{1 + exp(a^b + b^b resload_t + c^b nuclear_t)}. \tag{1}$$

Note that in the case of two regimes the probability to stay in the base regime, $P^{bb}(resload_t, nuclear_t)$, and the probability to switch from the base to the low-price regime, $P^{bl}(resload_t, nuclear_t)$, must add up to unity so that it is sufficient to specify one of these probabilities. In addition, the probability to stay in the low-price regime, $P^{ll}(resload_t, nuclear_t)$, is modeled accordingly.

While the model structure is similar to the approach by Mount et al. (2006), two features distinguish our analysis: First, we allow for a low-price regime instead of a regime capturing positive price spikes, which is motivated by our focus on price drops. Second, to avoid the problem of biased mean-reversion parameters, as for example described by Huisman and Jong (2003), we model regimes independently, so that the autoregressive process in the base regime in period t remains unaffected by price drops in $t-1$.

The model is estimated by maximum likelihood, where the log-likelihood is constructed recursively as detailed in Mount et al. (2006) and Hamilton (1994). Central to the construction of the log-likelihood are the state probabilities $P(s_t)$, which are computed in a sequence of forecast and update steps. Furthermore, the independence of the two regimes makes further adjustments necessary. When switches from the low-price to the base regime occur, the lagged price in the base process p^b_{t-1} is latent, so that the computation of the conditional densities becomes more burdensome. With a latent variable p^b_{t-1} in the base process, the conditional density of an observation in the base process not only depends on the lagged price, the explanatory variables and the state variable, but on the entire history of prices, on all possible paths of the state variable, and on the entire history of the explanatory variables (Janczura and Weron, 2011).

To minimize data storage requirements and to speed up the estimation procedure, we follow the approach by Janczura and Weron (2011), who propose a recursive formula to approximate the latent p_{t-1}^b by their conditional expectation $E(p_{t-1}^b|\mathbf{p_{t-1}}, \mathbf{z_{t-1}})$, where z_t denotes the explanatory variables and the bold letters indicate the entire information set up to period t-1. The model is estimated by using a nonlinear maximization routine in R.[6]

4. Results

In the following, we discuss the estimation results on the impact of intermittent renewable energies and the Nuclear Moratorium on the occurrence of low-price events. After evaluating the adequacy of the model to capture price dynamics, we conduct simulations of alternative energy policies to investigate their impact on the frequency of low-price events and particularly the economic viability of lignite- and hard coal-fired power plants. This has become a highly relevant issue for Germany's electricity market in the aftermath of the country's energy sector transition, characterized by a strong expansion of renewable energy technologies.

4.1. Model results

We focus the discussion on the trading hours for which the model is successful in separating two distinct regimes. For the trading hours 8, 21, 22 and 23, this is not the case, as we document in Section A of the Appendix. Recalling that prices in these trading hours have distinct characteristics, this finding does not come as a surprise and we do not consider those trading hours further.

Because the model estimates are very similar for the remaining off-peak trading hours 1 to 7 and 24, we focus the presentation of results on trading hour 7, while reporting the comprehensive set of estimates in Section B of the Appendix. Analyzing the parameter estimates given in Table 2, we find that $\hat{\beta}$ and $\hat{\gamma}$ are positive, indicating that higher residual load levels and coal prices are associated with higher day-ahead prices. With regard to the switching probabilities, the parameter estimate $\hat{b}^b$ is positive and statistically significant, which demonstrates that the probability to stay in the base regime increases in residual load. Conversely, as we have two

[6] As initial values for the filter inferences we assume $(0.5, 0.5)'$ for period 1. For the starting value needed to approximate the latent p_{t-1}^b, we set $E(p_1^b) = \mu_1$. To avoid non-defined functional values, we reparameterize the parameters θ, σ^b and σ^l. As the log-likelihood function turns out to have multiple local maxima, we randomly draw 50 starting values for the estimation routine and choose the coefficient estimates that lead to the highest log-likelihood.

Table 2: Estimation Results (Trading Hour 7)

Parameters of the base process						Parameters of the low-price process		
$\hat{\alpha}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\delta}$	$\hat{\phi}$	$\hat{\sigma^b}$	$\hat{\tau}$	$\hat{\mu}^l$	$\hat{\sigma}^l$
-12.74***	9.13***	0.27***	-0.59***	0.33***	4.66***	-1.08	2.63***	0.66***
(2.18)	(0.27)	(0.02)	(0.08)	(0.08)	(0.11)	(1.37)	(0.12)	(0.07)
Parameters of the switching probabilities						Log-Likelihood and number of obs.		
$\hat{a}^b$	$\hat{a}^l$	$\hat{b}^b$	$\hat{b}^l$	$\hat{c}^b$	$\hat{c}^l$	Log-likelihood	n	
-10.77***	11.27***	5.17***	-4.66***	-0.53***	0.45**	3,428.68	1,096	
(1.88)	(3.41)	(0.67)	(1.02)	(0.09)	(1.18)			

*Notes: Asymp. standard errors in parantheses. *, **,*** denote significance at the 10%, 5%, 1% level.*

regimes, this finding implies that higher residual load levels decrease the probability to switch from the base to the low-price regime, as illustrated in the first part of Figure 4. The parameter estimate on the effect of nuclear capacities, $\hat{c}^b$, is negative and statistically significant. By the same logic, it implies that switching probabilities to the low-price regime fall when nuclear capacities are reduced.

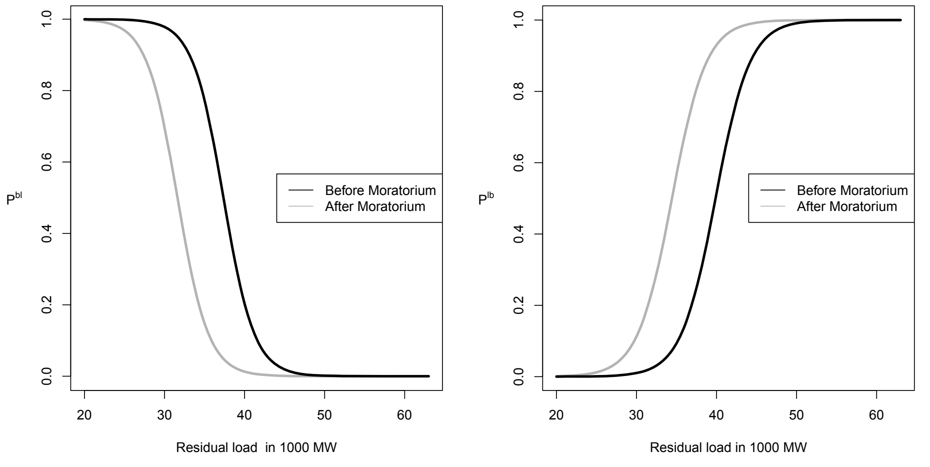
The second part of Figure 4 shows that switching probabilities from the low-price to the base regime increase in residual load and are higher after the Nuclear Moratorium reduced nuclear capacities. This pattern is reflected by the negative parameter estimates $\hat{b}^l$ and the positive estimate $\hat{c}^l$, both of which are statistically significant.

Furthermore, we use the functional form of the switching probabilities to determine the changes in residual load that would have had the same impact on switching probabilities as the Nuclear Moratorium.[7] As both a reduction in nuclear capacities and an increase in residual load lead to a higher utilization of dispatchable capacities, their effects on switching probabilities should be similar. Indeed, the results from Table 3 show that nuclear capacity reductions by the Nuclear Moratorium are equivalent to an increase in residual load between 4,100 and 6,400 MW, depending on the trading hour. Bearing in mind that the Nuclear Moratorium reduced nuclear power capacities by 8,409 MW, these findings imply that some 50 to 80% of the shut-down nuclear capacity translated into a shift of the switching probabilities, depending on the trading hour. Accordingly, lower residual load situations had to be reached for low-price observations to occur, so that their likelihood was reduced.

To investigate the nature of the different price regimes further, we calculate the smoothed

[7] Using the functional form as displayed in Equation (1), such changes in residual load can be calculated as: $\Delta resload_t = (\hat{c}_b/\hat{b}_b) \cdot (nuclear_{af} - nuclear_{be})$, where $nuclear_{af}$ ($nuclear_{be}$) corresponds to the average nuclear capacities after (before) the Nuclear Moratorium and $\hat{c}_b$ and $\hat{b}_b$ correspond to the estimates of the respective model parameters.

Figure 4: Switching Probabilities Before and After Germany's Nuclear Moratorium (Trading Hour 7)



Notes: P^{bl} (P^{lb}) represents the probability to switch from the base (low-price) to the low-price (base) regime. Switching probabilities before and after the Nuclear Moratorium are calculated using average nuclear capacities in the respective period.

Table 3: Nuclear Moratorium Effect in Terms of Equivalent Residual Load Changes, in MW

	Hour 1	Hour 2	Hour 3	Hour 4	Hour 5	Hour 6	Hour 7	Hour 24
P^{bl}:$\Delta resload$	4,775	5,796	6,162	6,429	6,187	6,333	5,744	4,112

Notes: The table gives the change in residual load that would have the same impact on switching probabilities as the Nuclear Moratorium.

probabilities that an observation belongs to the base or the low-price regime (a visualization of the regime classifications is given in Section C of the Appendix). Smoothed probabilities take advantage of the entire data to classify observations into regimes and are calculated using the method proposed by Kim (1994). In the following, an observation is classified into the low-price regime if the corresponding smoothed probability is larger than 0.5.

When comparing the median prices of the observations that are classified into the low-price regime to those of the base regime, as displayed in Table 4, we find that median prices in the low-price regime range from 13 to 27 EUR per MWh. Moreover, low-price observations occur rather frequently in 7 to 32% of the cases, depending on the trading hour. One might suspect that the regimes merely capture differences between workdays and weekends. To rule out this possibility, we analyse how often observations are classified into the low-price regime

Table 4: Differences Between Base and Low-Price Regime Observations

	Hour1	Hour2	Hour3	Hour4	Hour5	Hour6	Hour7	Hour24	Off-peak
Median price (low-price reg.)	24	21	19	16	18	18	13	26	27
Median price (base reg.)	41	38	37	35	36	38	44	43	42
Share (low-price reg.)	14%	19%	23%	26%	32%	20%	13%	7%	15%
Share among Saturdays	11%	13%	13%	16%	24%	26%	18%	13%	13%
Share among Sundays	29%	38%	44%	46%	57%	55%	56%	13%	41%
Coal (1970): Price < Cost	72%	86%	93%	97%	97%	89%	50%	55%	65%
Coal (2010): Price < Cost	19%	31%	45%	57%	55%	34%	20%	7%	17%
Lignite (1970): Price < Cost	12%	20%	27%	36%	34%	22%	15%	4%	10%
Lignite (2010): Price < Cost	3%	6%	11%	14%	13%	9%	8%	1%	2%

Notes: Median prices are in EUR per MWh. Shares of observations where prices are below variable cost are calculated for different generating technologies and given in percent.

during weekends. During trading hour 7, for example, only 56% of all Sundays and 18% of all Saturdays were classified into the low-price regime (Table 4).

Taken together, these findings show that the low-price regime not only captures negative prices, but also moderately positive prices that occur on a rather regular basis. To investigate the price regimes further, we compute the variable cost of producing 1 MWh of electricity from lignite- and hard coal-fired power plants with old and modern technology from 1970 and 2010.[8] For those plants, rows 6 to 9 of Table 4 present the share of trading hours when spot prices are below variable cost, ranging from 1% for modern lignite-fired power plants in trading hour 24 to some 97% for 1970 hard coal-fired power plants in trading hour 4.

Comparing the share of low-price regime observations from the third row of Table 4 with the share of trading hours when prices fall below variable cost of 1970 lignite-fired power plants (as given in row eight) shows that they coincide closely. This finding may indicate that the low-price regime captures situations when spot prices are close to the variable cost of inflexible baseload power plants, such as lignite-fired plants, which then become price-setting. Further model results support this interpretation. For inflexible baseload power plants, the decision not to produce in a given trading hour has opportunity costs, as it may prevent production in the hours that follow. Such opportunity costs are typically higher when the more profitable peak hours approach. Thus, baseload power plants should accept lower prices shortly before the peak hours compared to, for example, at midnight. This is the pattern we find when looking at the median spot price of low-price regime observations from Table 4, which is highest in trading

[8]Variable cost are composed of fuel cost, CO_2 emission cost and operations and maintenance cost (O&M). For hard coal-fired power plants with 1970 (2010) technology we assume (Klaus et al., 2009, IFEU, 2007): heat rates of 36% (46%), specific CO_2 emission rates of 0.939 t/MWh (0.735 t/MWh), O&M cost of 1 EUR/MWh as well as coal prices (API 2) as introduced in Table 1. For lignite-fired power plants with 1970 (2010) technology we assume (Klaus et al., 2009, BKartA, 2011): heat rates of 36% (46%), specific CO_2 emission rates of 1.263 t/MWh (0.940 t/MWh), combined fuel and O&M cost of 10 EUR/MWh (4 EUR/MWh). As the CO_2 emission price, we use the price of carbon emission futures due in December 2016 (CFI2Z6).

hour 24 and lowest in trading hour 7.

4.2. Model evaluation

To judge the ability of the model to capture the characteristics of electricity spot prices, we compare the quantiles from simulated to actual price trajectories. The results from Table 5 show that for most trading hours, the simulated and actual quantiles differ from each other by less than 2%. Only for the 10% quantiles and the trading hours 2-4 do we see deviations in the order of 5%, thereby indicating that the lognormal distribution cannot perfectly approximate the empirical distribution of low prices during these hours.

Table 5: Simulated and Actual Quantiles of Spot Prices, in EUR per MWh

	Q(0.1)	Q(0.25)	Q(0.5)	Q(0.75)	Q(0.9)
Hour 1(act.)	26.55	33.80	39.57	44.79	48.60
Hour 1(sim.)	26.74 (+0.7%)	34.02 (+0.7%)	39.69 (+0.3%)	44.62 (-0.4%)	48.58 (-0.0%)
Hour 2(act.)	21.16	29.83	36.86	41.95	45.94
Hour 2(sim.)	20.60 (-2.7%)	30.22 (+1.3%)	36.57 (-0.8%)	41.68 (-0.7%)	45.78 (-0.3%)
Hour 3(act.)	17.19	26.11	34.19	39.93	44.04
Hour 3(sim)	16.35 (-4.9%)	26.64 (+2.0%)	34.05 (-0.4%)	39.49 (-1.1%)	43.85 (-0.4%)
Hour 4(act.)	13.80	22.68	31.62	38.05	42.58
Hour 4(sim.)	13.34 (-3.3%)	22.97 (+1.3%)	31.43 (-0.6%)	37.33 (-1.9%)	41.96 (-1.5%)
Hour 5(act.)	14.62	23.36	31.94	37.96	42.86
Hour 5(sim)	14.46 (-1.1%)	22.90 (-2.0%)	31.54 (-1.2%)	37.53 (-1.1%)	41.94 (-2.1%)
Hour 6(act.)	18.07	28.88	35.55	41.17	45.47
Hour 6(sim)	17.62 (-2.5%)	28.64 (-0.8%)	35.74 (+0.5%)	40.95 (-0.5%)	45.10 (-0.8%)
Hour 7(act.)	19.30	35.62	43.03	48.99	54.25
Hour 7(sim.)	19.82 (+2.7%)	34.78 (-2.4%)	43.03 (+0.0%)	49.58 (+1.2%)	54.84 (+1.1%)
Hour 24(act.)	32.86	37.90	42.61	47.22	51.15
Hour 24(sim.)	32.67 (-0.6%)	37.59 (-0.8%)	42.49 (-0.3%)	47.19 (-0.1%)	51.11 (-0.1%)
Off-peak(act.)	27.55	34.76	40.79	45.97	50.73
Off-peak(sim.)	27.79 (+0.9%)	34.69 (-0.2%)	40.67 (-0.3%)	45.73 (-0.5%)	49.87 (-1.7%)

Notes: Q(0.1) denotes the 10% quantile, etc. Values represent means over 1000 simulations.

Table 6: Difference Between Actual and Simulated Spot Prices in Terms of Interquartile and Interdecile Ranges, in %

	Hour 1	Hour 2	Hour 3	Hour 4	Hour 5	Hour 6	Hour 7	Hour 24	Off-peak
Δ IQR	-3.6	-5.4	-7.0	-6.6	+0.2	+0.1	+10.7	-2.9	-1.5
Δ IDR	-0.9	+1.6	+2.5	-0.6	-2.7	+0.3	+0.2	+0.8	-4.

Notes: ΔIQR (ΔIDR) denotes the difference between simulated and actual interquartile (interdecile) ranges. Values represent means over 1000 simulations.

A further evaluation is based on calculating the interquartile range (IQR) and the interdecile range (IDR) as the difference between the first and third quartile and the first and ninth decile, respectively. Comparing the IDR of simulated and actual prices in Table 6 shows that in all cases the difference is below 3%, while the differences in terms of the IQR are slightly larger, reaching a maximum of some 10% in trading hour 7. These values can be compared to results by Janczura and Weron (2010), who evaluate different Markov regime-switching models. For their preferred model and EEX data, these authors obtain differences of the IQR in the range of -4 to 5% and differences of the IDR in the range of -2 to 3%. Compared to these values, our model performs well for the majority of trading hours, notably trading hours 1, 2, 5, 6, 24 and the off-peak index, while it has a slightly worse fit in terms of the IQR for the trading hours 3 to 4 and 7.

4.3. Simulation results

To demonstrate the effect of different energy policies on the profitability of conventional power plants, we use the Markov regime-switching models to simulate spot price trajectories based on the estimated model parameters, as well as the time series of load, wind power, coal prices and nuclear capacities. Comparing simulated prices to the variable cost of modern lignite- and hard coal-fired power plants with technology levels as of 2010, the simulations allow us to gauge the profitability of conventional production technologies that will be available in the upcoming decades. For expositional purposes, we present the results for trading hour 4, which experiences most price drops, and hour 1, where price drops are less frequent, as well as for an average over all considered off-peak trading hours, while reporting the comprehensive simulation results in Section D of the Appendix.

To establish a reference point for the price behavior, we first simulate price trajectories under the assumption of zero "green" electricity generation. As the first row of Table 7 illustrates, the share of off-peak trading hours with prices below variable cost lies between 0 and 3% for lignite-fired power plants, with an average of 2% in the off-peak trading hours. For hard coal-fired power plants, this share amounts to 18% on average, which reflects the larger variable cost of this generating technology. Furthermore, in a baseline scenario that corresponds to actual wind power levels and a 20% share of renewables in electricity production, the average share of trading hours with prices below variable cost increases to 8% for modern lignite-fired and 39% for hard coal-fired plants.

To provide for a future perspective, we consider the effect of reaching renewables shares of 35%, 50%, 65% and 80%, which are the official targets of the German government for 2020, 2030, 2040 and 2050, respectively. In these simulations, we scale up renewable electricity generation under the constraint that production levels cannot surpass total load, which mimics regulatory

Table 7: Policy Simulations on the Share of Trading Hours with Prices Below Variable Cost

	Lignite-Fired Plants (2010): Prices < Variable Cost			Hard Coal-Fired Plants (2010): Prices < Variable Cost		
	Hour 1	Hour 4	∅ off-peak	Hour 1	Hour 4	∅ off-peak
0% renew. share	0%	3%	2%	6%	37%	18%
Baseline (actual data)	3%	15%	8%	23%	63%	39%
Baseline; no moratorium	5%	28%	15%	38%	79%	52%
35% renew. share	10%	31%	19%	41%	75%	54%
50% renew. share	18%	45%	30%	55%	83%	64%
65% renew. share	26%	55%	39%	65%	87%	72%
80% renew. share	33%	63%	47%	72%	90%	77%
80% renew.; no moratorium	39%	75%	54%	80%	95%	84%
Adaptation strategies under an 80% renewables share						
1 GW storage	31%	60%	44%	69%	88%	75%
5 GW storage	24%	47%	35%	55%	78%	63%
10 GW storage	17%	34%	25%	40%	63%	48%
20 GW storage	8%	17%	12%	21%	34%	25%
0% nuclear	13%	24%	20%	36%	48%	43%

Notes: The table gives the share of days when prices are below variable cost of modern lignite- or hard coal-fired power plants (with 2010 technology) for the trading hours 1 and 4, as well as an average over all off-peak trading hours that are analyzed (1 to 7 and 24), denoted by ∅ off-peak. *Values represent means over 1,000 simulations.*

action that would cap electricity generation from renewables by command and control measures in case of excess supply. As visualized by Table 7, the average share of unprofitable trading hours increases dramatically with a rising share of renewables, amounting to 77% for hard coal-fired power plants and 47% for lignite-fired power plants in the scenario of an 80% renewables share. By demonstrating that even the profitability of modern lignite-fired power plants decreases considerably, the results indicate that substantial displacements of conventional generation can be expected upon reaching ambitious renewable targets.

By simulating spot prices under the assumption that average nuclear capacities after the moratorium match pre-Fukushima levels, we investigate the hypothetical scenario that the Nuclear Moratorium had not been issued. The simulation results in the second and third row of Table 7 establish that the moratorium had a mitigating effect on the share of unprofitable off-peak trading hours: in its absence, this share would have increased substantially for both lignite-fired power plants (from 8 to 15%) and hard coal-fired power plants (from 39 to 52%). Moreover, the mediating effect of the Nuclear Moratorium is still present when considering an 80% renewable scenario. As demonstrated by the seventh and eighth row of Table 7, the average share of unprofitable trading hours would increase from 47 to 54% for lignite-fired and from 77 to 84% for hard coal-fired power plants in the absence of the moratorium.

Finally, we analyze two developments that may reduce the occurrence of low-price events in the future: the advent of storage technologies for load-shifting and a phase-out of nuclear capacities. Both electrical storage solutions (Dunn et al., 2011) and deferrable demand systems that shift load into off-peak trading hours (Jeon et al., 2015) promise to ease the integration of intermittent renewable energies and to decrease the frequency of price drops. By treating storage technologies as additional load in the off-peak trading hours considered here, we simulate their impact on the occurrence of low-price events and the profitability of conventional power plants. The bottom part of Table 7 shows that additional storage capacities for load-shifting of 20 GW – a considerable increase, compared to the existing stock of 9.2 GW of pumped storage capacities in Germany (BNetzA, 2016) – can decrease the average share of unprofitable trading hours from 47 to 12% and from 77 to 25% for lignite- and hard coal-fired power plants, respectively.

To gauge the impact of a nuclear phase-out, we additionally simulate spot prices under an 80% renewable share and zero nuclear capacities. The last row of Table 7 illustrates that – compared to a 80% renewables scenario – the average share of trading hours with prices below variable cost is roughly cut by half, amounting to 20 and 43% for lignite- and hard coal-fired power plants, respectively. This result highlights that a phase-out of nuclear can contribute considerably to sustain the financial viability of lignite- or hard coal-fired power plants when reaching ambitious renewable energy targets.

5. Summary and conclusions

Using Markov regime-switching models with time-varying switching probabilities to separate times of normal prices from times of low or even negative prices, this article has investigated the effects of both Germany's rapid increase of renewable energy capacities in electricity production and the Nuclear Moratorium of 2011 on day-ahead power prices. Analyzing off-peak trading hours individually reveals that, apart from some exceptions, the model predicts price trajectories fairly well. Moreover, the investigation of the endogenously determined low-price regime indicates that the model not only captures extreme negative prices, but also low prices in the magnitude of 13 to 27 EUR per megawatt-hour (MWh) that result when lignite power plants become price-setting.

Our estimation results indicate that governmental regulations with respect to renewable energy and nuclear capacities have unintended side effects in influencing the occurrence of negative price spikes. Specifically, when renewable energy capacities cover a large share of the load, the probability of negative price spikes increases significantly. In contrast, our results indicate that negative price spikes were reduced substantially in the aftermath of the Nuclear Moratorium.

To investigate the impact of alternative energy policies on the economic viability of conventional power plants, we use the estimated Markov regime-switching models to compare simulated prices to variable cost of modern lignite- and hard coal-fired power plants. The simulation results demonstrate that reaching ambitious renewable energy shares of 80% threatens the financial viability of conventional plants: the share of unprofitable off-peak trading hours jumps to some 47 and 77% for modern lignite- and hard coal-fired plants, compared to 2 and 18%, respectively, in a scenario without renewables.

Further simulations document the potential of nuclear capacity reductions and increases in storage capacities for load-shifting to reduce the frequency of negative price spikes and to secure the economic viability of lignite- and hard coal-fired generation capacities. We find that in the hypothetical absence of the Nuclear Moratorium, the average share of unprofitable off-peak trading hours would have increased from 8 to 15% and from 39 to 52% for lignite- and hard coal-fired power plants, respectively. When considering a 80% renewables scenario, a full nuclear phase-out cuts the share of unprofitable off-peak trading hours roughly by half, from 47 to 20% and from 77 to 43% for lignite- and hard coal-fired plants, respectively. Similarly, increasing capacities for load-shifting by 20 GW per trading hour reduces the share of unprofitable off-peak trading hours to 12 and 25% for lignite- and hard coal-fired power plants.

In summary, our simulation exercise documents that reaching ambitious renewable energy shares of 80% can pose serious threats to the profitability of even modern conventional generation technologies, particularly if nuclear power or storage capacities were to remain at today's levels. To the extent that dispatchable conventional plants are necessary to meet peak demand when electricity from intermittent renewable energies is unavailable, regulatory instruments that ensure the financial viability of those plants – e.g. in the form of capacity markets – may therefore become increasingly relevant. However, our simulations also illustrate the potential of both a nuclear phase-out and additional storage capacities to sustain the profitability of dispatchable conventional technologies.

To account for the impact of energy policies on the financial viability of dispatchable generation technologies will become increasingly important as strategies to decarbonize electricity generation based on renewable energies progress all over the world. Because price drops can trigger reductions in the stock of dispatchable conventional capacities that are required to sustain system reliability, future research on the relationship between increasing shares of renewables and the frequency of price drops is warranted. For example, comparing electricity markets both with and without capacity payments could help to understand how different market designs moderate the impact of increasing shares of renewables on spot prices behavior. Moreover, given that the proposed econometric model is the first to capture negative spikes of spot electricity prices, some model refinements may prove useful. Econometric advances that account for the panel structure of day-ahead prices in a Markov regime-switching framework could help to further increase the model fit and thus the accuracy of spot price simulations.

Appendix

A. Estimation results for the trading hours 8, 21, 22 and 23

For the trading hours 8, 21, 22 and 23, hardly any observation is classified into the low-price regime. Table A.1 illustrate this finding by the blown-up threshold parameter estimates $\hat{\tau}$ for the trading hours 8, 21 and 22, and the very large standard errors of the estimates for the switching probability parameters $\hat{a}^l$, $\hat{b}^l$ and $\hat{b}^l$ in trading hour 23.

Table A.1: Estimation Results

		Hour 8	Hour 21	Hour 22	Hour 23
Parameters	$\hat{\alpha}$	-19.13	-0.58	6.17***	10.49***
of the		(x)	(3.11)	(2.22)	(2.23)
base process	$\hat{\beta}$	13.21***	6.88***	5.62***	4.68***
		(0.21)	(0.24)	(0.24)	(0.27)
	$\hat{\gamma}$	0.30***	0.35***	0.32***	0.31***
		(0.02)	(0.02)	(0.02)	(0.02)
	$\hat{\delta}$	-0.84***	-0.51***	-0.81***	-0.64***
		(0.07)	(0.10)	(0.08)	(0.07)
	$\hat{\phi}$	0.98	0.46***	0.72	0.46***
		(x)	(0.15)	(0.54)	(0.10)
	$\hat{\sigma}^b$	45.57***	5.65***	4.43***	4.07***
		(7.13)	(0.18)	(0.18)	(0.09)
Parameters	$\hat{\tau}$	118.41***	22.50***	44.96	-5.90
of the		(31.57)	(6.46)	(28.48)	(3.87)
low-price process	$\hat{\mu}^l$	4.87***	3.38***	3.84***	2.00***
		(0.23)	(0.22)	(0.61)	(0.59)
	$\hat{\sigma}^l$	0.05***	0.13***	0.08*	0.55*
		(0.01)	(0.03)	(0.04)	(0.31)
Parameters	$\hat{a}^b$	-5.20	0.51	-5.09**	-19.55***
of the		(172.09)	(3.28)	(2.30)	(4.29)
switching	$\hat{a}^l$	3.49*	3.91	-15.31*	25.42
probabilities		(2.03)	(2.87)	(9.23)	(2,097.15)
	$\hat{b}^b$	45.90	1.20*	0.44	6.41***
		(185.54)	(0.63)	(0.38)	(1.24)
	$\hat{b}^l$	0.99***	0.58	1.27	-11.12
		(0.32)	(0.70)	(1.34)	(2,097.15)
	$\hat{c}^b$	-21.29	-0.22**	0.44***	-0.21
		(75.00)	(0.11)	(0.12)	(0.16)
	$\hat{c}^l$	-0.31***	-0.23	0.84***	-1.23
		(0.09)	(0.18)	(0.30)	(3,632.38)
Log-likelihood		3676.64	3344.75	3152.70	3118.19
n		1,096	1,096	1,096	1,096

*Notes: Asymp. standard errors in parantheses. *, **,*** denote significance at the 10%, 5%, 1% level. (x) indicates that numerical issues occurred, leading e.g. to undefined standard error estimates.*

B. Estimation results for the hours 1-7, 24 and the off-peak index

Table B.1: Estimation Results

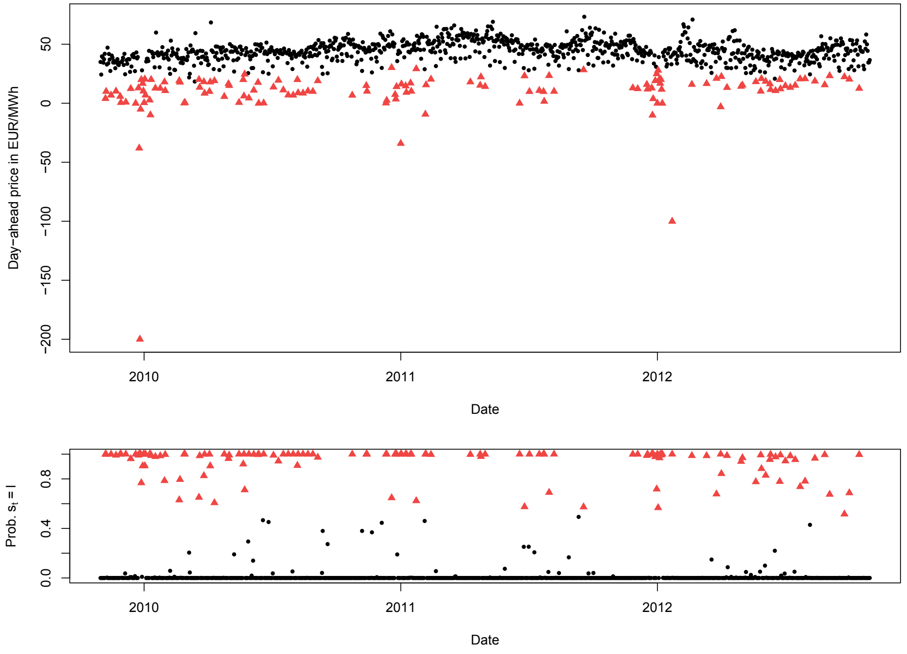
		Hour 1	Hour 2	Hour 3	Hour 4	Hour 5
Parameters of the	$\hat{\alpha}$	0.51	-4.99***	-7.15***	-3.65	-3.66
		(2.25)	(1.90)	(1.79)	(2.59)	(2.55)
base process	$\hat{\beta}$	5.88***	6.72***	7.48***	7.91***	6.84***
		(0.36)	(0.32)	(0.30)	(0.35)	(0.40)
	$\hat{\gamma}$	0.30***	0.30***	0.28***	0.23***	0.24***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
	$\hat{\delta}$	-0.57***	-0.55***	-0.63***	-0.91***	-0.67***
		(0.08)	(0.07)	(0.07)	(0.10)	(0.08)
	$\hat{\phi}$	0.50***	0.51***	0.56***	0.63**	0.74
		(0.14)	(0.15)	(0.18)	(0.26)	(0.53)
	$\hat{\sigma}^b$	3.43***	3.19***	3.23***	3.56***	2.92***
		(0.09)	(0.10)	(0.10)	(0.12)	(0.11)
Parameters of the	$\hat{\tau}$	1.88	-2.10**	-4.15***	-2.18**	2.20
		(1.68)	(1.00)	(0.58)	(0.85)	(1.41)
low-price process	$\hat{\mu}^l$	2.48***	2.24***	2.06***	2.27***	2.56***
		(0.15)	(0.12)	(0.10)	(0.10)	(0.11)
	$\hat{\sigma}^l$	0.57***	0.66***	0.79***	0.65***	0.49***
		(0.08)	(0.07)	(0.07)	(0.06)	(0.05)
Parameters of the	$\hat{a}^b$	-12.50***	-7.12***	-6.82***	-5.32***	-7.34***
		(2.79)	(1.18)	(1.14)	(1.06)	(1.27)
switching prbabilities	$\hat{a}^l$	9.45***	12.61***	7.36***	9.72***	10.31***
		(3.05)	(2.79)	(1.51)	(2.03)	(1.81)
	$\hat{b}^b$	5.43***	3.80***	3.85***	3.15***	3.64***
		(0.88)	(0.41)	(0.41)	(0.35)	(0.41)
	$\hat{b}^l$	-3.66***	-5.67***	-3.31***	-3.97***	-3.90***
		(0.99)	(1.14)	(0.52)	(0.70)	(0.60)
	$\hat{c}^b$	-0.46***	-0.39***	-0.42***	-0.36***	-0.40***
		(0.08)	(0.07)	(0.06)	(0.06)	(0.06)
	$\hat{c}^l$	0.33***	0.63***	0.37***	0.41***	0.39***
		(0.11)	(0.14)	(0.07)	(0.09)	(0.08)
Log-likelihood		3,164.15	3,186.79	3,272.88	3,374.21	3,262.94
n		1,096	1,096	1,096	1,096	1,096

		Hour 6	Hour 7	Hour 24	Off-peak
Parameters of the	$\hat{\alpha}$	-8.41***	-12.74***	0.90	-0.66
		(2.47)	(2.18)	(2.17)	(1.80)
base process	$\hat{\beta}$	6.87***	9.13***	5.40***	7.43***
		(0.26)	(0.27)	(0.29)	(0.23)
	$\hat{\gamma}$	0.29***	0.27***	0.32***	0.25***
		(0.02)	(0.02)	(0.02)	(0.02)
	$\hat{\delta}$	-0.43***	-0.59***	-0.48***	-0.81***
		(0.08)	(0.08)	(0.08)	(0.07)
	$\hat{\phi}$	0.64***	0.33***	0.57***	0.71**
		(0.24)	(0.08)	(0.15)	(0.30)
	$\hat{\sigma}^b$	2.79***	4.66***	3.39***	2.63***
		(0.09)	(0.11)	(0.08)	(0.07)
Parameters of the	$\hat{\tau}$	0.55	-1.08	2.49	-0.40
		(1.77)	(1.37)	(1.85)	(0.79)
low-price process	$\hat{\mu}^l$	2.54***	2.63***	2.43***	1.97***
		(0.15)	(0.12)	(0.20)	(0.13)
	$\hat{\sigma}^l$	0.53***	0.66***	0.62***	0.63***
		(0.07)	(0.07)	(0.11)	(0.07)
Parameters of the	$\hat{a}^b$	-7.91***	-10.77***	-15.69***	-16.38***
		(1.26)	(1.88)	(2.77)	(2.47)
switching probabilities	$\hat{a}^l$	11.11***	11.27***	4.78*	11.93***
		(1.96)	(3.41)	(2.81)	(3.01)
	$\hat{b}^b$	4.08***	5.17***	6.08***	6.05***
		(0.47)	(0.67)	(0.88)	(0.80)
	$\hat{b}^l$	-3.72***	-4.66***	-3.45***	-3.73***
		(0.55)	(1.02)	(1.15)	(0.75)
	$\hat{c}^b$	-0.46***	-0.53***	-0.45***	-0.42***
		(0.07)	(0.09)	(0.10)	(0.08)
	$\hat{c}^l$	0.28***	0.45**	0.57**	0.32***
		(0.08)	(1.18)	(0.26)	(0.11)
Log-likelihood		3,099.53	3,428.68	3,024.65	2,827.48
n		1,096	1,096	1,096	1,096

*Notes: Asymp. standard errors in parantheses. *, **,*** denote significance at the 10%, 5%, 1% level.*

C. Regime classifications (trading hour 7)

Figure C.1: Classifications of day-ahead prices into the base and low-price regime



Notes: The lower panel gives the smoothed probabilities that the respective observations belong to the low-price regime, $P(s_t = l)$. Observations with probabilities $P(s_t = l) > 0.5$ are displayed as triangles. The upper panel displays the time series of day-ahead prices and highlights observations that are classified into the low-price regime by triangles. The classifications work fairly well, as most observations have state probabilities close to zero or one and can thus be clearly attributed to one of the two regimes.

D. Detailed simulation results

Table D.1: Comprehensive Simulation Results for Hard Coal-Fired Plants (1970 Technology)

	Hard Coal-Fired Plants (1970): Prices < Variable Cost									
	Hour 1	Hour 2	Hour 3	Hour 4	Hour 5	Hour 6	Hour 7	Hour 24	Off-peak index	∅ off-peak
0% renew. share	50%	66%	76%	82%	83%	70%	35%	37%	43%	62%
Baseline (actual data)	86%	94%	97%	98%	98%	95%	66%	75%	81%	89%
Baseline; no moratorium	92%	97%	98%	99%	99%	97%	73%	84%	90%	92%
35% renew. share	91%	96%	98%	99%	99%	97%	76%	83%	88%	92%
50% renew. share	94%	97%	99%	99%	99%	98%	82%	87%	92%	94%
65% renew. share	95%	98%	99%	99%	99%	99%	86%	90%	95%	96%
80% renew. share	96%	99%	99%	100%	100%	99%	89%	93%	96%	97%
80% renew.; no moratorium	95%	98%	99%	99%	99%	98%	85%	90%	96%	95%
Adaptation strategies under an 80% renewables share										
1 GW storage	96%	98%	99%	99%	99%	99%	87%	91%	95%	96%
5 GW storage	91%	96%	97%	98%	98%	97%	79%	85%	90%	93%
10 GW storage	84%	90%	93%	95%	95%	91%	67%	76%	80%	86%
20 GW storage	60%	68%	73%	77%	81%	70%	42%	52%	51%	65%
0% nuclear	79%	89%	91%	88%	93%	94%	71%	72%	69%	85%

Notes: The table gives the share of trading hours when prices are below variable cost of hard coal-fired power plants (with 1970 technology). ∅ off-peak *presents the average share for all off-peak trading hours that are analyzed (1 to 7 and 24). Values represent means over 1,000 simulations.*

Table D.2: Comprehensive Simulation Results for Hard Coal-Fired Plants (2010 Technology)

	Hard Coal-Fired Plants (2010): Prices < Variable Cost									
	Hour 1	Hour 2	Hour 3	Hour 4	Hour 5	Hour 6	Hour 7	Hour 24	Off-peak index	∅ off-peak
0% renew. share	6%	13%	23%	37%	36%	19%	11%	2%	5%	18%
Baseline (actual data)	23%	37%	50%	63%	62%	42%	23%	10%	21%	39%
Baseline; no moratorium	38%	55%	67%	79%	77%	55%	30%	19%	36%	52%
35% renew. share	41%	55%	66%	75%	75%	58%	34%	25%	40%	54%
50% renew. share	55%	67%	76%	83%	83%	69%	44%	38%	55%	64%
65% renew. share	65%	75%	82%	87%	87%	77%	54%	49%	67%	72%
80% renew. share	72%	81%	86%	90%	90%	82%	61%	57%	75%	77%
80% renew.; no moratorium	80%	88%	92%	95%	95%	87%	67%	67%	83%	84%
Adaptation strategies under an 80% renewables share										
1 GW storage	69%	77%	84%	88%	88%	79%	58%	54%	71%	75%
5 GW storage	55%	64%	71%	78%	78%	66%	48%	42%	56%	63%
10 GW storage	40%	47%	55%	63%	62%	50%	36%	30%	40%	48%
20 GW storage	21%	25%	29%	34%	34%	26%	19%	15%	19%	25%
0% nuclear	36%	43%	49%	48%	53%	53%	37%	26%	34%	43%

Notes: The table gives the share of trading hours when prices are below variable cost of hard coal-fired power plants (with 2010 technology). ∅ off-peak *presents the average share for all off-peak trading hours that are analyzed (1 to 7 and 24). Values represent means over 1,000 simulations.*

Table D.3: Comprehensive Simulation Results for Lignite-Fired Plants (1970 Technology)

	Lignite-Fired Plants (1970): Prices < Variable Cost									
	Hour 1	Hour 2	Hour 3	Hour 4	Hour 5	Hour 6	Hour 7	Hour 24	Off-peak index	∅ off-peak
0% renew. share	2%	6%	10%	18%	17%	8%	6%	1%	2%	9%
Baseline (actual data)	12%	21%	30%	41%	40%	26%	16%	5%	11%	24%
Baseline; no moratorium	20%	37%	49%	62%	59%	38%	23%	8%	18%	37%
35% renew. share	27%	39%	49%	58%	57%	43%	26%	15%	25%	39%
50% renew. share	41%	53%	62%	69%	69%	56%	37%	26%	39%	52%
65% renew. share	51%	63%	71%	77%	76%	65%	46%	36%	51%	61%
80% renew. share	59%	71%	77%	82%	82%	72%	54%	44%	60%	68%
80% renew.; no moratorium	68%	81%	85%	90%	89%	79%	61%	52%	71%	76%
Adaptation strategies under an 80% renewables share										
1 GW storage	56%	67%	74%	79%	79%	69%	51%	42%	57%	65%
5 GW storage	44%	53%	60%	66%	66%	56%	41%	32%	44%	52%
10 GW storage	32%	39%	44%	50%	49%	41%	30%	23%	30%	39%
20 GW storage	16%	20%	23%	26%	26%	21%	16%	11%	14%	20%
0% nuclear	28%	34%	38%	37%	41%	40%	29%	19%	25%	33%

Notes: The table gives the share of trading hours when prices are below variable cost of modern lignite-fired power plants (with 1970 technology). ∅ off-peak *presents the average share for all off-peak trading hours that are analyzed (1 to 7 and 24). Values represent means over 1,000 simulations.*

Table D.4: Comprehensive Simulation Results for Lignite-Fired Plants (2010 Technology)

	Lignite-Fired Plants (2010): Prices < Variable Cost									
	Hour 1	Hour 2	Hour 3	Hour 4	Hour 5	Hour 6	Hour 7	Hour 24	Off-peak index	∅ off-peak
0% renew. share	0%	1%	2%	3%	3%	2%	2%	0%	0%	2%
Baseline (actual data)	3%	7%	11%	15%	14%	9%	8%	1%	2%	8%
Baseline; no moratorium	5%	12%	19%	28%	23%	14%	13%	2%	3%	15%
35% renew. share	10%	18%	25%	31%	28%	21%	17%	5%	7%	19%
50% renew. share	18%	30%	39%	45%	40%	33%	26%	10%	15%	30%
65% renew. share	26%	40%	49%	55%	50%	43%	35%	15%	23%	39%
80% renew. share	33%	48%	57%	63%	58%	51%	43%	21%	32%	47%
80% renew.; no moratorium	39%	56%	66%	75%	67%	57%	49%	25%	38%	54%
Adaptation strategies under an 80% renewables share										
1 GW storage	31%	45%	54%	60%	55%	48%	41%	20%	29%	44%
5 GW storage	24%	35%	42%	47%	43%	38%	32%	15%	22%	35%
10 GW storage	17%	25%	30%	34%	31%	27%	23%	10%	15%	25%
20 GW storage	8%	12%	15%	17%	16%	13%	12%	5%	7%	12%
0% nuclear	13%	21%	25%	24%	24%	25%	21%	7%	10%	20%

Notes: The table gives the share of trading hours when prices are below variable cost of modern lignite-fired power plants (with 2010 technology). ∅ off-peak *presents the average share for all off-peak trading hours that are analyzed (1 to 7 and 24). Values represent means over 1,000 simulations.*

References

Andor, M., Flinkerbusch, K., Janssen, M., Libeau, B., Wobben, M., 2010. Negative Strompreise und der Vorrang Erneuerbarer Energien. Zeitschrift für Energiewirtschaft 34, 91–99.

Andor, M., Voss, A., 2016. Optimal Renewable-Energy Promotion: Capacity Subsidies vs. Generation Subsidies. Resource and Energy Economics 45, 144–158.

Bierbrauer, M., Menn, C., Rachev, S. T., Trück, S., 2007. Spot and Derivative Pricing in the EEX Power Market. Journal of Banking & Finance 31 (11), 3462–3485.

BKartA, 2011. Sektoruntersuchung Stromerzeugung Großhandel. Bundeskartellamt. URL http://www.bundeskartellamt.de

BNetzA, 2016. Kraftwerksliste. Bundesnetzagentur. URL http://www.bundesnetzagentur.de

BRD, 2010. Energiekonzept. Bundesregierung. URL http://www.bmu.de/files/pdfs/allgemein/application/pdf/energiekonzept_bundesregierung.pdf

Diebold, F. X., Lee, J.-H., Weinbach, G., 1994. Regime Switching with Time-Varying Transition Probabilities. In: C. Hargreaves (Ed.), Nonstationary Time Series Analysis and Cointegration. Oxford University Press, pp. 283–302.

Dunn, B., Kamath, H., Tarascon, J.-M., 2011. Electrical Energy Storage for the Grid: A Battery of Choices. Science 334 (6058), 928–935.

Ethier, R., Mount, T. D., 1998. Estimating the Volatility of Spot Prices in Restructured Electricity Markets and the Implications for Option Values. PSERC working paper series 31. URL http://www.pserc.wisc.edu/documents/publications/papers/1998_general_publications/pserc_31.pdf

Hamilton, J. D., 1994. Time Series Analysis. Cambridge University Press, Cambridge.

Higgs, H., Worthington, A., 2008. Stochastic Price Modeling of High Volatility, Mean-Reverting, Spike-Prone Commodities: The Australian Wholesale Spot Electricity Market. Energy Economics 30 (6), 3172–3185.

Huisman, R., 2008. The Influence of Temperature on Spike Probability in Day-Ahead Power Prices. Energy Economics 30 (5), 2697–2704.

Huisman, R., Huurman, C., Mahieu, R., 2007. Hourly Electricity Prices in Day-Ahead Markets. Energy Economics 29 (2), 240–248.

Huisman, R., Jong, C. d., 2003. Option Pricing for Power Prices with Spikes. Energy & Power Risk Management 7 (11), 12–16.

Huisman, R., Mahieu, R., 2003. Regime Jumps in Electricity Prices. Energy Economics 25 (5), 425–434.

IFEU, 2007. Das Steinkohle-Kraftwerk Hamburg Moorburg und seine Alternativen. Institut für Energie- und Umweltforschung.
URL `http://www.ifeu.de`

Janczura, J., Weron, R., 2010. An Empirical Comparison of Alternate Regime-Switching Models for Electricity Spot Prices. Energy Economics 32 (5), 1059–1073.

Janczura, J., Weron, R., 2011. Efficient Estimation of Markov Regime-Switching Models: An Application to Electricity Spot Prices. Advances in Statistical Analysis 96 (3), 385–407.

Jeon, W., Lamadrid, A., Mo, J., Mount, T., 2015. Using Deferrable Demand in a Smart Grid to Reduce the Cost of Electricity for Customers. Journal of Regulatory Economics 47 (3), 239–272.

Jong, C. d., 2006. The Nature of Power Spikes: A Regime-Switch Approach. Studies in Nonlinear Dynamics and Econometrics 10 (3), 1–28.

Kim, C.-J., 1994. Dynamic Linear Models with Markov-Switching. Journal of Econometrics 60 (1-2), 1–22.

Klaus, T., Loreck, C., Müschen, K., 2009. Klimaschutz und Versorgungssicherheit: Entwicklung einer nachhaltigen Stromversorgung. Climate Change 9 (13), 1–94.

Knittel, C. R., Roberts, M. R., 2005. An Empirical Examination of Restructured Electricity Prices. Energy Economics 27 (5), 791–817.

Kosater, P., Mosler, K., 2006. Can Markov Regime-Switching Models Improve Power-Price Forecasts? Evidence from German Daily Power Prices. Applied Energy 83 (9), 943–958.

Mount, T. D., Maneevitjit, S., Lamadrid, A. J., Zimmerman, R. D., Thomas, R. J., 2012. The Hidden System Costs of Wind Generation in a Deregulated Electricity Market. Energy Journal 33 (1), 161–186.

Mount, T. D., Ning, Y., Cai, X., 2006. Predicting Price Spikes in Electricity Markets Using a Regime-Switching Model with Time-Varying Parameters. Energy Economics 28 (1), 62–80.

Nicolosi, M., 2010. Wind Power Integration and Power System Flexibility - An Empirical Analysis of Extreme Events in Germany under the New Negative Price Regime. Energy Policy 38 (11), 7257–7268.

Weron, R., 2009. Heavy-Tails and Regime-Switching in Electricity Prices. Mathematical Methods of Operations Research 69 (3), 457–473.

Weron, R., Bierbrauer, M., Trück, S., 2004. Modeling Electricity Prices: Jump Diffusion and Regime Switching. Physica A 336 (1/2), 39.

Zachmann, G., 2013. A Stochastic Fuel Switching Model for Electricity Prices. Energy Economics 35, 5–13.