The Influence of Underlying Fossil Fuels on Forward Electricity Prices.

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Abstract A power producer can hedge the risk of selling an electricity forward contract by indirectly storing electricity through storing the underlying fossil fuels or through buying forward contracts of these fuels. In this way the relationship between the forward prices of electricity and fossil fuels seems apparent. In this paper the Markov regime switching model is applied to identify the non-linear relationship between electricity and fossil fuels such as coal and natural gas, as well as carbon emission allowance forward prices. This model makes it possible to distinguish between the regime where electricity forward prices depend on forward coal prices or forward natural gas prices. We expect that in both markets the switching probability between marginal technologies is present, however more severe for the peak as the off-peak power prices. For this we examined the peak and off-peak forward prices of the calender 2011 contact from the Dutch and German market in which the power production is mainly based on the fossil fuels coal and natural gas. For the ENDEX and EEX markets the coal and natural gas regimes can be identified significantly by applying this model. For the ENDEX and EEX peak forward prices there is a higher percentage of switching from coal to natural gas and for the off-peak prices we see the opposite, from natural gas to coal. The percentage of switching is higher for the EEX then for the ENDEX, which is in line with the mixture of the fossil fuels used for power generation. Overall we see that the marginal production costs based on forward fuel prices have high explanatory power for the electricity futures prices.

Keywords: Electricity forward prices; Fossil fuel forward prices; Markov switching model;

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1 Introduction

The liberalization trajectory has caused significant changes in the electricity markets all over Europe. An evident change was that the electricity prices became based on the market rules of supply and demand. The competition in the electricity market also increased over time and as economic theory would predict higher competition should drive prices down to the marginal costs of electricity production. In Europe still a high percentage of the produced electricity is being generated using fossil fuels. It is not economically feasible to store electricity, therefore in literature electricity is being valued as a non-storable commodity. However there is a possibility to store fossil fuels, which can be used to generate electrical power. In this way, indirect storage of electricity can be achieved by storing the underlying fuels. However it is also possible as a power generating company, which sells electricity forward contracts, to buy coal or natural gas forward contracts equivalent to the sold quantity of forward power contracts. Thus, in order to hedge the risks of selling an electricity forward contract the wholesale company can store fuels needed for the electricity generation or buy forward contracts of these fuels. Therefore a relationship between the future prices of electricity and fossil fuels seems apparent.

In the academic literature there are different views in modeling forward electricity prices. The econometric approach models the expected spot market prices of electricity by relying on historical price data and data relating to fundamental factors such as fuel costs. Deng [2000] and Deng et al. [1999] applied real option theory to develop models that utilize the relationship between fuel prices and electricity prices to value electricity generation and transmission assets. The relationships between electric power supply chains and other energy markets have drawn considerable attention from researchers in various field. Routledge et al. [2001] use a model to link cross-commodity prices and physical conversion of fuels to electricity. In the model, symmetric demand shocks for electricity as well as for the underlying fuels can cause an asymmetrical distribution of electricity prices. This asymmetrical distribution can increase due to constraints to the storage of commodities used to generate electricity, causing price distributions of electricity to show skewness. Secondly, the authors show that the correlation between electricity and the fuels used to generate electricity change due to an exogenous demand and endogenous level of storage of the fuels. The changing correlations of electricity and fuel prices can be seen as a natural consequence of the option to decide which fuel to use for generating the marginal unit of electricity.

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Redl et al. [2009] examine the relationship between the risk premia of fuel markets and electricity using the German EEX and the Nord Pool forward contracts. In this model the authors test the forward price of electricity as a dependent variable through current and lagged spot prices and short run marginal production costs of gas and coal. As the European Commission introduced CO2 emission rights, the short run marginal production costs are a function of primary fuel costs (gas or coal) and the costs for CO2 emission rights. The EEX electricity prices show higher correlation with gas and coal than the Nord Pool electricity prices. Redl et al. [2009] explain this by stating that gas and coal are more often the marginal fuels for generating electricity than they are for Nord Pool where electricity is mainly generated by hydro power.

Another line of research is performed by Emery and Liu [2002]. They examine the relation between gas and electricity futures of the California-Oregon Border (COB) and Palo Verde (PV) using a cointegration test. In their research the authors use the electricity spark spread, defined as the difference between price of 1 Mwh of electricity and the price of the amount of natural gas needed to produce 1 Mwh of electricity. By using the augmented Engle and Granger [1987] test to determine whether the time series show co-integration, they conclude that the time series of prices for gas and electricity futures are indeed co-integrated. Furthermore they conclude that deviations from the equilibrium level of the spark spread are temporary. Emery and Liu [2002] use an error-correction model to examine deviations in prices of gas and electricity from the long-run equilibrium levels. Their results indicate that electricity prices respond to deviations from equilibrium price level by reverting to their mean, but gas prices do not show a significant reaction to adjustments from their equilibrium level. Hence gas is the marginal fuel used for generating electricity in the examined markets, Emery and Liu [2002] expect lower demand for electricity would also result in a lower demand for gas causing a symmetric response to deviations. However, as producing electricity is not the only use for natural gas, an asymmetric response can be explained.

Mohammadi [2009] examines long-relations and short-run dynamics between electricity prices and prices for coal, natural gas and oil using annual U.S. data covering the period 1960 - 2007. As Emery and Liu [2002], the relations are examined by testing for co-integration and using a vector error-correction model. Mohammadi [2009] only finds significant long-term relations between coal and electricity prices and an unidirectional short-run causality from coal and natural gas prices to electricity prices. The results may reflect the high capital investments needed in the electricity industry as fuel prices comprise only a small fraction of the total costs of generating electricity.

Zachmann [2012] proposes a Markov regime switching model, which allows to make electricity spot prices in different regimes conditional on distinct linear combinations of fuel and emission allowance prices. The electricity spot price is differentiated across four identified regimes, with important implications for market efficiency, price forecasting and market power monitoring. The model is applied to the German and the UK wholesale market prices.

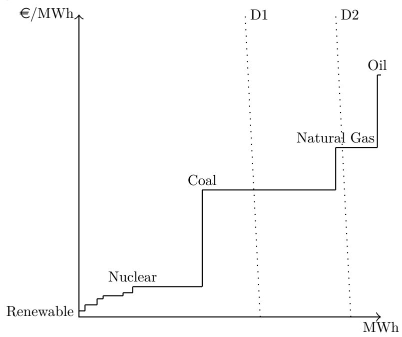
Hence the objective of this paper is to identify the non-linear relationship between electricity and fossil fuels such as coal and natural gas, as well as carbon emission allowance forward prices with a Markov-switching approach. For this we examined the peak and off-peak forward prices of the calender 2011 (Cal 2011) contact from the Dutch and German market in which the power production is mainly based on the fossil fuels coal and natural gas. The remainder of this paper is organized as follows. Section 2 focuses on the general theoretical model to gain insights on fundamental influence factors. In section 3, an overview of the data set is provided. Section 4 summarizes the results and a conclusion is drawn in the final section.

2 Methodology

A power producing generator has several motives to enter contractual agreements in the electricity market. One of them is the hedging incentive in which forward contracts are a means by which risk-averse producers may hedge price or cost uncertainties Chung et al. [2004]. If we only take the hedging incentive into account a power producer can sell an electricity forward contract at time t to deliver 1 Mwh at time T against the clearing price, F(t,T) to hedge itself against price uncertainty. He can make his position risk-free by buying the amount of underlying forward fuel contracts at time t equivalent to generate 1 Mwh of power at time T. In this way the producer can hedge itself against cost uncertainties. However the clearing price, F(t,T) depends on the amount of supply and demand for forward electricity contracts at time t.

In perfect markets prices will equal marginal production costs and therefore each technology is characterized by a marginal cost C (per Mwh). The production technology which uses coal is less costly per unit of electricity all through the year than the technology that is using natural gas. The price F is set at the marginal cost of the last unit called when all demand is satisfied. A generator will only produce with a certain fuel when the price is above its operating cost. When demand is less than the total capacity of all producers, which use coal to produce power (Q_C), the price is determined by the marginal cost of coal (F_C), and only firms with lower fuel cost will produce. When demand is equal or greater than Q_C the price is determined by the next fuel in line (F_G). This means that once the capacity limits in generation of the fuel with the lowest marginal cost is reached the electricity price gets decoupled and will be determined by the next marginal fuel price. This marginal cost curve for electricity is called the supply stack. The price and quantities are represented in fig.1

Figure 1: **Supply Stack function.**



In a market with perfect competition between the power generating plants we expect that, at the beginning of the trading period of a forward contract the forward price will be determined by the forward fuel price of the marginal fuel with the lowest cost (coal). When the to be hedged capacity of the plants with the lowest marginal cost is almost met, the forward price will be determined by the next marginal fuel in line (natural gas). When the "to be" hedged capacity of the power plants is almost forgone the expected spot prices at time T will set the forward price. During the trading period of a forward electricity contract the forward price switches from the forward price of an underlying fuel in the generation stack to the next forward fuel price. However the price can switch back, because a buyer can also take a short position when for example the expected electricity demand at time T ($E(D_T)$) of the end-user changes. We could simply see this as one extra unit of generation capacity re-entering the market. All individual power generators are aiming to maximize their expected profit, given by the cost that it can avoid by buying back the output, and its bid to do so, multiplied by the probability that it is called (Green, 1999). When generators have to buy back the forward electricity contract from the retailers because $E(D_T)$ is lower than the contracted volume the specific power generator is determined by the one with the highest profit. Thus the marginal technology is determined by the fuel stack, the level of demand and the capacity available for hedging purposes.

Regime-switching models are pricing models which were applied for modeling electricity spot prices by Ethier and Mount [1999]; Huisman and Mahieu [2003]; Weron et al. [2004] and Mount et al. [2006]. In general, regime-switching models divide the time series into several states that are called regimes. For each regime one can define separate and independent underlying price processes. The Markov regime switching model captures the phenomena of forward electricity prices switching from the coal to the natural gas state, this means that the model is able to distinguish whether the electricity forward price at time t depends on the marginal cost of producing with coal or natural gas. In each regime the electricity forward price is modeled as a different linear combination of fuel and carbon prices plus a constant.

$$F^e_{t,T} = \alpha + \beta * (h \times F^f_{t,T} + q \times F^{co2}_{t,T}) + \sigma\epsilon_t. \tag{1}$$

In regime one the electricity futures price is assumed to be a function of coal futures. The parameter α_C, the dark spread, is the estimated profitability from buying coal and selling power at current market prices. The efficiency at which a coal fired power plant converts fuel (C_t) into electricity is called the heat rate (h) and the needed amount of emission certificates per unit of electricity is q. The error consists of a normally (0,1) distributed random variable $\epsilon_{C,t}$ with a standard deviation equal to σ_C.

$$E(t) = \alpha_C + \beta_C * (C(t)/29.31)/0.2777) * (1/0.38) + 0.971 * CO2(t) + \sigma_C\epsilon_{C,t}. \tag{2}$$

In the second regime the marginal fuel is natural gas. The parameter α_G, the spark spread, is the estimated profitability from buying natural gas and selling power at current market prices. The efficiency at which a gas fired power plant converts fuel (G_t) into electricity is called the heat rate (h) and the needed amount of emission certificates per unit of electricity is $CO2_t$. The error consists of a normally (0,1) distributed random variable $\epsilon_{G,t}$ with a standard deviation equal to σ_G.

$$E(t) = \alpha_G + \beta_G * (2 * G(t) + 0.404 * CO2(t) + \sigma_G\epsilon_{G,t}. \tag{3}$$

The transition probability between the fuel regimes is determined by a random variable that follows a Markov chain with different possible states.Let R_t be the regime in which the electricity market is on day t ($R_t = C, G$). R_t is assumed to follow a Markov process that switches between the two regimes with constant transition probabilities. Let $p_{i,j}$ be the probability that the electricity market is in regime i in day t given that the market was in regime j the day before: $p_{i,j} = Pr\{R_t = i | R_{t-1} = j\}$. Hence, $p_{C,C}$ is the probability that the electricity market was in regime C and remains in regime C the following day and $p_{G,C} = 1 - p_{C,C}$ is the probability that the electricity market was in regime C and switches to regime G the following day. We do not estimate the probabilities $p_{C,C}$ and $p_{G,G}$ directly, but we apply a logistic transformation to ensure that the estimated probabilities are between zero and one. To do so, we introduce the parameters λ_C and λ_G such that a logistic transformation of these parameters yields the transition probabilities:

$$p_{i,i} = \frac{1}{1 + e^{-\lambda_i}}. \tag{4}$$

The parameters (α_C, α_G, σ_C, σ_G, λ_C, and λ_G) of the switching regimes model are estimated using maximum likelihood.

3 Data and descriptive analysis

To assess the functioning of the electricity prices in the derivatives market the model can be applied to the Netherlands and Germany. In both countries a high percentage of storable fuels, which are being traded on a derivatives market, is being used to produce electrical power. In the Netherlands 23.4 % of the total electricity generation coal is being used and 60.5 % is produced by natural gas. In Germany a higher percentage of coal 44.2 % is being used to generate electricity and natural gas is only being used in 13.8 % of the time.

Table 1: **Electricity generation by source in 2009 %˙**

Fuel	**The Netherlands**	**Germany**
Nuclear	3.7	23
Wind	4.1	6
Coal	23.4	44.2
Natural Gas	60.5	13.8
Oil	1.3	1.2
Other	7	11.8

The data set for this study consists of daily forward electricity prices for the Dutch ENDEX and the European Energy Exchange (EEX) for Germany. The Cal 2011 base load[1], peak load[2] and off-peak load prices are

[1]Delivering 1MW of power in any hour of a specific year.

[2]Delivering 1MW of power from Monday to Friday between 08.00 and 20.00 in a specific

included. The sample period for the ENDEX and EEX market is from 4 January 2007 through 30 December 2010, having approximately 900 daily forward price observations.

For the Netherlands the natural gas price in €/MWh is obtained by using Title Transfer Facility (TTF) forward contracts traded at the ENDEX exchange. To obtain the daily coal prices in €/ 1,000 tonnes and emission right prices the Rotterdam coal and the European Climate Exchange (ECX) carbon futures contracts traded at the ICE are used. The daily closing prices from 4 January 2007 through 30 December 2010 are used for the Rotterdam coal, TTF and ECX EUA forward contracts with delivery in 2011.

For Germany the natural gas price in €/MWh is obtained by the Net-Connect Germany (NCG) forward contract traded at the EEX. The coal prices in €/ 1,000 tonnes and the emission rights derivative prices are obtained by the yearly Amsterdam-Rotterdam-Antwerp (ARA) coal forward contract and the European Carbon Future (ECF) forward contract traded at the EEX. For the one year forward ARA coal, NCG and the European Carbon Future forward 2011 contracts we used the daily closing prices from 4 January 2007 through 28 December 2010. All prices are measured in natural logs.

Table 2: **Descriptive statistics (€/MWh)**

Endex	**Peak**	**Off-peak**	**Rotterdam Coal**	**TTF**	**EUA**	**Coal**	**Gas**
Mean	78.462	38.955	71.129	18.001	18.777	41.229	43.589
St. dev	14.233	7.719	22.765	6.874	5.120	11.554	15.181
Observations	981	981	981	981	981	981	981
EEX	**Peak**	**Off-peak**	**ARA**	**NCG**	**ECF**	**Coal**	**Gas**
Mean	80.835	34.420	75.400	24.194	18.663	42.500	55.928
St.dev	15.749	5.047	15.340	5.707	5.280	8.822	13.169
Observations	889	889	889	889	889	889	889

According to the descriptive statistics reported in table 2 for both markets the mean and standard deviation for the forward electricity prices and forward fuel prices converted with the heat rate are almost comparable. However the mean value of the peak electricity price for the EEX market is slightly higher then the Endex peak mean price level. This is coherent with the natural gas prices converted with the heat rate for the EEX market, which is higher then the mean value of the natural gas prices in the Endex market.

year.

Figure 2: **Commodity Prices**

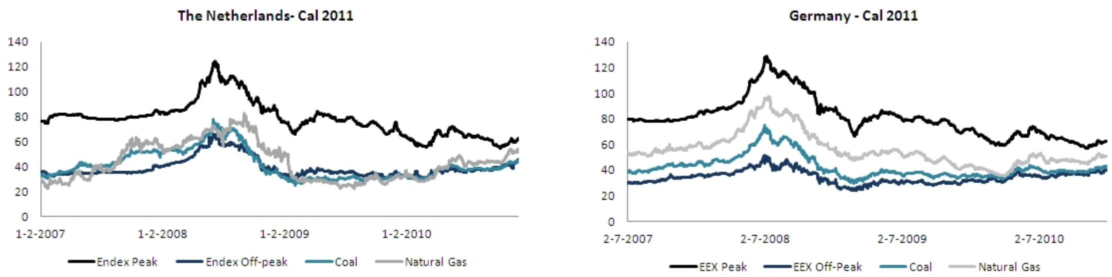


Fig. 2 presents the evolution of the commodity prices. It is evident that the electricity forward prices are being influenced by the forward fuel prices. Towards the end of the trading period of the Cal 2011 contract in both markets the power forward prices show conversion to the fuel prices. To observe the correlation between the different commodities the exponentially-weighted moving average (EWMA) correlation approach is used. The EWMA correlation gives recent data more weight, which declines exponentially. $\lambda(0, 1)$ is the decay factor that determines the relative weights applied to the observations. In our analysis we will use $\lambda = 0,94$ as proposed by RiskMetricsTM. The exponentially weighted moving average (EWMA) correlation estimator at time T is defined as:

$$\rho^t = \frac{\hat{\sigma}_{12t}}{\hat{\sigma}_{1t}\hat{\sigma}_{2t}} \tag{5}$$

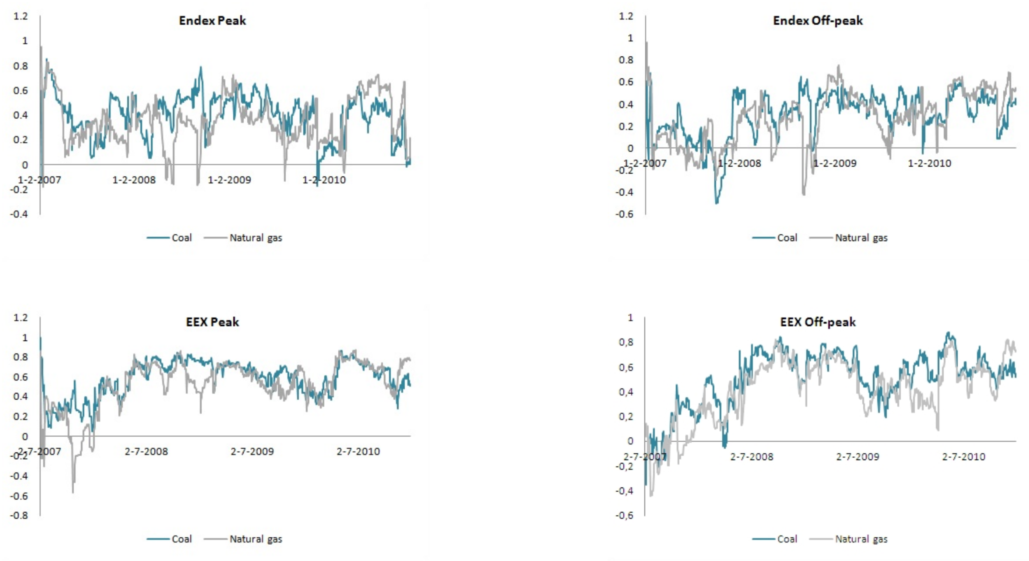
with

$$\hat{\sigma}^2_{1t} = (1 - \lambda)r^2_{1t-1} + \lambda\hat{\sigma}^2_{1t-1} \tag{6}$$

$$\hat{\sigma}^2_{2t} = (1 - \lambda)r^2_{2t-1} + \lambda\hat{\sigma}^2_{2t-1} \tag{7}$$

$$\hat{\sigma}_{12t} = (1 - \lambda)r_{1t-1}r_{2t-1} + \lambda\hat{\sigma}_{12t-1} \tag{8}$$

Figure 3: **EWMA correlation**



In fig. 3 the exponentially weighted moving average (EWMA) correlation of the commodity prices is shown. We notice that there are periods in which the correlation between the power prices and coal prices is increasing and the correlation with natural gas is declining or vice versa. Also the EWMA correlation between power and coal prices intersect the correlation between power and natural gas prices quite often. These are hints towards the fact that the dependency of the forward electricity price formation on underlying fuels changes over the trading period. Near to delivery the Cal 2011 power prices for both markets show even a higher correlation with natural gas.

4 Results

We estimate (2) and (3) for the peak and off- peak prices for the Dutch (Endex) and German (EEX) electricity market using maximum likelihood. We apply the Markov regime switching model in which the electricity forward prices are explained by the coal, natural gas and emission allowance forward prices. Table 3 presents the estimates, which are all significantly different from zero at 95% confidence level. The parameter p_{CC} indicates the transition probability of being in a regime where the forward electricity price is based on the forward coal price at time $t-1$ and staying in this coal regime at time t, therefore non-switching. p_{GG} denotes the transition probability of having forward electricity prices based on forward natural gas prices at $t-1$ and also at time t. Switching from one marginal technology to another occurs when the to be hedged capacity of the plants with the lowest marginal cost (coal) is almost met, the forward price will be determined by the next marginal fuel in line (natural gas). However because short selling is permitted switching back from the more expensive fuel to the cheaper fuel in the fuel stack is possible.

For both markets we observe that p_{CC} and p_{GG} are lower than one and therefore the switching behavior of the marginal technology is obviously present in these results. Firstly for both markets we observe that the estimated parameter p_{CC} for the off-peak is higher than for the peak power prices. The off-peak prices are mainly explained by coal, which indicates that coal fired power plants are most of the time the marginal producers. p_{GG} is higher for the peak than for the off-peak prices, therefore we can state that the peak prices are more influenced by natural gas futures prices. Secondly for both markets we notice that for the peak power prices the probability of switching from coal to natural gas [1-p_{CC}] is higher than the probability of switching from natural gas to coal [1-p_{GG}]. For the off-peak prices we see the opposite [1-p_{GG}] is higher than [1-p_{CC}]. The switching behavior is clearly present in both markets.

In the Endex and EEX off-peak periods generators with lower marginal costs (nuclear, wind) are generating the marginal unit of power, which leads to lower electricity prices and less influence of coal and natural gas prices on the power prices. This can also be concluded from the parameter α, the spread, which is negative for the off-peak period. In the peak period for both markets the dark spread (α_C) is higher than the spark spread (α_G), this is evident since the marginal production cost of natural gas, which is higher than the marginal cost of coal, will determine the power price.

At last the volatility of the prices in the coal and natural gas regime we observe mixed results. For the peak and off-peak Endex prices the σ_G, price volatility in the natural gas regime, is lower than σ_C, price volatility in the coal regime and for the EEX market the σ_C for the peak prices is lower then σ_G, however higher for the off-peak prices. Lower volatility should implied that the variation is small and the electricity prices will remain close to the certain fuel price.

Table 3: **Parameter estimates for the regime switching model**

(a) ENDEX

Cal2011	λ_C	λ_G	α_C	α_G	σ_C	σ_G	p_{CC}	p_{GG}
Peak	5.555	6.117	0.813	0.380	0.129	0.101	0.996	0.998
	(0.711)	(1.001)	(0.006)	(0.005)	(0.004)	(0.003)		
Off-Peak	5.839	4.922	0.010	-0.339	0.111	0.093	0.997	0.993
	(0.710)	(0.711)	(0.004)	(0.006)	(0.003)	(0.004)		

Standard errors are in parenthesis.

(b) EEX

Cal2011	λ_C	λ_G	α_C	α_G	σ_C	σ_G	p_{CC}	p_{GG}
Peak	4.584	5.119	0.598	0.389	0.031	0.084	0.990	0.994
	(0.581)	(0.579)	(0.002)	(0.004)	(0.001)	(0.003)		
Off-Peak	5.826	4.522	-0.174	-0.657	0.076	0.037	0.997	0.989
	(0.710)	(0.712)	(0.003)	(0.003)	(0.002)	(0.002)		

Standard errors are in parenthesis.

To examine whether the merit order switching probability differs over the whole trading period of a forward power contract, we analyze the parameter estimates of this model over time. To do so, we estimate the parameters for every year from 2007 through 2010 for both peak and off peak power prices for the Netherlands and Germany. For the Endex off-peak and EEX peak electricity prices we observe in table /ref4 that the switching probability is much higher at the start of the trading period of a forward contract. For the Endex peak and EEX off-peak power prices we observe more constant fuel switch probabilities.

Table 4: **Parameter estimates for the regime switching model**

(a) ENDEX Peak

Cal2011	λ_C	λ_G	α_C	α_G	σ_C	σ_G	p_{CC}	p_{GG}
2007	5.228	3.765	0.656	0.719	0.168	0.039	0.995	0.977
	(1.008)	(1.101)	(0.012)	(0.006)	(0.009)	(0.004)		
2008	4.484	4.188	0.490	0.401	0.028	0.106	0.989	0.985
	(0.738)	(1.004)	(0.002)	(0.012)	(0.002)	(0.009)		
2009	4.034	3.642	0.903	0.986	0.032	0.091	0.983	0.974
	(0.603)	(0.707)	(0.003)	(0.010)	(0.002)	(0.007)		
2010	5.483	3.130	0.547	0.251	0.103	0.013	0.996	0.958
	(1.008)	(1.020)	(0.007)	(0.003)	(0.005)	(0.002)		

Standard errors are in parenthesis.

(b) Endex Off-Peak

Cal2011	λ_C	λ_G	α_C	α_G	σ_C	σ_G	p_{CC}	p_{GG}
2007	4.659	1.620	-0.167	-0.039	0.140	0.011	0.991	0.835
	(0.770)	(0.767)	(0.010)	(0.003)	(0.007)	(0.002)		
2008	3.256	3.457	-0.134	-0.282	0.072	0.032	0.963	0.969
	(0.487)	(0.510)	(0.007)	(0.003)	(0.005)	(0.002)		
2009	4.598	3.830	0.129	0.148	0.059	0.037	0.990	0.979
	(0.716)	(1.017)	(0.004)	(0.006)	(0.003)	(0.004)		
2010	5.154	3.752	-0.019	0.082	0.033	0.055	0.994	0.977
	(1.023)	(1.087)	(0.003)	(0.010)	(0.002)	(0.007)		

Standard errors are in parenthesis.

(c) EEX Peak

Cal2011	λ_C	λ_G	α_C	α_G	σ_C	σ_G	p_{CC}	p_{GG}
2007	2.884	3.356	0.609	0.377	0.011	0.038	0.947	0.966
	(0.792)	(0.595)	(0.003)	(0.004)	(0.002)	(0.003)		
2008	3.552	5.382	0.721	0.319	0.022	0.049	0.972	0.995
	(1.039	(1.002)	(0.004)	(0.003)	(0.003)	(0.002)		
2009	4.294	3.574	0.769	0.450	0.018	0.044	0.987	0.973
	(0.729)	(0.727)	(0.002)	(0.006)	(0.001)	(0.004)		
2010	4.891	4.797	0.541	0.303	0.023	0.112	0.993	0.992
	(1.010)	(1.004)	(0.002)	(0.010)	(0.002)	(0.007)		

Standard errors are in parenthesis.

(d) EEX Off-Peak

Cal2011	λ_C	λ_G	α_C	α_G	σ_C	σ_G	p_{CC}	p_{GG}
2007	3.359	2.723	-0.258	-0.507	0.022	0.010	0.966	0.938
	(0.608)	(0.754)	(0.002)	(0.002)	(0.002)	(0.001)		
2008	4.236	4.125	-0.246	-0.659	0.026	0.040	0.986	0.984
	(0.728)	(0.788)	(0.002)	(0.004)	(0.002)	(0.003)		
2009	4.818	3.034	-0.195	-0.676	0.036	0.019	0.992	0.954
	(0.781)	(0.782)	(0.003)	(0.003)	(0.002)	(0.002)		
2010	3.787	3.246	-0.103	-0.234	0.035	0.015	0.978	0.963
	(0.528)	(0.595)	(0.003)	(0.002)	(0.002)	(0.001)		

Standard errors are in parenthesis.

5 Conclusion

In this paper the Markov regime switching model is applied to identify the non-linear relationship between electricity and fossil fuels such as coal and natural gas, as well as carbon emission allowance forward prices. For this we examined the peak and off-peak forward prices of the calender 2011 contact from the Dutch and German market in which the power production is mainly based on the fossil fuels coal and natural gas. For the ENDEX and EEX markets the coal and natural gas regimes can be identified significantly by applying this model. We observed that for the ENDEX and EEX futures prices there is a higher percentage of switching in the off-peak prices. The percentage of switching from the natural gas regime to the coal regime is higher for the EEX then for the ENDEX, which is in line with the fossil fuel coal used abundantly for power generation during the off-peak hours. Overall we see that the marginal production costs based on forward fuel prices have high explanatory power for the electricity futures prices.

6 Appendix

Figure 4: **Regime switching probability p_{CC} for Endex Peak**

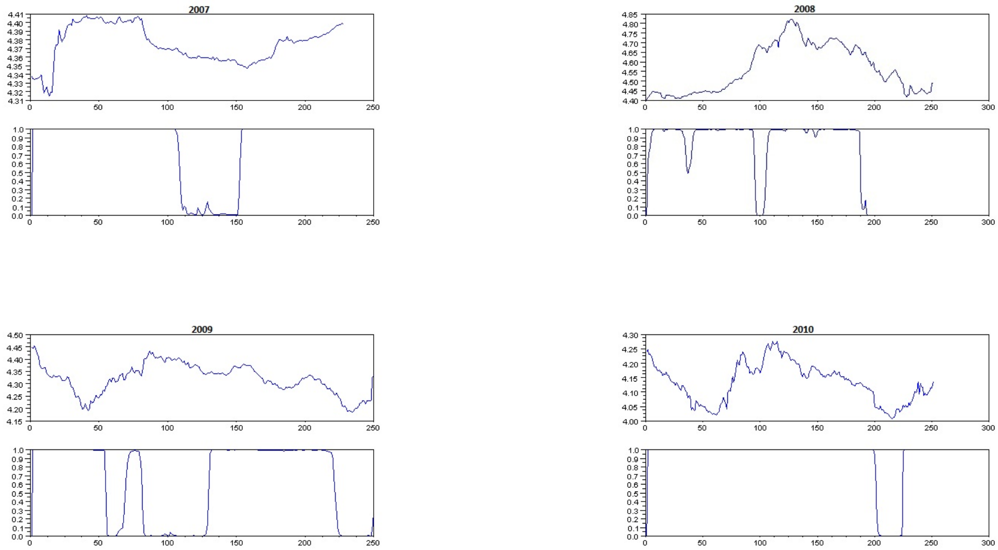


Figure 5: **Regime switching probability p_{CC} for Endex Off-Peak**

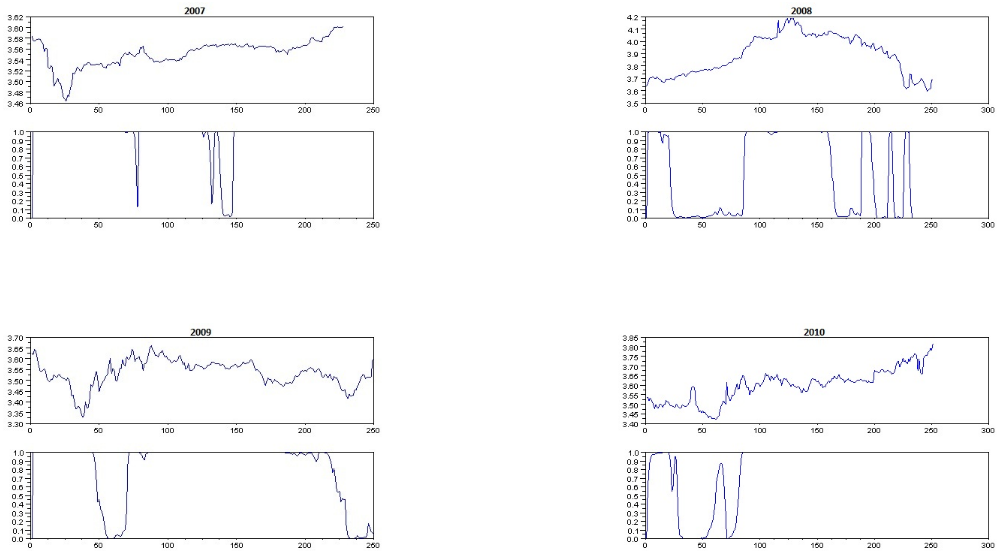


Figure 6: **Regime switching probability p_{CC} for EEX Peak**

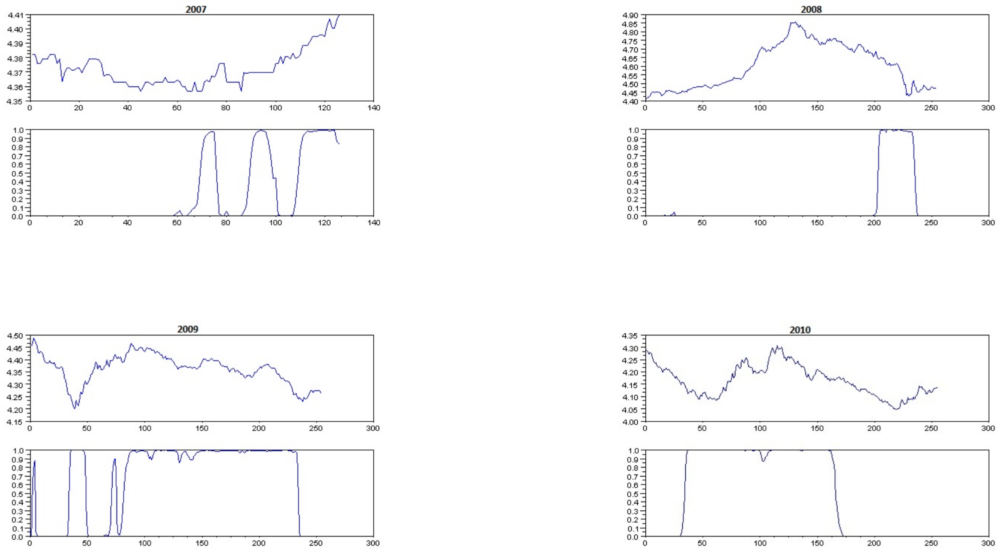
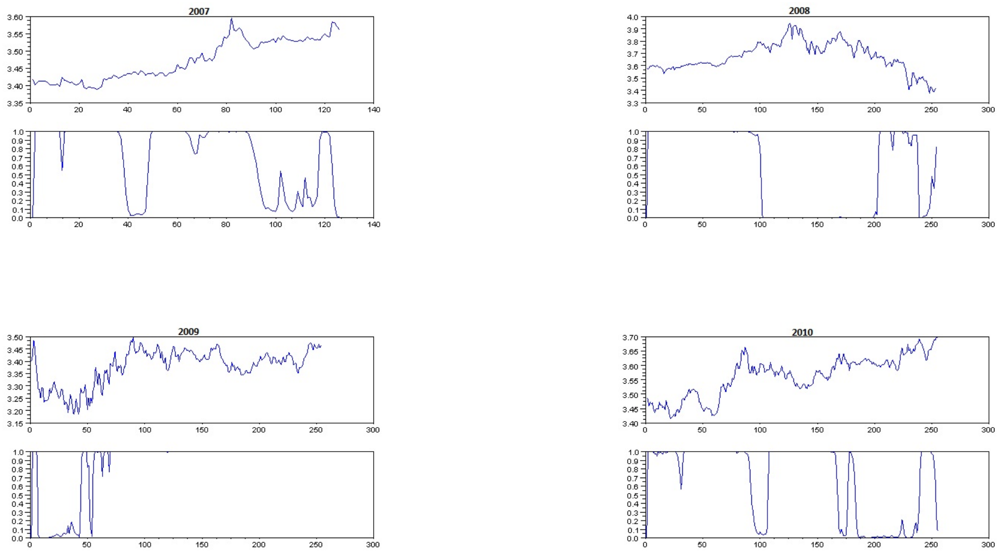


Figure 7: **Regime switching probability p_{CC} for EEX Off-Peak**



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