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A Markov Switching Model of the Merit Order to Compare British and German Price Formation[1]

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Abstract

The objective of this paper is to develop a model to determine the price formation of wholesale electricity markets. For that purpose, we model wholesale electricity prices depending on the prices of fuels (coal and natural gas) and of CO2 emission allowances using a Markov Switching Regression. We apply the model to wholesale electricity prices in the UK and in Germany. While British electricity prices are quite well explained by short-run cost factors, we find a decoupling between electricity prices and fuel costs in Germany. This may be evidence that the German electricity generation sector does not work competitively.

Keywords: Electricity Prices, Markov Switching Models

JEL classification: L94, C22, D43

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1 Introduction

Electricity markets differ from other commodity markets in various respects. Demand for electricity is inelastic in the short term, storing it is expensive, parts of the value chain exhibit characteristics of natural monopolies and reliable electricity supply has high macroeconomic importance. In the potentially competitive wholesale sector, remaining vertical and horizontal integration as well as the widespread existence of national incumbents are often providing significant market power. Whether this market power is actually exercised in one market or the other is an open issue. To detect strategic behaviour it would be desirable to compare the cost curves for each market participant to its actual bids. But the true cost functions are private information. In addition, individual bid curves are unavailable for scientific inquiries in many markets.

Nevertheless to enquire whether wholesale electricity markets determine justifiable prices, various indirect approaches have been proposed. Analyzing bidding data of electricity auctions, Hortacsu and Puller (2004), Wolfram (1998) and Sweeting (2004) are able to provide evidence for strategic bidding. Sweeting (2004) finds that bidding behaviour became consistent with tacit collusion after 1995-96 in the English and Welch wholesale market. Studying the bidding behaviour of National Power and PowerGen in the English and Welch market, Wolfram (1998) provides evidence for strategic bidding. And Hortacsu and Puller (2005) compares firm-level marginal cost and bids in the Texas electricity spot market, finding that smaller firms especially were bidding strategically. Wolfram (1999) estimates the price-cost margin in the British market, finding that the strictly positive margins were lower than implied by theoretical models, which she explained by regulation, threat of entry and supplier-customer relations. Finally, Müsgens (2006), Schwarz and Lang (2006) and Hirschhausen et al. (2007) simulate the marginal cost of the German electricity system and compare those to the actual prices. All three studies find that prices decoupled from short-run marginal cost. The simulations of electricity generation cost are based on extensive models of the German market using large-scale power plant databases. Essentially, the models optimize the German system with respect to the actual demand. The marginal costs of the last required generator set the marginal cost of the entire system. Despite the accurate representation of the markets Swider et al. (2007) challenge the validity of the marginal-cost simulation results as substantial uncertainties arise from the lack of data and simplifying assumptions. In this paper we propose a different approach. Instead of calculating the absolute deviation of the electricity price from the respective generation cost, our goal is to obtain a relative indicator for the cost-reflectiveness of national electricity prices. Therefore, we first set up a stylized model of the marginal electricity generation cost. In a second step, the model is estimated over time assuming that prices equal marginal cost. Finally, the coefficients and the residuals of the estimation are compared across countries to assess where and when prices are best explained by their fundamentals. Thus, the model should also be able to identify deviations from competitive price setting. The paper is structured in the following way: the next section introduces some stylized facts on the countries to which we apply the model: the UK and Germany. Section 3 presents the model. Section 4 presents the results and an interpretation and section 5 concludes.

2 Data

The analysis is carried out to compare the price formation in the UK and German electricity market. In terms of size, the German is comparable to the UK electricity system (see Table 1). Conventional thermal power plants account for most of the electricity generation in both countries (65% in Germany and 77% in the UK). One obvious difference between both systems is that the UK does not use lignite for which it compensates by an increased share of natural gas. Market structure and design in both countries differ markedly. Whereas the UK has two decades of experience with market opening and regulation, Germany has addressed sector reforms only in the first part of this decade, and a regulator was set up in mid-2005. The four privately owned transmission system operators in Germany have significant stakes in generation (together 80% of total capacity) and distribution. The integration of the two major German players - E.on and RWE - with their natural gas affiliates further increases their dominating position. In the UK the situation is more balanced. The transmission system operator is unbundled and regulation is effective. The nine biggest generation companies together own only 68% of the capacities. Although these are integrated with electricity and gas suppliers, none of them has a position comparable to the "big four" in Germany.

Table 1: Gross electricity generation (2005)

	Germany	UK
Hydro power plants	4 %	2 %
Nuclear power plants	26 %	20 %
Coal-fired power stations	21 %	34 %
Lignite-fired power stations	23 %	
Natural gas-fired power stations	11 %	38 %
Others	15 %	6 %
Annual gross electricity generation in TWh	**620**	**401**
Source: Eurostat		

Both wholesale markets are particularly suited to be analyzed using the model described in the next section as: *First*, neither of these markets is endowed with significant hydro power capacity. This is an advantage since the model is unable to reproduce the dynamic opportunity cost assessment required for analyzing the marginal cost of a hydro power plant. *And second*, both countries feature electricity wholesale markets that provide reference prices.

Hourly spot electricity prices for Germany are obtained from the European Energy Exchange in Leipzig (EEX). There prices are formed by day-ahead two-side one-shot sealed-bid uniform-price auctions. UK half-hourly spot prices at the UKPX, by contrast, are obtained in 48 hour continuous trading until a half hour ahead of delivery.

Table 2: Summary of the data sample (February 2002 to December 2006)

		Germany			United Kingdom		
		Source	Mean	Variance	Source	Mean	Variance
Electricity off-peak	€/MWh_{el}	EEX	29.5	160	UKPX	31.4	220
Electricity peak	€/MWh_{el}	EEX	48.3	839	UKPX	44.9	764
Gas spot price	€/MWh_{th}	TTF (NL)	13.5	26	NBP	14.1	70
Coal spot price	€/MWh_{th}	ARA	5.8	1	ARA	5.8	1
Emission allowance	€/tCO_2	EEX	6.8	90	EEX	6.8	90

Because the model (described in the next section) is only meaningful in the short and medium run, daily price notations are used for all commodities. As no daily German gas and coal prices are available for the entire sample, the respective values of the Dutch markets for natural gas (TTF) and coal (ARA) were selected.[3] The sample contains data from February 2002 to December 2006. Because gas and coal prices are only available for working days, week-ends and holidays are omitted from the sample.[4] The fuel prices are converted into €/MWh_{th} to ease the interpretation. The respective data sources for the three commodities for Germany and the UK are summarized in Table 2.

Figure 2 depicts the series of spot prices. Peak and off-peak electricity prices approximately doubled between 2002 and 2006. Gas prices also doubled, whereas coal prices reached their initial level at the end of 2006.[5] Emission allowance prices increased from 10 € to 30 € to fall back to 10 €.

Figure 1: Development of the spot price series 2002-2006 (in €/MWh)

3 Model

In contrast to other homogenous goods, electricity can be generated by a set of different production technologies with very different marginal cost. The non-storability of electricity allows that large nuclear power plants with low variable costs, coal-fired generators with medium variable costs, and

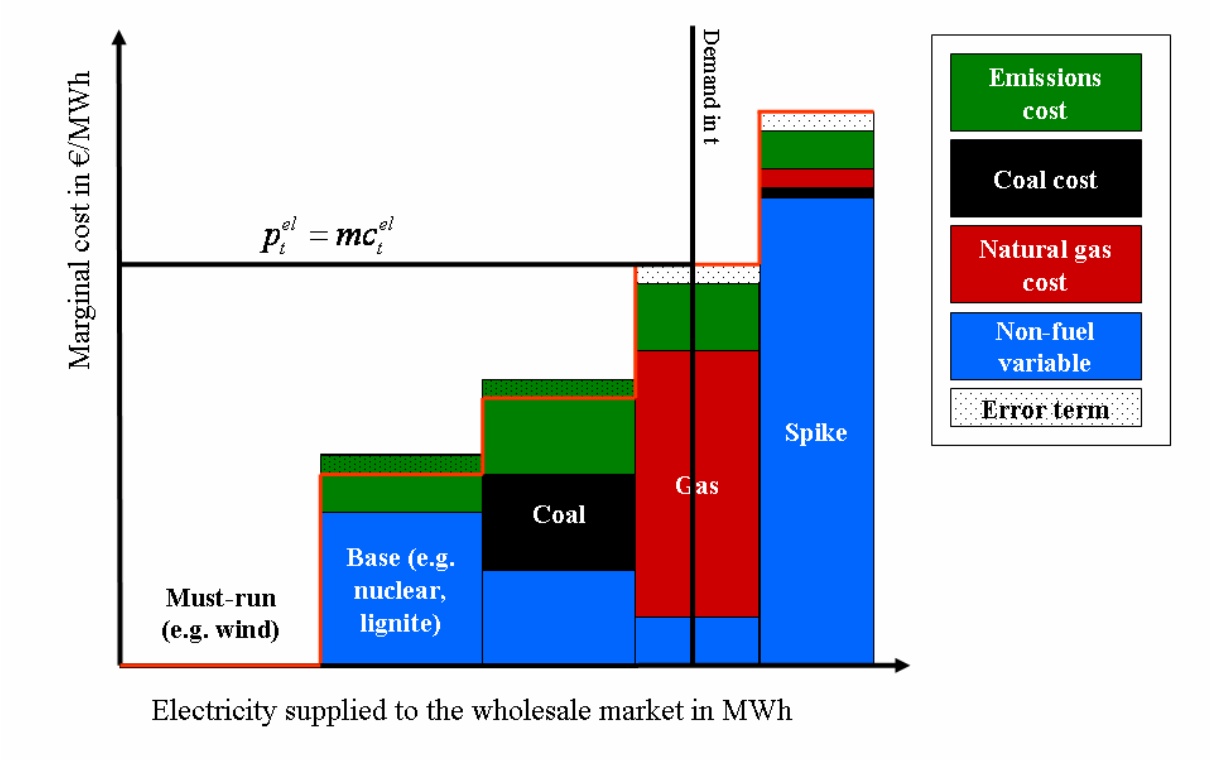
[3] It should be noted, that gas and especially coal prices in Germany should exceed Dutch fuel prices by some constant because of transportation cost.

[4] This has the positive side effect of reducing weekly seasonalities significantly.

[5] Datastream derives the daily coal price notations by converting the monthly coal prices in dollar into euro using the daily exchange rate. Thus, the increasing dollar-euro exchange rate limited the effect of rising coal prices for European coal consumers.

small gas turbines with high variable costs coexist. Because the differences of marginal costs of power plants of the same technology are small compared to the cost difference between dissimilar technologies, the marginal cost curve of the entire electricity system can be approximated by a stepwise function (see Figure 1).[6]

Figure 2: Stylized example of the stepwise marginal cost function



Based on this assumption, one can model the electricity price at time *t* as the marginal cost of the last required technology to meet the demand. In the short run the costs of a power plant should be highly correlated with its fuel and emission costs. Since the fuel efficiency of technologies changes rather slowly, fuel and emission costs are predominantly determined by the respective prices. Thus, a time series model that endogenously infers the cost structures of each class of power plants and that deduces which class is marginal at each point in time can be set up using fuel, emission and electricity prices as only input. Generally the model consists of two procedures: a routine that decides which class of power plants sets the price (i.e., is marginal) and a mechanism that reproduces the electricity price formation for each class.

For each technology $S_t=1,\ldots,m$ we assume the marginal costs at time $t \in 1\ldots T$ to be the sum of a weighted linear combination of the k explanatory variables $\beta(S_t) \times X_t$ and a stochastic component $\varepsilon_t(S_t)$. The set of explanatory variables stored in the k columns of the matrix X might contain for example a constant, a time trend, different dummy variables as well as gas, oil, coal and emission certificate prices.

[6] Typical non-dispatchable must-run generation are wind, run-of-river hydro and combined heat and power plants (in winter).

Thus, depending on the chosen explanatory variables and the technologies the model can be written as:

$$p_{el,t} = \begin{cases} \beta_1 \times X_t + \varepsilon_{t,1} & S_t = 1 \\ \beta_2 \times X_t + \varepsilon_{t,2} & S_t = 2 \\ \vdots & \\ \beta_m \times X_t + \varepsilon_{t,m} & S_t = m \end{cases} \tag{1}$$

When the process that determines the marginal technology at time *t* is assumed to be Markovian[7], (1) can be estimated using a Markov Switching Regression. To do this, the model has to be converted into state space form with the states (or regimes) of the model representing the different technologies. To make the model computable, the Markovian Process is specified as $P(S_t = i \mid S_{t-1} = j) = p_{i,j}$, i.e. with time invariant exogenous switching probabilities.[8] Thus the model is fully described by

$$p_{el,t} = \beta_{S_t} \times X_t + \varepsilon_{t,S_t}, \quad \forall \quad S_t = 1...m \tag{2}$$

$$P(S_t = i \mid S_{t-1} = j) = p_{i,j}, \quad \forall \quad i, j \leq m \tag{3}$$

where X_t is the ($k \times T$) matrix of explanatory variables, β_{S_T} is the state dependent ($1 \times k$) row vector ($\beta_{S_t,1}, \beta_{S_t,2}, ...\beta_{S_t,n}$), and P is a ($m \times m$) matrix containing the probability to switch from state *i* to state *j*.

The presented stylized merit order (see Figure 1) implies that only four types of power plants with different cost structures exist.[9] The marginal cost for each of these technologies only depends on its fuel consumption, emissions and non-fuel variable costs. As the marginal cost of coal power plants should not depend on the gas price certain zero restrictions on β_{S_T} can be imposed. The interpretation of the remaining coefficients is then straightforward: The constant represents the non-fuel variable cost of this type of power plants. The fuel coefficient for the used fuel is the inverse of the heat rate of this type of power plants (when electricity price and fuel price are both measured in the same unit, i.e. €/MWh). And the coefficient for the emission certificate prices represents the amount of emissions per unit of electricity.[10] An issue which we do not address in this context is the endogeneity problem. That is, we ignore that gas and emission allowance prices also depend on electricity prices. This has been kept in mind for the interpretation of the results.

In our non-linear model it is difficult to deduce theoretically the distribution of the parameters conditioned on the data. This challenge can be addressed by using the Gibbs sampling technique.[11] The idea is to repeatedly draw each parameter conditioning on the data and all other parameters. This procedure is iterated a large number of times, always conditioning on the latest draws of the other

[7] A Markovian process is characterized by the fact that each observation only depends on the last period realization.

[8] Including demand and weather conditions into the switching probabilities could improve the estimation and modelling switching cost as threshold variables in the state-equation might make the estimates even more realistic. The probably tricky implementation is, however, left to further research.

[9] Must-run generation like wind and run-of-river hydro are not considered as they can be considered as a reduction of net electricity demand.

[10] The units match accordingly: $€/MWh_{el} = €/MWh_{el} + MWh_{el}/MWh_{th} \times €/MWh_{th} + tCO_2/MWh_{el} \times €/tCO_2$

[11] See Krolzig (1997).

parameters. To estimate (2) and (3) via Gibbs sampling, the density function of the model can be separated as:

$$g\left(S_{1:T},\beta_{S_t},\Sigma_{S_t},P \mid y_{1:T},X_{1:T}\right)=g\left(\beta_{S_t},\Sigma_{S_t} \mid y_{1:T},X_{1:T},S_{1:T}\right)g\left(P \mid S_{1:T}\right)g\left(S_{1:T} \mid y_{1:T},X_{1:T}\right) \quad (4)$$

Therefore one proceeds in four steps:

1 Deduce $g\left(S_{1:T} \mid y_{1:T},X_{1:T}\right)$ from $g\left(S_T \mid y_{1:T},X_{1:T}\right)$ and $g\left(S_t \mid S_{t+1},y_{1:t},X_{1:T}\right)$ by backward iteration. Thereby $g\left(S_t \mid S_{t+1},y_{1:t},X_{1:T}\right)$ is calculated from $g\left(S_t \mid y_{1:t},X_{1:T}\right)$ which is obtained by the Hamilton filter.

2 Draw the beta-distributed switching probabilities P given $S_{1:T}$.

3 Draw the β_{S_T} given $y_{1:T}$, $X_{1:T}$, $S_{1:T}$ and Σ_{S_T}.

4 Draw the Σ_{S_T} given β_{S_T}, $S_{1:T}$ $y_{1:T}$ and $X_{1:T}$.

A detailed description of the four steps can be found in Schweri (2004) who also provides the corresponding Matlab code.

4 Results

4.1 Estimation Results

To estimate (2) & (3) a sensible choice of the dependent variable i.e., the electricity price series is crucial. As demand is highly volatile throughout the day one could expect that up to five regime switches (nuclear->coal->gas->coal->nuclear) occur every day. Therefore, using a continuous hour-by-hour series is inadequate because regime persistency (P(i,i)>>P(i,j)) is decisive for stable estimates. A better choice is to separate the continuous series into 24 day-by-day series each of which represents one hour of the day. However, estimating (2) & (3) for 24 (or even 48) series is impractical especially because some of those series are very similar (e.g. 3rd and 4th hour data) and the estimation procedure is computationally burdensome. Reducing the number of series to two while keeping most information is attained by drawing on a weighted average of peak (8am-8pm) and off-peak (8pm-8am) electricity prices. The optimal weighting vector (in terms of variance explained) is obtained by principle component analysis.[12] Further on, dates with electricity prices above 200€/MWh are excluded as extreme price-spikes would possibly distort the analysis and cannot be explained by fuel cost fundamentals.[13]

We estimate (2) & (3) for the off-peak and peak series for the German (EEX) and the British (UKPX) market. In all four cases (EEX off-peak, EEX peak, UKPX off-peak and UKPX peak) we apply a model in which spot electricity prices are explained by spot gas prices, spot coal prices and the

[12] For details see Härdle and Simar (2003).
[13] Even burning expensive oil (50€/barrel) in an inefficient generator (heat rate of 20%) would only justify marginal cost of ~ 150€/MWh_{el} (0.625 barrel/MWh_{th} x 5 MWh_{th}/MWh_{el} x 50 €/barrel). For the modelling of electricity price spikes see Lang and Schwarz (2007).

respective emission allowance price. Oil prices and a trend are omitted after initial estimations suggested that they are not significant for any state. Variance and all β coefficients are selected to be state dependent.[14] To capture the effect that switching from one marginal technology to another only occurs when demand or supply conditions change significantly some persistency was predefined.[15]

Choosing the number of states is driven by three considerations: goodness-of-fit, interpretability with respect to the stylized merit order and comparability. The goodness-of-fit is measured in terms of the Schwartz information criterion (BIC). The BIC suggests that, depending on the case, either three or four regimes are appropriate. [16] The assumed stylized merit order suggests, that there are three regimes in off-peak (base, coal, gas) and three regimes in peak (coal, gas, spike). For ease of presentation and to obtain results that are comparable the paper thus focuses on the three state specification. Using informative priors it is possible to induce model outcomes that are plausible with respect to the stylized merit order. In all four cases (EEX off-peak, EEX peak, UKPX off-peak and UKPX peak) certain coefficients are constrained to zero by applying tight prior distributions with mean zero.[17]

Setting the mean and variance priors for the coefficients as well as the starting values according to Table 6 the model is estimated using the described procedure.[18] This selection induces that in each case three technology regimes (in off-peak: base, coal and gas; in peak: coal, gas and spike) exist that can be clearly distinguished. The coal and gas price coefficient priors, for example, imply that each fuel is only significant in the corresponding regime.

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[14] Note that state dependent variance is straightforward since high electricity price regimes are characterized by higher variance.

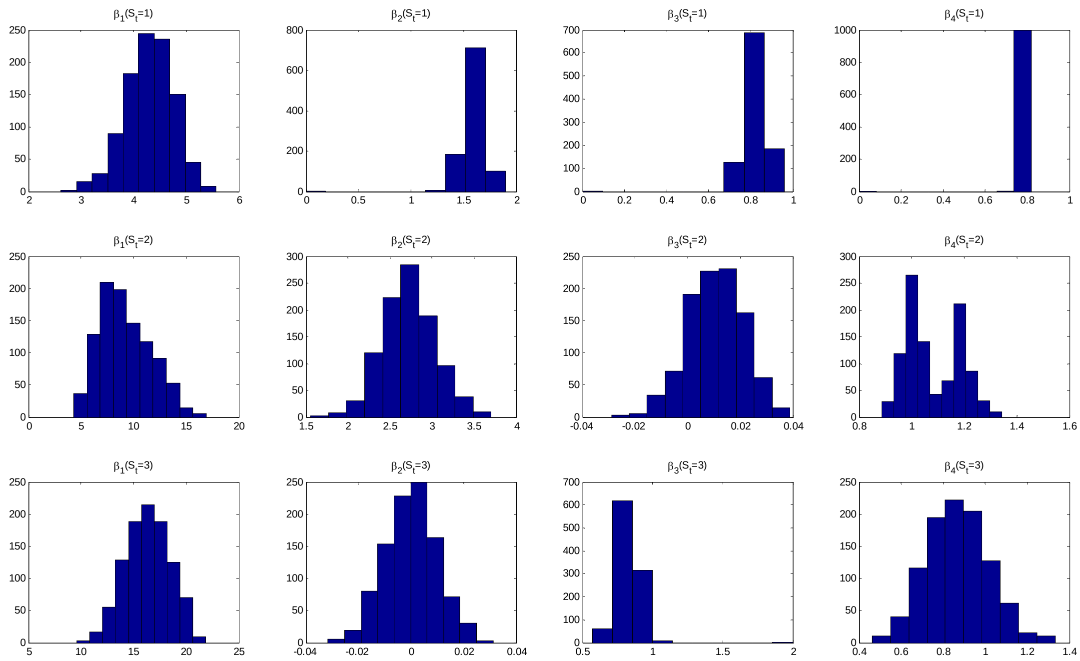
[15] The probability to remain in the current state was set to 0.67 whereas the probability to switch to each other state was adjusted to 0.16. Giving the prior a modest variance of approximately 0.1, this implies that the beta-distribution of the p_{ij} -values is set to $u_1 = 2$ and $u_2 = 1$ on the main diagonal and $u_1 = 1$ and $u_2 = 6$ beyond the main diagonal.

[16] The BIC has been calculated for each case for one to four regimes using a model specification with non-informative priors for the entire sample. While for the UK off-peak case the BIC favours a three-regime specifications, a four-regime specification is preferred for all other cases. This reflects the higher diversity of the German off-peak generation structure and should be kept in mind for the interpretation.

[17] In each of the steps the posterior distribution $p(\theta|y)$ is given by the likelihood function $L(\theta|y)$ times the prior distribution $g(\theta)$: $p(\theta|y)= g(\theta) \times L(\theta|y)$.

[18] Due to the identification restriction the sorting of the no-fuel state has been crucial. Setting it as the first state implied it to have the lowest constant of all states and thus resulted in a ”baseload state”.

Figure 3: Coefficient densities for the UK off-peak case (informative priors)



The estimation results (see Table 3) indicate a good fit of the model and the estimated regime characteristics allow for a straightforward interpretation: *First*, each state can meaningfully be attributed to a unique technology. *Second*, the average electricity prices in each regime are sorted according to the presented stylized merit order. *Third*, the estimated parameters are in an intuitive order of magnitude. In all four cases the coal coefficient in the coal state is always bigger than the gas coefficient in the gas state, and the emissions allowance price has a stronger influence on the coal then on the gas state. And *fourth*, almost all coefficient densities have a single maximum and are approximately normally distributed. This is illustrated at the UK off-peak example in Figure 3 where only the emission allowance coefficient has two maxima.[19] This indicates that the model is generally well specified but that potentially two different coal states (e.g., “new” and “old”) with different emission intensity might exist.

Each of the four technology regimes (“base”, “coal”, “gas” and “spike”) features unique characteristics: In the **base regime** electricity prices modestly depends on both fuel prices and emission allowance prices. Whether the gas and coal price dependence can be explained by ramping and balancing cost that enter the marginal cost of typical base-load power plants (nuclear, wind, lignite) or whether this is due to endogeneity (e.g., base-load electricity as substitute for coal and gas) cannot be decided. Interestingly the base state is the dominant state in the UK (80%) while it plays only a modest role in Germany (38%). The **coal states** in all four cases feature highly significant influences of coal prices (1.57-4.10), insignificant influence of gas prices and a highly significant influences of emission allowance prices (0.94-1.63). The average electricity prices in the coal state vary between around 40 in the UK off peak and 30 in all other cases. In the **gas state** all but the coal price coefficients are significantly positive. The gas price coefficients vary between 0.79 and 1.87, and the emission allowance price coefficients between 0.87 and 1.37. Finally the **spike state** is characterized by high prices, high variance and low frequency.

Table 3: Results of the Switching Regression with informative priors

	freq	$\beta_{Constant}$	β_{Coal}	β_{Gas}	β_{CO2}	Mean
Germany Peak (R^2=80%, F_{Stat}=-43.6)						
State1 ("Coal)	30%	**7.4** (+/-4.6)	**2.00** (+/-.92)	0.00 (+/-.02)	**1.63** (+/-.13)	33.42
State2 ("Gas")	57%	**14.7** (+/-3.5)	0.00 (+/-.02)	**1.87** (+/-.26)	**1.37** (+/-.14)	44.64
State3 ("Spike")	13%	**91.9** (+/-6.1)	-0.41 (+/-.61)	-0.18 (+/-.43)	**0.93** (+/-.43)	97.05
Germany Off-Peak (R^2=90%, F_{Stat}=39.5)						
State1 ("Base)	38%	**6.8** (+/-2.9)	**1.11** (+/-.43)	**0.35** (+/-.28)	**0.76** (+/-.13)	22.8
State2 ("Coal")	34%	**13.7** (+/-2.8)	**1.57** (+/-.54)	0.01 (+/-.02)	**0.94** (+/-.16)	29.52
State3 ("Gas")	28%	**19.8** (+/-1.9)	0.00 (+/-.02)	**0.71** (+/-.13)	**0.94** (+/-.11)	38.6
UK Peak (R^2=87%, F_{Stat}=66.0)						
State1 ("Coal)	37%	**2.6** (+/-1.5)	**4.10** (+/-.27)	0.01 (+/-.02)	**1.19** (+/-.07)	29.55
State2 ("Gas")	53%	**13.2** (+/-2.4)	0.00 (+/-.02)	**1.79** (+/-.20)	**0.87** (+/-.12)	45.12
State3 ("Spike")	10%	**89.2** (+/-6.2)	-0.59 (+/-.63)	**0.98** (+/-.30)	-0.30 (+/-.45)	103.64
UK Off-Peak (R^2=95%, F_{Stat}=-28.6)						
State1 ("Base)	80%	**4.3** (+/-.9)	**1.59** (+/-.17)	**0.82** (+/-.09)	**0.77** (+/-.03)	26.87
State2 ("Coal")	11%	**9.2** (+/-4.5)	**2.72** (+/-.62)	0.01 (+/-.02)	**1.08** (+/-.17)	39.37
State3 ("Gas")	9%	**16.4** (+/-4.0)	0.00 (+/-.02)	**0.83** (+/-.14)	**0.87** (+/-.28)	62.15

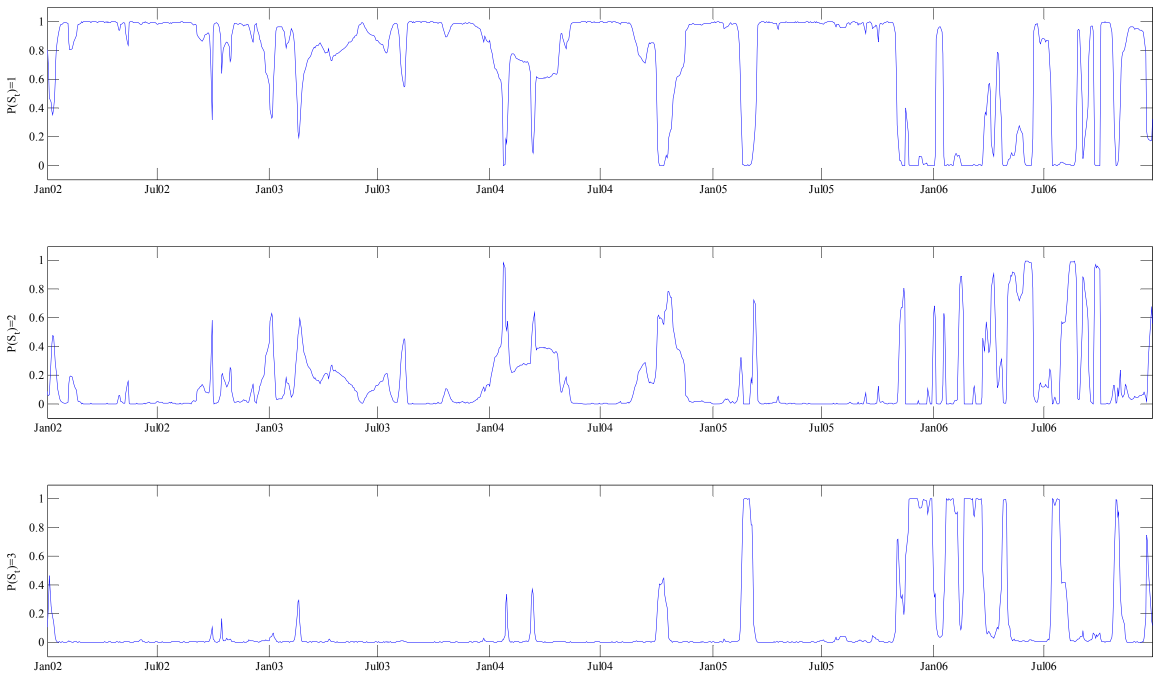
(+/-) = Half of the two-sided 95% confidence interval width. Bold coefficients are significantly different from zero.
F_{Stat}= the F statistic for the test of the null hypothesis of an unrestricted versus the alternative of a restricted model (6 restrictions). This statistic is purely illustrative as tight priors are no restrictions in the strict sense and the distribution of errors is autocorrelated and encompasses heteroskedastisity.

While the presented model outcomes fit well in the picture of the stylized merit order, also some reservations have to be made: *First*, it is difficult to explain that, despite the straightforward identification of technology regimes, the cost structures of the technologies are unstable across countries and load periods. In fact, the 95% confidence intervals for the same coefficient in the same regime do often not intersect. For example the confidence interval of the gas price coefficient in the gas regime for the German peak (1.87+/-.26) does not intersect with the same interval for the German off-peak (0.71+/-.13). *Second*, some coefficients are far off their expected values. For example the inverse heat rate of a gas fired power plant should be somewhere around 2.5 but the estimated values are significantly smaller. And *third*, the assumption of normality for the residuals has to be rejected for eight of the twelve cases at the five percent significance level (see Table 7).

[19] The results for all other cases are to be obtained from the author upon request.

These deviations of the estimation results from expectations might have two potential causes: Either, the model is misspecified with respect to the real marginal cost of electricity production, and/or, the underlying assumption that electricity prices are based on marginal cost is wrong. While the first explanation probably holds to some degree,[20] there are reasons to belief that the second cause is not implausible, neither. As the cost structure of a national power generation systems is rather stable, intertemporal and international comparison of the model outcomes allows tracking differences in the deviations of electricity prices from marginal cost.

Figure 4: Regime probabilities in for the UK off-peak case (informative priors)



4.2 Intertemporal and international comparison of price formation

The *first* fact that merits noting is that the "goodness of fit" of the model is better in the UK case in both load periods (see Table 4). Using the Kruskal-Wallis test this discovery is supported by finding that the median errors are significantly bigger in the German case. *Second*, the constant is smaller and the fuel price coefficients are generally bigger in the corresponding UK cases, indicating that fuel cost explain a higher proportion of the UK than of the German electricity prices. Furthermore, the coefficients variance is generally smaller in the UK.

Thus we find that in general the UK market is better captured by the regime switching model than the German market. The better performance of the proposed model for the UK might be explained by several features: *First*, electricity generation in the UK relies more on the two modelled fuels (34% of gas and coal in the German electricity production vs. 72% in the UK) and estimations suggest that

[20] One cannot expect that a stochastic model with a very parsimonious specification can completely track the marginal cost of a complex electricity system. Probably, increasing the number of technologies (i.e., states) and including more data (e.g.

more than the considered three technology-regimes might be present in the German market. *Second*, the UK natural gas market and the UK electricity market feature a stronger link via common demand drivers and substitution than the Dutch natural gas and the German electricity market.[21] *Third*, Germany is better integrated in the European electricity market than the UK leading to a stronger influence of foreign power and fuel prices that are not considered in the stylized model. *Fourth*, the UKPX price may include more information as the gate closure in the UK is only one hour ahead of schedule, compared to Germany where it is on the day before (12am for all hours). *Fifth*, the German electricity prices have to reflect the higher extra-costs for reliability under stochastic wind and heat guided combined heat and power (CHP) electricity production. *Sixth*, the start up cost and cost for reserve capacity are more important in an electricity system that is based to a larger degree on coal and lignite units. As those cost types are not considered in the model, the price-cost difference is potentially overestimated in the German market. And finally the British market is considered to be more competitive leading to more short-run cost dependent electricity prices.

Table 4: Goodness of fit (R^2) of the regime switching model with informative priors

	Germany	UK	KW ($\sum(\varepsilon_{t,GER})^2 > \sum(\varepsilon_{t,UK})^2$)
Peak	80%	87%	54.89***
Off-Peak	90%	95%	167.69***

The intertemporal comparison is also interesting. Estimating the model for two sub-samples 2002-2004 and 2005-2006 the constants rose significantly from the earlier to the later stage (Table 5). Consequently a significant proportion of the electricity price increases in both the UK and Germany were not driven by fuel and emission cost increases. This development can be attributed to two factors: First, it has been argued that in the sample period electricity pricing switched from over-capacity driven short-run marginal cost (SRMC) pricing after the liberalization to a less fuel cost dependent long-run marginal cost pricing. This switching has been attributed to the reduction of excess capacities in the process of liberalization. A second explanation might be that increasing concentration in the wholesale sector eased the exercise of market power to raise prices.

Table 5: Regime-dependent constant in the early (2002-04) and late (2005-06) sub-sample

	Germany Off-peak			Germany Peak			UK Off-peak			UK Peak		
State	1	2	3	1	2	3	1	2	3	1	2	3
2002-04	5.5	14.2	17.8	4.6	9.3	17.1	8	13.1	86.8	2	12.3	90.7
2005-06	11.6	13.6	19.8	11.3	13.9	17	7.4	15.4	101.5	5.6	10.9	96.3

demand) could improve the outcomes.

[21] Note, that also the feedback effects of the British electricity price on the British gas price might play a role. Knowing that the UK natural gas market is more mature and natural gas prices are less linked to the oil price than in Germany it could well be that endogeneity UK > endogeneity Germany.

In Figure 3 the marginal state for every point in time as estimated in the model with informative priors for the UK off-peak case is depicted: what is striking in this example is that the dominance of the base regime ceased in the second half of 2005 while the coal and gas regime gained importance. This structural change (that is to be found in all four cases) might have been due to a fuel switch caused by high emission certificate prices or lower base load generation margins produced by increasing base load demand and/or decreasing base load generation capacities.

5 Conclusion

The paper compares the wholesale price formation mechanism in the UK and Germany. Applying a Markov switching regression we provide evidence that the electricity wholesale prices in the UK are more closely related to the prices of coal, gas and emission allowances than their German counterparts. These differences in the German and British price formation mechanism shed light on the insufficient integration of these markets. In addition it is shown that the frequency at which high-price fuels became marginal increased in both countries. Given that demand did not increase significantly in the sample period, this can be interpreted as a leftward shift of the supply function, indicating a reduction of available cheap production capacities. Furthermore we provide evidence that non-fuel-based coefficients explain some of the electricity price increases. These findings are in line with conjectures that the initially strong link between short-run marginal cost and prices gradually vanished due to decreasing generation margins or increasing exercise of market power. Although, several extensions remain desirable the presented new approach to model electricity wholesale prices based on fuel and emission prices proved very powerful for understanding the nonlinear nature of electricity price formation.

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7 Appendix

Table 6: Prior mean (prior variance) and starting values of the model with informative priors

	Off-peak			Peak		
	Base	Coal	Natural Gas	Coal	Natural Gas	Spike
β_{const}	5 (10)	10 (10)	15 (10)	5 (10)	10 (10)	100 (10)
β_{coal}	0 (0.1)	3 (1)	0 (0.0001)	3 (1)	0 (0.0001)	0 (0. 1)
β_{gas}	0 (0.1)	0 (0.0001)	2 (1)	0 (0.0001)	2 (1)	0 (0. 1)
β_{C02}	0 (0.1)	1 (1)	1 (1)	1 (1)	1 (1)	0 (1)

Table 7: Jarque-Bera Test Statistics for the Normality of the Residuals

	State 1	State 2	State 3
German Peak	38.24^{**}	42.65^{*}	38.97^{**}
German Off-peak	44.83^{**}	$0.49^{[]}$	74.73^{**}
UK Peak	7.87^{**}	27.96^{*}	11.94^{**}
UK Off-peak	11.89^{**}	$1.89^{[]}$	4.73^{**}

*, **, *** the null hypothesis of residuals normality can be rejected at the 10%, 5%, 1% significance level. $^{[]}$ the null cannot be rejected at the 10% significance level.

Table 8: List of Abbreviations

EEX	European Energy Exchange or respectively the electricity spot price thereof
UKPX	UK Power Exchange or respectively the electricity spot price thereof