Fundamental Insights in Power Futures Prices

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Fundamental Insights in Power Futures Prices

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To my parents

Preface

The process of writing a dissertation had its ups-and-downs, however I feel lucky enough to say that I experienced more ups than downs in these past four years. Many have contributed in this in different ways and I would like to take this opportunity to thank them. First and foremost I would like to thank my co-promotor Dr. Ronald Huisman. Your great enthusiasm and insight in real world energy issues, creativity and capability of seeing everything in a bigger picture were stimulating to bring this PhD to a good end. Working together was really valuable and I definitey learned a lot. Second, I would like to thank my promotor Prof.dr. Enrico Pennings who gave me the opportunity to work in his department.

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This is an excellent opportunity to thank my beloved family too. Emine, by pursuing a PhD, as my elder sister you at least made me aware of what a PhD-study implies. Even though you are in a totally different field your experiences were of usefull during my PhD. I cannot thank you enough for this. I also would like to thank my other sisters Ayşe, Hacer and Sebiha and brother Şukru for their unconditional support and understanding. Also Riza, Hakan, Erol and Ruth thank you for your support. Of course the youngest members of the family cannot be forgotten; Burak, Bahar, Kaan, Berfu, Ezği, Beyza, Ardan, Anıl and Ferah thank you for being there.

Sevgili Anneciğim ve Babacığım bana her türlü bilgi edinme fırsatını elime verdiğiniz için, başarılı olmamı tesvik ettiğiniz için ve her zaman her türlü desteğinizi benden esirgemediğiniz için size sonsuz teşekkür ederim.

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1.1 Introduction

"All compromise is based on give and take, but there can be no give and take on fundamentals. Any compromise on mere fundamentals is a surrender. For it is all give and no take" Mahatma Gandhi

Transformations are prevailing phenomena in the energy market. In the 1990's the electricity market transitioned from regulated to liberalized markets, which was initiated by the objective of the European Union to create one single European electricity market. By deregulation, ending monopolies and inefficiencies one of the desired results was to lower the prices for end-users, while giving the European Union a competitive position regarding electricity for the future. In the course of deregulation, markets for financial contracts on electricity emerged and electricity became a tradable asset. Electricity was traded on the power exchanges by the new players, who appeared in the restructured electricity market: the producers, the retailers and the end-users. The publicly quoted market price in the deregulated electricity market is set by the free interaction between supply and demand. These power price determining components are subject to change, therefore new uncertainties are introduced to the market. Identifying fundamentals that influence the forward price formation is valuable for understanding and managing risk and as the quote above emphasises there is no compromise when it becomes to fundamentals.

In Europe UK was the first country that restructured its electricity market in 1990 with their Electricity Act (Mork [2001]). Shortly after the UK, Norway began its transformation as well. The country passed the Norwegian Electricity Act in 1990, which allowed a progressive number of consumers to select their electricity supplier. Two years later Norway operated an official spot market for electricity, while trading in futures and forwards started in 1996. It was this power exchange that grew into the Nord Pool market[1], which now includes Norway, Finland, Sweden and Denmark (Mork [2001]). More countries followed; the APX (the Netherlands) opened in 1999, Powernext (France) in 2001 and the EEX (Germany) in 2002. The liberalization of the electricity market has created additional risks and new challenges for the players in the market. In particular, power cannot be directly stored on a large scale. As a consequence demand and supply have to be in balance at all time as any imbalance cannot be corrected via physical inventories. This lack of storability, in combination with the volatile demand and the convexity of the supply stack has consequences for the pricing and trading of electricity at power exchanges. A physical imbalance in demand and supply is reflected in high price volatility and frequently occurring price spikes. Spot prices also exhibit strong seasonal patterns like daily, weekly and seasonal cycles and since electricity is driven by the balance between supply and demand, the prices tend to mean-revert. The specific features of power price behaviour creates challenges in modelling the spot price dynamics. Starting with traditional stochastic commodity modelling approaches the specific features of electricity prices are identified and captured via mean-reverting one- or two-factor models (Lucia and Schwartz [2002]). Historical data is thereby necessary for the estimation of the main stochastic parameters, e.g. mean and volatility. Jump diffusion process (e.g. Deng [2000]) and or regime-switching approaches (e.g. Ethier and Mount [1999], Huisman and Mahieu [2003] among others) are included for the model to capture the stylized facts of electricity spot prices dynamics. However electricity prices are very much influenced by exogenous factors. This is why the dynamics in the power spot price can also be seized by fundamental factors, such as demand or scarcity of supply (Karakatsani and Bunn [2008]). The impact of movements in physical variables such as temperature, rainfall patterns, inflow to hydro reservoirs and different demand-side factors on power prices are also studied by several authors (e.g Huisman [2008]; Vehviläinen and Pyykkönen [2005]; Fleten et al. [2002]).

This high volatility and these price spikes in the spot prices makes the use of electricity derivatives, like future contracts more applicable for risk hedging purposes. Risk-averse hedgers who produce or need electricity can transfer spot price risks by trading future contracts and therefore can stabilize their future cash flows. With a future contract[2] an amount of energy

[1]Before 1 November 2010 the financial energy market NASDAQ OMX Commodities Europe was known by the name Nord Pool

[2]We assume no differences between futures and forward contracts and we shall use both words in the chapters as synonyms.

is agreed for delivery over a specified period in the future and delivered at a certain price per unit. Power is a flow commodity. For each period, suppliers assess demand in advance and sign contracts with generators for the given volume of electricity. During the contracted period, generators are expected to produce and deliver the contracted volume of electricity and suppliers are expected to use their contracted power. In most electricity markets contracts are available for the period of a month, quarter, half year and full year. The expectations theory is the starting point for many electricity forward pricing models. Power is not yet economically storable and, as a consequence, the power futures prices reflect expectations and risk premiums (see Fama and French [1987]; Lucia and Schwartz [2002]; Eydeland and Wolyniec [2003]; and Huisman [2009] among others). The price of an electricity forward contract reflects the expected spot price during the delivery period plus or minus a risk premium. Power futures prices do not necessarily depend on the spot price of power and therefore their price dynamics should be modeled as a stand-alone process. Research is roughly divided in reduced-form and fundamental models that price electricity forwards contracts. Lucia and Schwartz [2002] is an important example of valuating forward electricity prices stochastically. Lucia and Schwartz [2002] focus primarily on expectations. By modelling the expected spot price during a future time period they derive a formula for the forward price of electricity. The expected spot price equals the sum of two prices: an equilibrium long-term spot price level and a mean-reverting short-term price. In addition to these expectations, they assume a constant risk premium[3]. However like spot price modelling in order to valuate commodity derivatives it is essential to identify the fundamental features and risk factors that influence the forward price dynamics. In fundamental pricing models state variables influencing supply or demand are also considered in modelling the expectations or risk premiums embedded in forward prices (e.g. Bessembinder and Lemmon [2002], Routledge et al. [2001] and Douglas and Popova [2008]). A specific characteristic of electricity is its homogeneity even though electricity is generated from different sources such as renewables (e.g. wind, solar and hydro), nuclear or fossil fuels like coal, gas and oil. All these means of power generation have different characteristics and costs. In particular, due to the non-storability of electricity, there is a closer link between power and its fundamental underlying price drivers (in particular fuel prices, load and generating capacity) than in other markets.

[3]Two risk premiums actually: one for each source of uncertainty (long-term and short-term price uncertainty).

This thesis concentrates on the influence of fundamentals on electricity prices in the derivatives market. The main contribution is to provide arguments and evidence that electricity prices do reflect the underlying fundamentals. Secondly, power prices cannot only be modeled pure stochastically, because the real world dynamics in the demand and supply side will not be totally captured and so electricity derivatives should be valued according to these facts. The thesis illustrates that price formation in the futures markets for electricity, to some extent, can be explained based on fundamentals.

1.2 Outline

The first part of this thesis analyses the electricity futures prices with stochastic models. In chapter 2, we examine the development of day-ahead prices in five European markets which became more connected over recent years. Where previous studies examined the convergence of price levels over time, we focus on patterns in estimates for the parameters in a switching regimes model. This makes it possible to distinguish between prices under normal market conditions and under non-normal market conditions, those market conditions that can cause extreme price spikes. We expect that increased connectivity yields additional supply in the short-term and consequently will reduce the impact of price spikes.

Chapter 3 of this thesis focuses on price risk in power futures prices. We analyze the occurrence of extreme price changes in power delivery forward and futures contracts by examining to what extent changes in power futures prices can be modeled using a normal distribution function or whether another method should be applied. We apply extreme value theory to assess the level of tail-fatness, i.e. the frequency with which large price movements occur, such that we can observe whether these price changes can be modeled using a normal distribution or not.

The second part of this thesis emphasises an empirical inquiry on investigating derivatives prices with respect to fundamentals. Chapter 4 examines to what extent electricity futures prices contain expected risk premiums or have power to forecast spot prices and whether this might be dependent on the type of electricity supply. This analysis is performed according to the expectations theory, which describes that the forward price of a commodity equals the expected spot price of the underlying commodity during the delivery period plus an expected risk premium that compensates producers for bearing the uncertainty of delivering against fixed prices. We analyse futures prices from the Dutch market, a market in which power is produced with storable fossil fuels, and futures prices from the NordPool market, where electricity is mostly produced by hydropower.

In chapter 5, the long-run relations and short-run dynamics between electricity and fossil fuel futures prices are analysed to identify to what extent power futures price formations are driven by fundamentals, based on fuel prices. This analysis is performed for the one-month and one-year-ahead peak and off peak electricity futures contracts for the Dutch and German market where power is primarily generated by fossil fuels. The augmented Engle-Granger (1987) test and the error correction model are used to test for cointegration between power, coal and natural gas futures prices.

Chapter 6 analyses the time varying impact of underlying forward prices of fossil fuels such as coal and natural gas, as well as carbon emission allowance on the forward electricity price formation over the trading period of a calendar contact, which delivers power during a year. To capture the dynamics in the price formation we apply a univariate unobservable component model in which the explanatory variables are functions of time and the parameters are time varying. We expect that at the beginning of the trading period of a forward power contract the price will be determined by the forward fuel price of the marginal fuel with the lowest cost and 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. For this we examined the peak and off peak forward prices of the calendar 2013 contract from the German market (EEX) in which the power production is mainly based on the fossil fuels coal and natural gas.

Finally, chapter 7 summarizes and draws conclusions from the thesis.

2 | A History of European Electricity Day-Ahead Prices

Chapter 2 is based on Huisman and Kiliç [2013].

2.1 Introduction

The liberalisation process has caused significant changes in the electricity markets all over Europe. Electricity is now a commodity traded on markets that facilitate trading short-term and long-term delivery contracts. Over the past decade, knowledge has accumulated about the characteristics of electricity prices. Considering day-ahead markets, where power can be traded one day before delivery, electricity prices exhibit seasonality, mean-reversion, time-varying volatility and price spikes[1]. These characteristics of electricity prices can be attributed to the convex supply curve, price inelastic demand in the short-run (Borenstein [2002]) and non-storability of electricity. Supply or demand shocks due to for instance unexpected outages of generation units, transmission constraints or unexpected weather change, cannot be compensated by additional supply from inventories. As a consequence, sudden jumps in the price of electricity (so-called spikes) may occur, especially in those periods where demand is high or - alternatively stated - where reserve capacity is low (Mount et al. [2006] and Huisman [2008]).

In this chapter, we examine how the typical characteristics of electricity spot prices have changed in several European markets from 2003 through 2010[2], a period characterised by the liberalisation process towards a single European energy market and an economic crisis in the second part. The integration of European power markets offers benefits in terms of economic

[1] For an overview of the characteristics of electricity price dynamics and a summary of the literature we refer to Eydeland and Wolyniec [2003], Pilipovic [2007], and Huisman [2009].

[2] These years are chosen because of availability of data.

efficiency and security of supply (Robinson [2007] and Buglione et al. [2009]). Increased connectivity, through improved cross-border rules and expansion of cross-border transmission links, increases competition in the European power market (Zachmann [2008]). An example of this is the Trilateral Market Coupling between the day-ahead markets of Belgium, France, and the Netherlands as initiated in November 2006.

There is mixed evidence on the effects of this integration process in Europe on day-ahead wholesale market prices. Bower [2002] applies a correlation and cointegration analysis on day-ahead prices from 15 European electricity markets. The author concludes that the Nordic countries and the Netherlands were already integrated to a certain extent by 2001. Boisselau [2004] applies a regression and correlation analysis and finds that the level of integration in European markets is quite low. Armstrong and Galli [2005] analyses the evolution of price differences between France, Germany, the Netherlands and Spain from 2002 through 2004, concluding that European electricity prices indeed converged during this period. Zachmann [2008] analyses the integration of the electricity markets in Europe between 2002 and 2006 and finds significant differences between prices thereby concluding that a single European market for electricity had not been accomplished by 2006. de Jonghe et al. [2008] study the effects of the before mentioned Trilateral Market Coupling on day-ahead prices and find evidence for price convergence between the three markets due to the coupling.

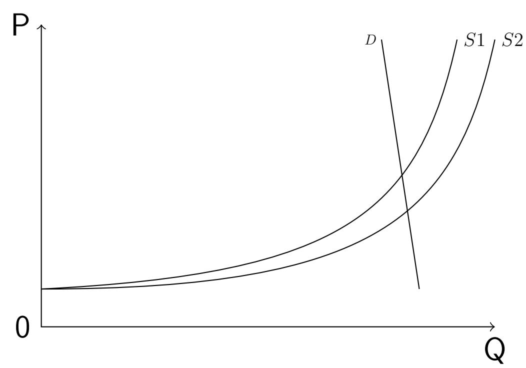
These studies focus only on daily average day-ahead electricity prices without accounting for seasonality and price spikes and without making a distinction between base load and peak load prices[3]. Bunn and Gianfreda [2010] study the integration of the British, Dutch, French, German, and Spanish power markets for day-ahead, week-ahead, one-month-ahead and two-month-ahead delivery. They find more evidence of integration (price convergence) in base load than in peak load prices and more evidence of integration in spot (short time to delivery) than in forward prices (longer time to delivery). Overall, they find evidence for market integration, increasing over time, despite an underlying inefficiency in each market with respect to the forward and spot price convergence.

In this chapter, we focus not directly on price convergence but we question what impact

[3]The base load price is the equally weighted average over the prices paid for delivery of 1MW of power during each hour on a specific day. The peak load price is the equally weighted average over the prices paid for delivery of 1MW of power during peak hours (between 8 a.m. and 8 p.m.) on a specific day.

the liberalisation process has on the occurrence of price spikes. These spikes are higher than normal prices that last for a short period of time caused by short-term frictions in demand or supply conditions. Based on Borenstein [2002], Fig. 2.1 shows the typical supply and demand curves for electricity. The line *D* represents the demand for electricity at some moment in time. The demand curve is almost vertical as demand is price inelastic in the short-run. The supply curve *S1* is the supply curve and let this be the supply curve for an electricity market that is not connected to another market. Note the typical convex "hockey stick" shape of the supply curve. Supply capacity is fixed in the short run. Suppose now that the market gets connected to another electricity market. Given connection capacity constraints and the type of power supply installed in the other market, the supply curve will shift to the right as represented by *S2*. We do not focus here on whether the new market clearing price under *S2* will be lower than under *S1* because the hight of the supply curve depends on the installed capacity in the other market. Instead we focus on another effect. If demand suddenly increases, then the market clearing price will increase more under *S1* than under *S2*. The same holds if there is an outage of a power plant that results in a shift to the left of the supply curve. The probability that extreme high prices, i.e. spikes, will occur is lower under supply conditions *S2* than under *S1*. As discussed before, the current literature on electricity market integration focuses on the convergence of price levels and not specifically on price spikes. This is the motivation behind this chapter. We question whether the risk of price spikes has decreased over time.

Figure 2.1: **Supply and demand in electricity markets.**



To do so, we examine day-ahead prices from the Belgian, Dutch, German, French and Nordic electricity markets over the years 2003 until 2010. In order to be able to observe the impact on price spikes, we estimate the parameters of a regime-switching model for every year and market in our sample. Regime-switching models have been used with success to model the spiky behaviour of electricity prices (see among others Deng [2000], Huisman and Mahieu [2003], Mount et al. [2006] and Huisman [2008]). Typically, these models assume that the electricity markets can be in one of two or three regimes. One regime is the electricity markets in its normal fashion, where prices behave normally. In a two regime model, the second regime is the spike regime that represents the electricity market in an abnormal situation due to short-term frictions in supply and demand conditions yielding high and volatile prices. A three regime model typically distinguishes between positive and negative price spikes. We use a two regime model in this chapter as it depends on less parameters and as we think it is sufficient to observe changes in the occurrence of spikes over time. Given this setup, our contribution to the literature is that we analyse changes of electricity prices from these markets over time, by analysing the development of parameters in a two regime model that makes it possible to observe changes in spike behaviour over time.

2.2 Methodology

Our research goal is to examine whether the risk of price spikes has declined over time. To do so, we examine the development of parameter estimates of a two regimes switching model which makes it possible to distinguish behaviour under normal and non-normal market conditions. Such a model is often applied to describe the behaviour of day-ahead electricity prices and the model we employ is in line with the ones used by Mount et al. [2006] and Huisman [2008][4]. Let s_t be the natural logarithm of the day-ahead price for delivery of 1 MW on day t (note that in day-ahead markets the price for delivery on day t is determined on the previous day $t-1$). The day-ahead price is assumed to be the sum of a deterministic component d_t and a stochastic component x_t. d_t is a deterministic component accounting for predictable factors that affect the day-ahead price such as seasonality and x_t is a stochastic component representing unpredictable factors that affect the day-ahead price:

$$s_t = d_t + x_t. \tag{2.1}$$

We assume that the deterministic component d_t consists of a mean price level μ_1 and allows for lower prices during weekend days through a dummy variable w_t that equals one if t is a weekend day and 0 if it is any other day:

[4]Hamilton [1989] was the first to apply regime switching models to analyse price behaviour in financial markets. We refer to this paper for a detailed discussion of this model and estimation issues.

$$d_t = \mu_1 + \beta w_t. \tag{2.2}$$

The parameter β measures the amount with which prices deviate for delivery in weekend days from prices for delivery in non weekend days. The stochastic component x_t differs over the two regimes. The normal regime, regime 1, represents the day-ahead market in its normal fashion. In this market, prices change from day to day according to a mean reversion model. The motivation for using a mean reversion model to describe daily price changes is that commodity prices are known to be mean reverting because if a commodity becomes to expensive, consumers will purchase substitute products thereby lowering the demand for the commodity and therefore its price (Schwartz and Smith [2000]). A similar argument holds in case a commodity becomes to cheap. In electricity markets, a sudden rise in demand will increase the electricity price as supply is fixed in the short run. But if demand remains high, additional supply becomes online and therefore lowers the price. Hence, the motivation for using a mean reversion model to describe the stochastic behaviour of electricity prices. Let α be the speed of mean reversion and the error term in regime 1 $\epsilon_{1,t}$ is assumed to be standard normally distributed multiplied with σ_1 that represent the standard deviation of the error term in regime 1. The mean reverting stochastic component then equals:

$$x_t = (1 - \alpha)x_{t-1} + \sigma_1\epsilon_{1,t}. \tag{2.3}$$

The second regime, regime 2, represents the electricity price under non normal market conditions such as a sudden increase in demand or a decrease in supply due to a power plant failure. This may result in a sudden price shock. In this regime, we model the stochastic component as a random price shock mean price level μ_2 and a normally (0,1) distributed error term $\epsilon_{2,t}$ multiplied with the standard deviation of the electricity price in regime 2, σ_2:

$$x_t = \mu_2 + \sigma_2\epsilon_{2,t}. \tag{2.4}$$

Let R_t be the regime in which the electricity market is on day t ($R_t = 1, 2$). 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, $p_{1,1}$ is the probability that the electricity market was in regime 1 and remains in regime 1 the following day and $p_{2,1} = 1 - p_{1,1}$ is the probability that the electricity market was in regime 1

and switches to regime 2 the following day. We do not estimate the probabilities $p_{1,1}$ and $p_{2,2}$ 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_1 and λ_2 such that a logistic transformation of these parameters yields the transition probabilities:

$$p_{i,i} = \frac{1}{1 + e^{-\lambda_i}}. \tag{2.5}$$

We estimate the parameters (μ_1, β, α, σ_1, μ_2, σ_2, λ_1, and λ_2) of this two regimes switching model using maximum likelihood estimation.

To examine whether the risk of price spikes changed over time, we analyse the changes in the parameter estimates of this model over time. To do so, we estimate the parameters for each year from 2003 through 2010 for Belgium, Germany, France, the Netherlands, and Nordic countries. We expect that increased connectivity between the markets should lead to changes in the parameters estimates for the second regime. We discuss these parameter estimates in section 2.4.

2.3 Data and descriptive analysis

Our sample consists of daily observed average day-ahead prices, the equally weighted average over the day-ahead prices for each of the 24 delivery hours[5], between 1 January 2003 and 31 December 2010 for Belgium[6] (BELPEX), France (EPEX), Germany (EEX), the Netherlands (APX), and the Nordic countries Norway, Denmark, Sweden and Finland (NPX)[7]. The selection of countries and period is based on the proximity of countries and availability of prices. The data were obtained from Bloomberg. The day-ahead prices for the five markets are represented in figures 2.2 through 2.6 and summary statistics are reported in Table 2.1.

[5] Therefore, the prices reflect a base load profile.

[6] Before November 2006, Belgium had no organised market. In the absence of an exchange, Electrabel published the Belgian Power Index (BPI), which allowed participants to buy and sell day-ahead base load power in blocks and we use these prices as a proxy for Belgium day-ahead prices before November 2006.

[7] The names of the specific exchanges are in parentheses. We use NPX to abbreviate NordPool Power Exchange here.

Figure 2.2: **Day-ahead electricity prices in Belgium.**

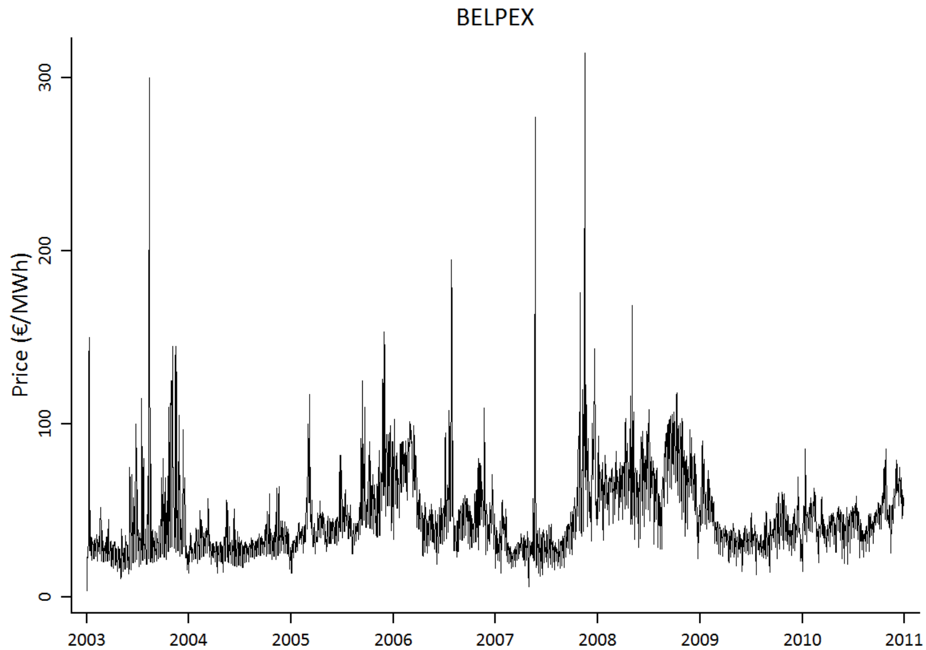


Figure 2.3: **Day-ahead electricity prices in France.**

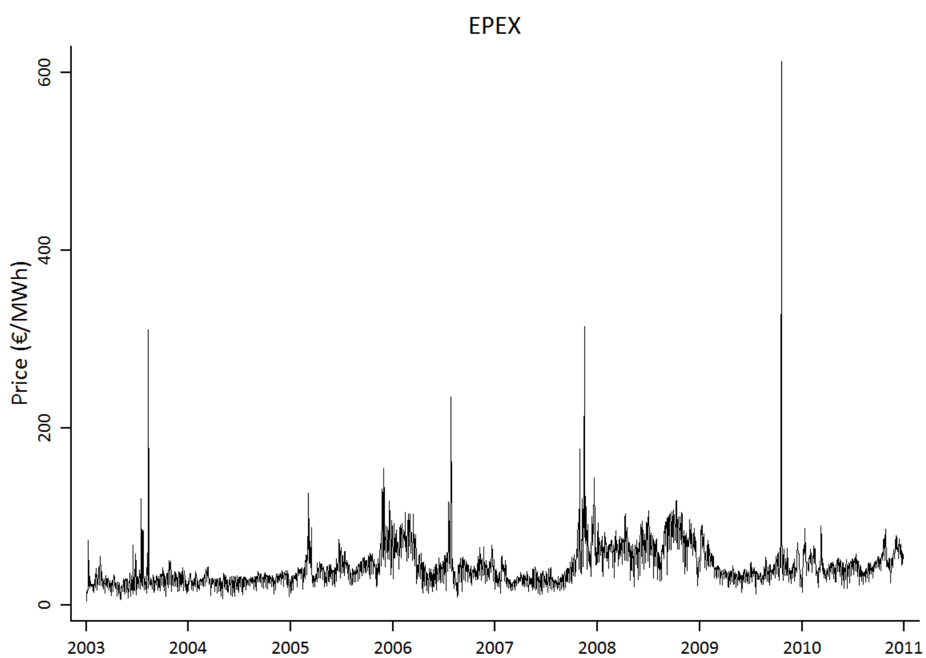


Figure 2.4: **Day-ahead electricity prices in Germany.**

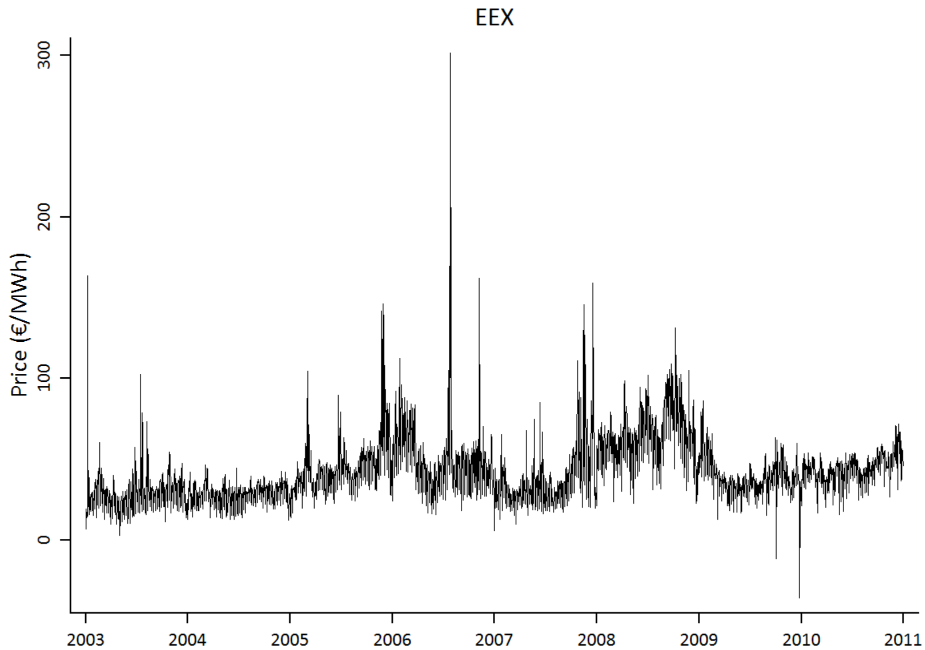


Figure 2.5: **Day-ahead electricity prices in the Netherlands.**

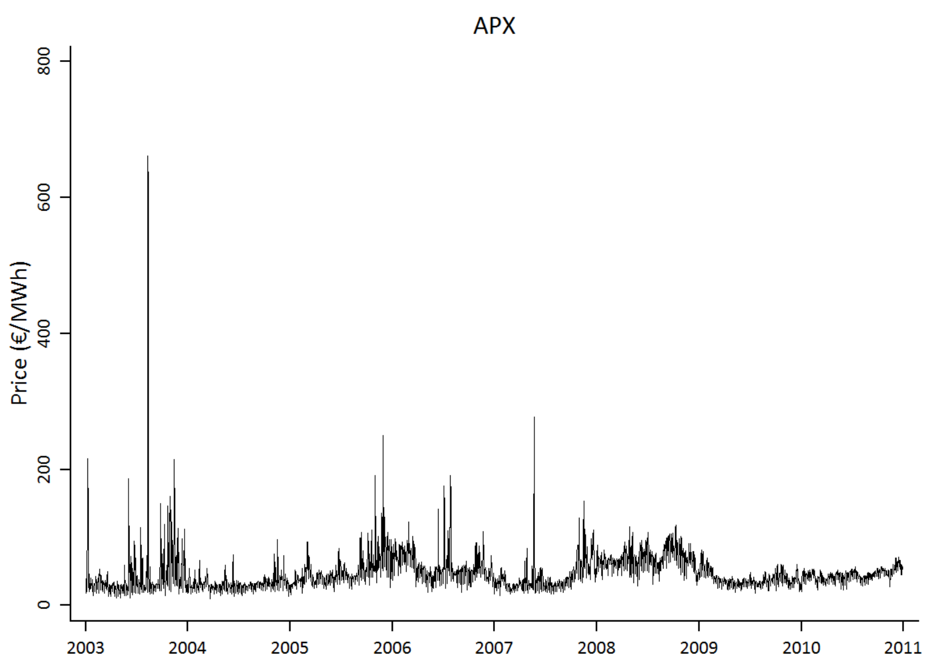
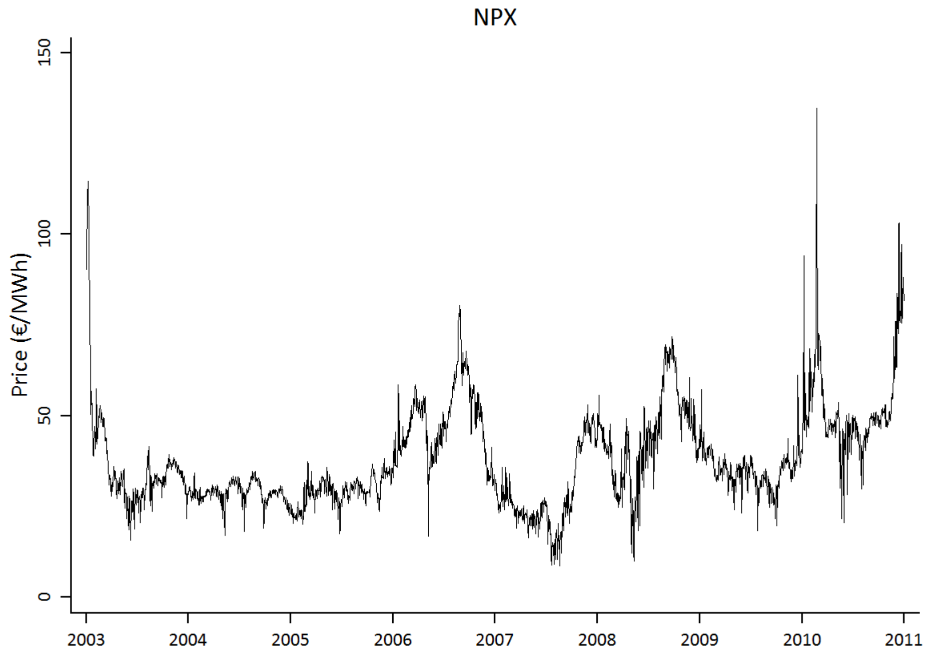


Figure 2.6: **Day-ahead electricity prices in Nordic countries.**



The first observation from Table 2.1 is that the variation in prices reduced over time. The standard deviations of the day-ahead prices declined over time in all markets. Furthermore, the maximum and minimum prices became less extreme. The decreasing skewness and kurtosis also show that extreme price uncertainty decreased. The Dutch and French markets exhibit the most pronounced upward spikes. In 2003, a maximum price of 660 €/MWh was observed where the mean price was 46.5 €/MWh. In 2009, the day-ahead price reached a maximum of 613 €/MWh. In 2009, the minimum price for Germany decreased to -35.6 €/MWh; a negative price due to an oversupply of wind power.

Table 2.1: **Descriptive statistics for the day-ahead prices.**

	2003	2004	2005	2006	2007	2008	2009	2010
Belgium								
Mean	40.1	30.6	49.7	54.7	41.8	70.6	39.4	46.3
Median	30.5	30.3	43.25	49.5	32.9	69.1	37.6	45.7
Max.	300.0	64.0	153.5	195.0	314.3	168.5	90.3	85.9
Min.	4.0	14.0	14.0	19.3	6.2	22.5	13.3	15.1
Std. dev.	29.4	8.2	21.1	22.5	30.1	18.4	11.6	11.0
Skew.	3.5	0.8	1.8	1.7	4.4	0.5	1.2	0.6
Kurt.	19.8	1.6	3.9	6.0	29.9	1.7	2.2	1.2
# of Obs.	365	366	365	365	365	366	365	365
France								
Mean	29.2	28.1	46.7	49.3	40.9	69.2	43.0	47.5
Median	27.3	29.0	42.1	43.3	32.6	68.0	38.7	46.7
Max.	310.4	43.8	154.8	234.4	314.3	118.2	612.8	89.8
Min.	4.9	7.76	13.6	9.5	12.2	21.1	13.3	15.1
Std. dev.	19.0	6.2	20.2	23.6	27.6	17.9	32.4	11.8
Skew.	9.5	-0.6	2.3	2.5	4.2	0.0	15.0	0.6
Kurt.	133.3	0.5	6.7	13.3	29.5	0.0	263.3	1.0
# of Obs.	365	366	365	365	365	366	365	365
Germany								
Mean	29.5	28.5	46.0	50.8	38.0	65.8	38.8	44.4
Median	29.1	29.4	42.4	46.9	32.7	65.7	37.9	44.8
Max.	163.5	46.6	146.0	301.5	159.0	131.4	86.4	72.1
Min.	3.1	12.1	13.6	14.0	5.8	21.0	-35.6	15.9
Std. dev.	13.1	6.5	18.4	24.5	19.9	18.1	11.9	8.8
Skew.	3.8	-0.4	2.5	4.4	2.4	0.3	0.6	-0.1
Kurt.	32.6	0.0	9.1	36.7	8.0	0.2	2.5	1.0
# of Obs.	365	366	365	365	365	366	365	365
The Netherlands								
Mean	46.5	31.6	52.4	58.1	41.9	70.1	39.2	45.4
Median	31.9	30.7	45.2	54.0	35.3	68.9	37.3	45.8
Max.	660.3	96.6	250.7	191.8	277.4	118.6	82.3	71.3
Min.	10.9	10.5	15.6	19.6	14.8	28.9	18.6	21.0
Std. dev.	57.3	9.7	24.7	23.0	23.5	16.3	10.5	8.2
Skew.	7.3	2.0	2.8	2.1	4.0	0.3	1.1	0.1
Kurt.	69	8.3	14.3	8.3	29.5	0.1	1.5	0.6
# of Obs.	365	366	365	365	365	366	365	365
Nordic countries								
Mean	36.7	28.9	29.3	48.6	27.9	44.7	35.0	53.1
Median	33.1	29.0	29.5	48.4	25.0	44.8	35.0	49.1
Max	114.6	34.9	38.3	80.4	53.0	71.8	61.2	134.8
Min	15.8	17.2	17.4	16.9	8.8	10.0	18.5	20.7
Std. dev.	14.9	2.7	3.9	10.4	10.1	12.4	4.8	13.7
Skew.	3.3	-0.6	-0.4	0.4	0.8	0.0	0.5	1.8
Kurt.	12.9	1.6	-0.2	0.2	-0.3	-0.1	3.7	4.9
# of Obs.	365	366	365	365	365	366	365	365

The different markets under study are directly or indirectly physically interconnected. The Dutch electricity market has an interconnection with the Belgian, German and Nordic markets. The Belgian market is also connected with the French electricity market and the German market has next to its interconnection with the Dutch market also an interconnection with the Nordic market. Since November 2006, a Trilateral Market Coupling for the day-ahead market was initiated between France, Belgium and the Netherlands. According to de Jonghe et al. [2008] this market coupling increased price convergence between the three markets. In case of a single integrated European electricity market, we would expect to see a increased level of price correlation. Table 2.2 shows the level of correlation between day-ahead electricity prices of different markets. Between 2003 and 2010, price correlation between the Netherlands, Belgium and Germany increased from respectively, 66.9 percent and 41 percent to around 90 percent and correlation increased from 16 percent in 2003 to 48 percent in 2010 between the Netherlands and Nordic countries. From this increase in correlation, we conclude that the level of integration increased between these power markets. Also between other markets, price correlation increased over time. Correlation between German and Nordic prices increased from 19 percent to 44 percent and correlation between French and Belgium prices increased from 43 percent to 94 percent

Table 2.2: **Price correlation between electricity markets.**

Year	**NL-BE**	**NL-GE**	**NL-FR**	**NL-NO**	**BE-GE**	**BE-FR**	**BE-NO**	**GE-FR**	**GE-NO**	**FR-NO**
2003	0.67	0.41	0.65	0.16	0.54	0.43	0.15	0.59	0.19	0.06
2004	0.78	0.64	0.65	0.18	0.73	0.73	0.22	0.91	0.33	0.27
2005	0.83	0.81	0.80	0.47	0.86	0.87	0.52	0.89	0.52	0.52
2006	0.88	0.75	0.82	0.10	0.80	0.91	0.07	0.79	0.16	0.03
2007	0.91	0.78	0.76	0.61	0.76	0.91	0.63	0.80	0.64	0.72
2008	0.95	0.88	0.90	0.50	0.83	0.88	0.42	0.88	0.60	0.58
2009	0.98	0.89	0.45	0.58	0.87	0.45	0.62	0.40	0.51	0.25
2010	0.91	0.93	0.83	0.48	0.86	0.94	0.47	0.79	0.44	0.49

Notes: Robust t-statistics are in parentheses. BE: Belgium, FR: France, GE: Germany, NL: The Netherlands and NO: Nordic countries

2.4 Results

In this section, we describe and compare the estimates of the parameters of the regime switching model in section 2.2 for the power markets in our sample. Tables 2.3 through 2.7 present the estimates, which are all significantly different from zero at the 95-percentage confidence level.

Focusing firstly on the different parameters of the regime switching model for the Dutch, Belgian, German and French markets, we observe that the different parameters develop comparably. μ_1, which is the mean log price level in the normal regime, is increasing. The price level in the abnormal regime (μ_2) declines for all four markets, indicating that extreme price levels decreased in magnitude over time. In fact, the estimates for μ_2 became negative (in log terms). We observe that the probability that a spike occurs, i.e. $1 - p_{11}$, decreases for the Dutch, Belgian and French markets and increases for the German and Nordic countries. Apparently, price spikes did not disappear, but their impact reduced as the lower values for μ_2 indicate. In the tables, the speed of mean reversion under normal market conditions, α, shows a significant decline for all four markets. Meaning that it will take longer to return to the mean price level. Seen from Eq. (2.3), a reduction in the speed of mean-reversion is equivalent to saying that price changes become more random. To see this, rewrite Eq. (2.3) by subtracting x_{t-1} from both sides of the equation. We then obtain:

$$x_t - x_{t-1} = -\alpha x_{t-1} + \sigma_1 \epsilon_{1,t}. \tag{2.6}$$

Equation (2.6) then shows that when the speed of mean-reversion declines, i.e. the value of α becomes smaller, the influence of x_{t-1} on the price change $x_t - x_{t-1}$ reduces and price changes behave more randomly. According to financial markets theory, prices behave at random in an efficient market and therefore we conclude, from observing an increase in randomness, that the electricity markets that we examine became more efficient over time.

Studying the volatility of the prices in the normal and abnormal regime we see a decline in the values of σ_1 and σ_2. This indicates a decrease in the volatility of the prices in both regimes. Low volatility in the abnormal regime implies that the level of expected price spikes is quite predictable, since the variation is small and will remain close to the mean spike size. Therefore the spikes are becoming less variable over time. The low volatility in the abnormal regime combined with the lower mean price spike level indicates that the day-ahead prices in

Table 2.3: **Parameter estimates for Belgium.**

Year	λ_1	λ_2	μ_1	β	α	μ_2	σ_1	σ_2	p_{11}	p_{22}
2003	2.903	2.436	3.451	-0.459	0.437	0.483	0.126	0.534	0.948	0.920
	(0.395)	(0.389)	(0.024)	(0.021)	(0.050)	(0.056)	(0.010)	(0.033)		
2004	2.904	1.857	3.465	-0.370	0.271	0.065	0.074	0.269	0.950	0.865
	(0.373)	(0.401)	(0.019)	(0.013)	(0.039)	(0.038)	(0.006)	(0.021)		
2005	3.321	1.647	3.863	-0.310	0.083	0.314	0.101	0.348	0.965	0.840
	(0.385)	(0.434)	(0.077)	(0.013)	(0.028)	(0.095)	(0.007)	(0.035)		
2006	3.249	1.254	4.005	-0.386	0.069	-0.021	0.105	0.478	0.963	0.778
	(0.382)	(0.430)	(0.092)	(0.012)	(0.023)	(0.128)	(0.005)	(0.060)		
2007	4.163	1.072	3.629	-0.331	0.159	0.467	0.200	0.914	0.985	0.745
	(0.521)	(0.579)	(0.066)	(0.023)	(0.029)	(0.247)	(0.009)	(0.147)		
2008	3.321	1.612	4.360	-0.295	0.371	-0.269	0.130	0.350	0.965	0.834
	(0.438)	(0.540)	(0.022)	(0.018)	(0.047)	(0.056)	(0.006)	(0.036)		
2009	3.601	2.242	3.784	-0.271	0.181	-0.290	0.127	0.193	0.973	0.904
	(0.501)	(0.631)	(0.042)	(0.016)	(0.035)	(0.048)	(0.006)	(0.019)		
2010	3.123	0.896	3.896	- 0.228	0.157	- 0.177	0.101	0.240	0.958	0.710
	(0.398)	(0.474)	(0.037)	(0.012)	(0.033)	(0.057)	(0.005)	(0.031)		

Notes: Standard errors are in parenthesis.

Table 2.4: **Parameter estimates for France.**

Year	λ_1	λ_2	μ_1	β	α	μ_2	σ_1	σ_2	p_{11}	p_{22}
2003	3.138	1.107	3.395	-0.377	0.471	-0.006	0.177	0.671	0.958	0.752
	(0.392)	(0.509)	(0.024)	(0.023)	(0.045)	(0.101)	(0.009)	(0.075)		
2004	2.632	2.685	3.277	-0.308	0.690	0.211	0.221	0.102	0.933	0.936
	(0.446)	(0.446)	(0.040)	(0.019)	(0.168)	(0.047)	(0.015)	(0.010)		
2005	4.114	0.146	3.840	-0.296	0.197	0.323	0.169	0.558	0.984	0.536
	(0.719)	(0.871)	(0.050)	(0.020)	(0.032)	(0.312)	(0.009)	(0.132)		
2006	3.640	2.543	3.923	- 0.341	0.169	- 0.151	0.250	0.111	0.974	0.927
	(0.483)	(0.485)	(0.088)	(0.021)	(0.036)	(0.090)	(0.011)	(0.011)		
2007	5.180	1.657	3.617	-0.339	0.147	1.064	0.196	0.458	0.994	0.840
	(0.725)	(0.847)	(0.068)	(0.021)	(0.028)	(0.165)	(0.007)	(0.099)		
2008	3.224	1.757	4.354	-0.271	0.326	-0.348	-0.127	0.295	0.962	0.853
	(0.406)	(0.464)	(0.025)	(0.018)	(0.048)	(0.047)	(0.007)	(0.026)		
2009	3.869	0.709	3.773	-0.242	0.150	-0.075	0.128	0.688	0.980	0.670
	(0.448)	(0.486)	(0.046)	(0.015)	(0.029)	(0.156)	(0.006)	(0.112)		
2010	3.435	1.182	3.920	-0.217	0.160	-0.237	0.112	0.204	0.969	0.765
	(0.460)	(0.597)	(0.042)	(0.014)	(0.033)	(0.056)	(0.005)	(0.028)		

Notes: Standard errors are in parenthesis.

Table 2.5: **Parameter estimates for Germany.**

Year	λ_1	λ_2	μ_1	β	α	μ_2	σ_1	σ_2	p_{11}	p_{22}
2003	3.667	1.116	3.476	-0.480	0.474	-0.300	0.195	0.667	0.975	0.753
	(0.479)	(0.580)	(0.026)	(0.025)	(0.050)	(0.135)	(0.010)	(0.103)		
2004	3.128	2.495	3.500	-0.330	0.630	-0.218	0.111	0.217	0.958	0.924
	(0.412)	(0.526)	(0.015)	(0.017)	(0.063)	(0.025)	(0.006)	(0.015)		
2005	3.888	3.212	3.832	-0.319	0.193	-0.087	0.208	0.107	0.980	0.961
	(0.517)	(0.530)	(0.078)	(0.018)	(0.046)	(0.080)	(0.010)	(0.008)		
2006	3.430	3.160	4.037	-0.438	0.265	-0.145	0.288	0.144	0.969	0.960
	(0.475)	(0.465)	(0.078)	(0.022)	(0.052)	(0.079)	(0.016)	(0.010)		
2007	3.630	3.3678	3.840	-0.385	0.304	-0.395	0.289	0.165	0.974	0.967
	(0.561)	(0.514)	(0.078)	(0.025)	(0.055)	(0.078)	(0.016)	(0.012)		
2008	3.015	1.181	4.289	-0.312	0.320	-0.287	0.135	0.325	0.953	0.765
	(0.378)	(0.559)	(0.028)	(0.018)	(0.042)	(0.055)	(0.008)	(0.044)		
2009	3.661	0.831	3.734	-0.258	0.232	-0.305	0.144	0.405	0.975	0.696
	(0.471)	(0.479)	(0.035)	(0.017)	(0.038)	(0.091)	(0.006)	(0.062)		
2010	2.765	0.818	3.881	- 0.227	0.317	- 0.198	0.100	0.231	0.941	0.694
	(0.477)	(0.607)	(0.022)	(0.015)	(0.054)	(0.044)	(0.009)	(0.036)		

Notes: Standard errors are in parenthesis.

Table 2.6: **Parameter estimates for the Netherlands.**

Year	λ_1	λ_2	μ_1	β	α	μ_2	σ_1	σ_2	p_{11}	p_{22}
2003	3.274	2.320	3.503	-0.488	0.574	0.675	0.215	0.650	0.964	0.911
	(0.467)	(0.400)	(0.031)	(0.034)	(0.064)	(0.080)	(0.018)	(0.045)		
2004	3.226	1.790	3.467	-0.339	0.523	0.170	0.133	0.334	0.962	0.857
	(0.600)	(0.545)	(0.020)	(0.021)	(0.061)	(0.076)	(0.011)	(0.037)		
2005	3.894	3.056	3.804	-0.294	0.352	0.487	0.139	0.349	0.980	0.956
	(0.541)	(0.490)	(0.033)	(0.022)	(0.054)	(0.042)	(0.009)	(0.024)		
2006	4.522	0.972	4.070	-0.327	0.286	0.420	0.199	0.470	0.989	0.726
	(0.659)	(0.740)	(0.039)	(0.023)	(0.041)	(0.192)	(0.008)	(0.103)		
2007	3.762	1.569	3.685	-0.311	0.130	0.079	0.176	0.464	0.977	0.828
	(0.497)	(0.686)	(0.074)	(0.021)	(0.029)	(0.119)	(0.009)	(0.069)		
2008	3.292	1.322	4.309	-0.261	0.239	-0.089	0.121	0.268	0.964	0.790
	(0.479)	(0.537)	(0.030)	(0.015)	(0.042)	(0.057)	(0.006)	(0.033)		
2009	3.643	2.498	3.780	-0.246	0.163	-0.254	0.115	0.152	0.974	0.924
	(0.470)	(0.571)	(0.042)	(0.013)	(0.034)	(0.046)	(0.005)	(0.013)		
2010	3.724	2.611	3.887	- 0.206	0.155	- 0.108	0.083	0.129	0.976	0.932
	(0.549)	(0.656)	(0.036)	(0.010)	(0.039)	(0.039)	(0.004)	(0.014)		

Notes: Standard errors are in parenthesis.

Table 2.7: **Parameter estimates for the Nordic countries.**

Year	λ_1	λ_2	μ_1	β	α	μ_2	σ_1	σ_2	p_{11}	p_{22}
2003	3.754	1.251	3.500	-0.061	0.035	-0.188	0.044	0.314	0.977	0.777
	(0.429)	(0.431)	(0.080)	(0.006)	(0.010)	(0.095)	(0.003)	(0.041)		
2004	4.245	1.555	3.385	-0.463	0.062	-0.150	0.029	0.136	0.986	0.826
	(0.527)	(0.647)	(0.199)	(0.003)	(0.022)	(0.038)	(0.001)	(0.020)		
2005	3.580	1.143	3.372	- 0.056	0.040	- 0.046	0.039	0.155	0.973	0.758
	(0.412)	(0.410)	(0.057)	(0.004)	(0.018)	(0.065)	(0.002)	(0.018)		
2006	4.665	1.609	3.900	-0.060	0.017	-0.281	0.039	0.216	0.991	0.833
	(0.686)	(0.598)	(0.125)	(0.004)	(0.010)	(0.133)	(0.002)	(0.032)		
2007	4.608	2.554	3.474	-0.088	0.020	-0.751	0.063	0.233	0.990	0.928
	(0.645)	(0.694)	(0.060)	(0.007)	(0.012)	(0.071)	(0.003)	(0.026)		
2008	4.300	2.567	3.900	-0.087	0.022	-0.491	0.058	0.343	0.987	0.929
	(0.558)	(0.581)	(0.057)	(0.007)	(0.015)	(0.073)	(0.003)	(0.032)		
2009	3.858	1.328	3.570	-0.076	0.089	-0.070	0.042	0.244	0.979	0.790
	(0.443)	(0.446)	(0.027)	(0.005)	(0.023)	(0.049)	(0.002)	(0.032)		
2010	3.288	2.656	3.946	- 0.061	0.073	- 0.052	0.117	0.027	0.964	0.934
	(0.397)	(0.392)	(0.088)	(0.006)	(0.032)	(0.088)	(0.006)	(0.002)		

Notes: Standard errors are in parenthesis.

the Dutch, Belgian, German and French markets have become more stable. We also observe that the estimates for σ_2 converge to the volatility in the normal regime (σ_1). This can be explained with more liquidity in and increased connectivity between the day-ahead markets. To examine the convergence of the volatility parameters, the significance of the difference between σ_1 and σ_2 is analysed by conducting an independent two-sample t-test. The results are shown in Table 2.8 and indicate that the volatility in the normal and abnormal regime are significantly different, however the t-statistic decreases over time. The weekend factor β, which is the difference in mean price level between weekend and workdays shows a significant rise from -0.5 for the Dutch, Belgian and German markets to -0.4 and for the French market to -0.2, implying that the difference between weekend and workdays mean log price is smaller and thus less weekend seasonality.

The Nordic market shows a total different pattern with increasing parameters. Unlike for the Dutch, Belgian, German and French markets α, μ_2 and σ_1 increases over time. In the normal regime, there is more price fluctuation, however after a fluctuation the prices revert faster to the mean price level. The normal regime is characterised by low volatility and the abnormal regime by high volatility, however for the Nordic market we observe that over the years σ_1 is increasing and σ_2 is decreasing and in 2010 σ_1 (0.117) becomes even higher then σ_2 (0.027).

Table 2.8: **T-test values volatility σ_1 and σ_2.**

Year	NL	BE	GE	FR	NO
2003	-8.975	-11.832	-4.561	-6.534	-6.568
2004	-18.271	-32.500	-17.666	7.782	-107.000
2005	-8.193	-6.920	7.887	-2.935	-6.405
2006	-2.623	-6.195	7.632	22.476	-5.520
2007	-4.139	-4.848	6.200	-2.641	-6.495
2008	-4.383	-6.028	-4.249	-15.588	-8.867
2009	-2.656	-3.312	-4.190	-5.006	-6.300
2010	-3.159	-4.427	-3.530	-3.241	14.230

Notes: In this table the independent two-sample t-test coefficient is conducted to analyze if the volatility estimates are statistically different with function: t = $\frac{(X1-X2)}{\sqrt{SE1+SE2}}$ where $X1 = \sigma_1$, $X2 = \sigma_2$, $SE1$ = the standard error of σ_1 and $SE2$ = the standard error of σ_2. BE: Belgium, FR: France, GE: Germany, NL: the Netherlands NO: Nordic markets

Secondly, we observe in Tables 2.3 through 2.7 that the parameters of the different markets are converging through time. To study if the parameters of the markets who are physically interconnected are really converging through time, the significance of difference between the parameters is analysed by conducting an independent two-sample t-test. The results are shown in Table 2.9 and several interesting outcomes are apparent. First of all the Dutch electricity market is connected with the Belgian, German and Scandinavian markets and is indirectly influenced by the French market through its interconnection with Belgium. The Nordic market does not show any sign of convergence with the Netherlands. In 2010, we observe that for the Netherlands, Belgium, Germany and France the mean log price level in the normal regime(μ_1) converges to 3.9 and μ_1 does not significantly differ between these markets according to Table 2.9. μ_2 converges to -0.2, however for the Dutch market μ_2 is -0.1. The increase of the mean log price level in the abnormal regime (μ_2) shows a decrease in the significance level and in the year 2010 this difference is not significant anymore. The weekend seasonality β converges significantly to -0.2. The speed of mean reversion α converges significantly to 0.2, except for Germany α is 0.3 and is significantly different. The volatility of the prices in the normal regime σ_1 converges to 0.1 and for the abnormal regime σ_2 to 0.2, except for the Netherlands σ_2 is 0.1. However the t-statistics of σ_1 and σ_2 are increasing over time, meaning that the difference between the parameters are significant at the 95-percentage confidence level. Secondly the Belgian market is also connected with the French electricity market. All parameter estimations show convergence and the decline of the t-statistic indicates that there is no significant difference between these parameters.

Table 2.9: **T-test values of the parameter estimates.**

NL/BE	p_{11}	p_{22}	μ_1	β	α	μ_2	σ_1	σ_2
2003	0.607	-0.208	1.326	-0.726	1.687	1.966*	4.322*	2.079*
2004	0.456	-0.099	0.072	1.255	3.481*	1.236	4.709*	1.528
2005	0.863	2.153*	-0.704	0.626	4.422*	1.666	3.333*	0.024
2006	1.671	-0.329	0.650	2.274*	4.616*	1.911	9.964*	-0.067
2007	-0.557	0.554	0.565	0.642	-0.707	-1.415	-1.886	-2.771*
2008	-0.045	-0.381	-1.371	1.451	-2.094*	2.253	-1.061	-1.679
2009	0.061	0.301	-0.067	1.213	-0.369	0.541	-1.536	-1.781
2010	0.886	2.119*	-0.174	1.408	-0.039	0.999	-2.811*	-3.263*
NL/GE	p_{11}	p_{22}	μ_1	β	α	μ_2	σ_1	σ_2
2003	-0.587	1.709	0.667	-0.190	1.231	6.213*	0.971	-0.151
2004	0.135	-0.931	-1.320	-0.333	-1.220	4.850*	1.756	2.930*
2005	0.008	-0.216	-0.331	0.879	2.241*	6.353*	-5.129*	9.566*
2006	1.344	-2.504*	0.378	3.488*	0.317	2.721*	-4.975*	3.150*
2007	0.176	-2.099*	-1.442	2.266*	-2.798*	3.331*	-6.156*	4.269*
2008	0.454	0.182	0.487	2.177*	-1.364	2.500	-1.400	-1.036
2009	-0.027	2.237*	0.841	0.561	-1.353	0.500	-3.713*	-3.994*
2010	1.319	2.006*	0.142	1.165	-2.432*	1.531	-1.726	-2.641*
NL/NO	p_{11}	p_{22}	μ_1	β	α	μ_2	σ_1	σ_2
2003	-0.757	1.818	0.035	-12.368*	8.321*	6.949*	9.371*	5.519*
2004	-1.276	0.278	0.410	5.845*	7.109*	3.766*	9.416*	4.708*
2005	0.462	2.994*	6.559*	-10.644*	5.481*	6.887*	10.847*	6.467*
2006	-0.150	-0.670	1.298	-11.437*	6.374*	3.001*	19.403*	2.355*
2007	-1.039	-1.009	2.215*	-10.074*	3.505*	5.990*	11.911*	3.133*
2008	-1.371	-1.574	6.350*	-10.512*	4.866*	4.340*	9.391*	-1.632
2009	-0.333	1.615	4.206*	-12.205*	1.803	-2.738	13.556*	-2.664*
2010	0.644	-0.059	-0.621	-12.434*	1.625	-0.582	-4.715*	7.212*
BE/FR	p_{11}	p_{22}	μ_1	β	α	μ_2	σ_1	σ_2
2003	-0.421	2.073*	1.667	-2.603*	-0.510	4.232*	-3.857*	-1.671
2004	0.468	-1.380	4.216*	-2.688*	-2.426*	-2.402*	-8.931*	7.130*
2005	-0.972	1.543	0.245	-0.588	-2.671*	-0.028	-5.834*	-1.533
2006	-0.636	-1.988*	0.646	-1.852	-2.353*	0.831	-11.666*	9.649*
2007	-1.139	-0.570	0.125	0.244	0.301	-2.011*	0.359	2.572*
2008	0.162	-0.204	0.167	-0.961	0.669	1.085	28.885*	1.228
2009	-0.398	1.925	0.181	-1.325	0.687	-1.315	-0.090	-4.366*
2010	-0.513	-0.375	-0.437	-0.621	-0.055	0.756	-1.546	0.854
GE/NO	p_{11}	p_{22}	μ_1	β	α	μ_2	σ_1	σ_2
2003	-0.135	-0.187	-0.285	-16.297*	8.609*	-0.678	14.463*	3.184*
2004	-1.670	1.127	0.576	7.704	8.512*	-1.495	13.481*	3.240*
2005	0.466	3.088*	4.762*	-14.263*	3.097*	-0.398	16.572*	-2.437*
2006	-1.480	2.047*	0.930	-16.905*	4.683*	0.879	15.442*	-2.148*
2007	-1.144	0.943	3.719*	-11.440*	5.045*	3.375*	13.883*	-2.375*
2008	-1.907	-1.719	6.125*	-11.650*	6.682*	2.232*	9.012*	-0.331
2009	-0.305	-0.759	3.710*	-10.271*	3.219*	-2.274*	16.128*	2.308*
2010	-0.843	-2.544*	-0.717	-10.275*	3.887*	-1.484	-1.572	5.658*

Notes: In this table the independent two-sample t-test coefficient is conducted to analyze if the two parameter estimates are statistically different with function: t = $\frac{(X1-X2)}{\sqrt{SE1+SE2}}$ where $X1$ = the parameter estimation of market 1, $X2$= the parameter estimation of market 2 , $SE1$ = the standard error of the parameter estimation of market 1 and $SE2$ = the standard error of the parameter estimation of market 2. *,denote a test statistic is statistically significant at the 5% level of significance. BE: Belgium, FR: France, GE: Germany, NL: the Netherlands, NO: Nordic markets

2.5 Concluding remarks

In this paper, we examine the development of day-ahead prices in five European markets which became more connected over recent years. Where previous studies examined the convergence of price levels over time, we focus on patterns in estimates for the parameters in a switching regimes model. This makes it possible to distinguish between prices under normal market conditions and under non-normal market conditions, those market conditions that can cause extreme price spikes. We expect that increased connectivity yields additional supply in the short-term and therefore will reduce the impact of price spikes. Our results indicate that the impact of price spikes and volatility decreased over time, that prices behave more random, and that the parameter estimates between various connected markets seem to have converged between the Belgian, Dutch, French, German, and Nordic day-ahead markets over the years 2003 through 2010. These results can be explained by increased connectivity and improved liquidity.

3 | Extreme Changes in Prices of Electricity Futures

Chapter 3 is based on Huisman and Kiliç [2011].

3.1 Introduction

In this chapter we focus on the occurrence of extreme price changes in power delivery forward or futures contracts. These contracts are traded on exchanges worldwide and energy companies use these contracts to hedge themselves against market risk. For instance, an energy company that needs to deliver power to clients in the year 2011, can buy a power futures contract somewhere in 2010 and fixate the price against which it will purchase power for its clients. We refer to these contracts as both power delivery forward and futures contracts in the remainder of this chapter. The pricing of these contracts is not as straightforward as pricing futures contracts on stocks, for instance. As discussed by Fama and French [1987] and many others traders use the availability of storage capacity to valuate futures contracts. A trader that sells a futures contract can make his position risk free by purchasing the commodity on the spot market. As a result, the futures price should reflect the spot price of the commodity plus interest forgone, storage costs, and a convenience yield that reflects the value that can be derived out of having the commodity physically. Power is not yet economically storable and, as a consequence, the power futures prices reflect expectations and risk premiums (see Fama and French [1987]; Lucia and Schwartz [2002];Eydeland and Wolyniec [2003]; and Huisman [2009] among others). Power futures prices do not necessarily depend on the spot price of power and therefore their price dynamics should be modeled as a stand-alone process.

Risk managers in the power sector use these contracts to actively manage market risk. For instance, consider a power company that has agreed to deliver power against a fixed price to clients in 2011. When the company will buy the power during the delivery period 2011 in the spot market, it faces the risk that the average price, paid in the spot market, is higher than what is agreed with the clients. By purchasing a power forward delivery contract, the risk manager can fixate the price against which the company will purchase power in the market in 2011 and by doing so price risk is reduced. However, the timing of when to purchase these forward contracts is a difficult decision. One can buy such a contract today or perhaps tomorrow when prices might be lower. It depends on the risk of a potential price increase that might occur between today and tomorrow, whether a company wants to purchase today or wait.

In this chapter, we focus on this price risk. We examine to what extent changes in power delivery futures prices can be modeled using a normal distribution function or whether another method should be applied. We apply extreme value theory to assess the level of tail-fatness, i.e. the frequency with which large price movements occur, such that we can observe whether these price changes can be modeled using a normal distribution or not. Bernhardt et al. [2008] apply extreme value theory to estimate high quantiles dynamically for day-ahead electricity prices in Singapore. Byström [2005] applies extreme value theory to model electricity prices on the NordPool market, making quantile (VaR) forecasts allowing both for fat tails and time-varying volatility. Both papers find strong support for the existence of fat tails in day-ahead prices and for the superior quantile estimates that extreme value theory produces. Ren and Giles [2007] present an extreme value analysis of daily Canadian crude oil prices and find strong support for fat tails. Although the amount of tail-fatness is examined in oil markets and for day-ahead power prices, it has never been examined for changes in the price of power futures delivery contracts. This is the goal set in this chapter.

We analyse the occurrence of extreme price change in power delivery forward and futures contracts. Our results indicate that the distribution of price changes are significantly fatter tailed than a normal distribution function and we discuss that risk managers in the power industry can obtain better insight in the amount of risk their companies face by applying extreme value theory.

3.2 Extreme value theory

Extreme value theory is a field within statistics that deals with the frequency with which extreme observations occur. We follow Hull [2007] and Huisman [2009] in discussing extreme value theory and we start with the key result in extreme value theory found by Gnedenko [1943]. Suppose $F(\nu)$ is the cdf of a variable ν: $F(\nu) = Pr\{V \leq \nu\}$. As extreme value theory focuses on the structure of the tail, consider a value u that is a value of ν somewhere in the right tail of the distribution function of ν. The probability that ν lies between u and $u + y$ equals $F(u + y) - F(u)$ for $y > 0$. Define $F_u(y)$ as the probability that ν lies between u and $u + y$ conditional on $\nu > u$. Thus, $F_u(y) = Pr\{u \leq \nu \leq u + y|\nu > u\}$. Gnedenko [1943] shows that for large values for u, $F_u(y)$ converges to the generalized Pareto distribution for many probability distribution functions F (.). The generalized Pareto distribution $G_{\alpha,\beta}(y)$ is:

$$G_{\alpha\beta}(y) = 1 - (1 + \frac{y}{\alpha\beta})^{-\alpha} \tag{3.1}$$

Hull (2007) continues reasoning that the probability that $\nu > u + y$ given that $\nu > u, 1 - F_u(y)$, then equals $1 - G_{\alpha\beta}(y)$. Furthermore, the probability that $\nu > u$ is $1 - F(u)$. The unconditional probability that ν exceeds a value x, $Pr\{\nu > x\}$ equals:

$$\begin{aligned} Pr\{\nu > x\} &= Pr\{\nu > u\}Pr\{\nu > u + (x - u)|\nu > u\} \\ &= (1 - F(u))(1 - G_\alpha, \beta(x - u)). \end{aligned} \tag{3.2}$$

This result of Gnedenko [1943] implies that many distribution functions follow a generalized Pareto distribution in the tails. When we approximate $1 - F(u)$ by its empirical counterpart $\frac{n_u}{n}$, where n is the number of observations in the sample and n_u is the number of observations that exceed the value u, Eq. (3.2) can be written as:

$$\begin{aligned} Pr\{\nu > x\} &= \frac{n_u}{n}(1 - G_{\alpha,\beta}(x - u)) \\ &= \frac{n_u}{n}(1 + \frac{x - u}{\alpha\beta})^{-\alpha}. \end{aligned} \tag{3.3}$$

If we now set $u = \beta\alpha$ and $K = \frac{n_u}{n}(\frac{1}{\alpha\beta})^{-\alpha}$, then we obtain what is called the power law:

$$Pr\{X > x\} = Kx^{-\alpha}. \tag{3.4}$$

We have now formalised the main ideas within extreme value theory. Beyond a certain threshold, fat tailed distribution functions exhibit power decay. The speed of decay is measured by α in Eq. (3.4). This parameter is called the tail-index. The bigger α is, i.e. the steeper the decay, the thinner the tails become and vice versa. The normal distribution, being a thin tailed distribution function, exhibits exponential decay, which is obtained when $\alpha \to \infty$.

The goal of this chapter is to examine the tail structure of log-price changes of electricity forward prices. To do so, we estimate the tail-index α using the procedure outlined in the following paragraph.

3.3 Estimating the tail-index α

Let us focus on estimating the tail-index of the right tail of the distribution function. Let k be the number of tail observations that we include in the estimation, such as the k highest or lowest returns. Let x_i be the i^{th} order statistic, such that $x_i \geq x_{i-1}$. Hill [1975] shows that the estimate of the inverse of the tail-index, $\gamma = \frac{1}{\alpha}$, for k tail-observations equals:

$$\gamma_k = \frac{1}{k}\sum_{j=1}^{k} ln(x_{n-j+1}) - ln(x_{n-k}), \tag{3.5}$$

where n is the total number of observations in the entire sample. How to select k, the number of tail observations to include in the estimate? Initially, researchers calculated estimates for α for different values for k and then state their conclusions in terms of the average result. Others tried to approximate the optimal k by assuming that the data came from some distribution function and then select k that would lead to the best results in a simulation study. Examples of these approaches are (among others) Jansen and de Vries [1991], Koedijk and Kool [1994], and Kearns and Pagan [1997] who estimated the tail-index for the return distributions of exchange rates and stocks. The results indicated fat tails, but one is left with the uncomfortable feeling that the tail-index estimates suffer from a bias in choosing k. One way to limit the influence of this bias is proposed by Huisman et al. [2001], a method that we apply in this chapter. It is an extension of the Hill [1975] estimator.

Huisman et al. [2001] observe that the expected value for the estimate γ_k equals $\frac{1}{\alpha}$ plus some function $f()$ that depends on k:

$$E(\gamma_k) = \frac{1}{\alpha} + f(k). \tag{3.6}$$

Huisman et al. [2001] show for several distribution functions, among them the Student-t, that the function f () is almost linear. They formulate the following regression equation:

$$\gamma_k = \beta_0 + \beta_1 k + \epsilon_k, \tag{3.7}$$

and the estimate for β_0 is then an accurate estimate for $\gamma = \frac{1}{\alpha}$. Basically, the Huisman et al. [2001] estimator combines information from different choices of k to reduce the bias in the Hill [1975] estimator. Still, a number k of observations needs to be chosen, however Huisman et al. [2001] show that the estimates of γ are not that sensitive to a wrong choice for k. In this chapter, we set $k = \frac{n}{4}$ as suggested by Huisman et al. [2001][1]. They applied their method to changes in the values of exchange rates, finding values for α between 3 and 5.

3.4 Data and descriptive analysis

The primary data for this study consists of daily forward closing prices for two markets, the European Energy Exchange (EEX) in Germany and the Nordic Power Exchange (NordPool, NPX), which is the single power market for Norway, Denmark, Sweden and Finland. The forward contracts for the EEX market include the base and peak load delivery contracts for the years 2009, 2010, and 2011[2]. These contracts are traded for several years before delivery on the exchanges. We limit ourselves to study the forward prices obtained in the period between one year before maturity until the last trading day before delivery starts as commonly the next years delivery contract is the most liquid. Therefore, we study the prices as quoted in 2008 for the 2009 delivery contracts, the prices quoted in 2009 for the 2010 delivery contracts and the prices quoted in 2010 for the 2011 delivery period. Our data set spans the trading days between January 1, 2008 through December 17, 2010, having approximately 250 daily forward price observations per year. Table 3.1 contains descriptive statistics for the daily changes in

[1]We refer to Huisman et al. [2001] for the weighted least squares method to estimate the tail-index and for the procedure to obtain standard errors.

[2]For instance, the base load 2009 contract involves the delivery of 1MW of power in any hour of the calendar year 2009 and the peak load 2009 contract involves the delivery of 1MW of power in any hour on weekdays between 8 a.m. and 8 p.m. in 2009.

the natural logarithms of the forward prices for the EEX and NPX base and peak load forward contracts.

Table 3.1: **Statistics for the observed daily log forward price changes.**

	2009		**2010**		**2011**	
EEX	Base	Peak	Base	Peak	Base	Peak
Mean	0.000	0.000	-0.001	-0.001	0.000	-0.001
Median	0.000	0.000	-0.001	-0.002	-0.002	-0.002
Max.	0.065	0.049	0.052	0.045	0.037	0.038
Min.	-0.059	-0.057	-0.046	-0.035	-0.033	-0.025
Std. dev.	0.015	0.014	0.014	0.012	0.010	0.010
Skew.	-0.229	-0.618	0.295	0.395	0.558	0.696
Kurt.	2.386	2.574	1.926	2.029	0.926	1.253
# of Obs.	251	251	251	251	247	247
NPX	Base	Peak	Base	Peak	Base	Peak
Mean	-0.001	-0.001	0.000	0.000	0.001	0.001
Median	0.001	0.000	0.000	0.001	0.002	0.000
Max.	0.067	0.059	0.092	0.099	0.064	0.061
Min.	-0.090	-0.090	-0.068	-0.086	-0.056	-0.059
Std. dev.	0.023	0.023	0.023	0.024	0.017	0.020
Skew.	-0.720	-0.736	0.248	0.336	0.099	0.327
Kurt.	2.094	1.587	1.339	1.957	1.040	1.292
# of Obs.	249	248	248	244	243	243

Notes: Descriptive statistics of daily base and peak load electricity log forward price changes for the period of January 1, 2008 through December 17, 2010 for Germany (EEX) and the Nordic countries (NPX).

Table 3.1 shows that the daily mean log-price change was about -0.001 in 2010, or -0.1%, for the 2011 peak load delivery contract. The maximum price change was 3.8% on one day and the minimum was 2.5%. The daily log-price changes for the peak load 2011 contract were positively skewed, 0.696, and exhibit excess kurtosis of 1.253 (in excess of the normal distribution function) indicating fatter tails than a normal distribution function. All excess kurtosis values are positive, which is a sign of fat tails in all years. On average, it seems that the tails of the distribution of log-price changes for EEX contracts are fatter than for the distribution of log-prices changes in the NPX.

3.5 Results

This section shows the tail-index estimates for the power delivery forward contracts. Table 3.2 shows the tail-index estimates for the base load contracts and Table 3.3 shows those estimates for the peak load contracts. Lets focus on the base load results in Table 3.2 first. The γ estimate for the 2009 delivery contract as traded on the EEX is significantly different from zero, being 0.267 with a standard error of 0.118. This γ estimate yields a value of 3.748 for α. The left tail of the empirical distribution of log-price changes of the EEX 2009 delivery contract has a γ estimate of 0.286 and the right tail has a γ of 0.386, implying that the right tail is fatter than the left tail, i.e. more extreme positive than negative price changes occurred for the EEX 2009 delivery contract.

The first result we learned from Tables 3.2 and 3.3 is that the tail-index estimates (in terms of α) vary between 1.837 and 6.609 for the EEX base load contracts and between 2.461 and 12.040 for the NPX base load contracts[3]. For the peak load contracts these values vary between 2.313 and 6.399 for the EEX and 3.015 and 31.707 for the NPX contracts. These levels are in line with the tail-index estimates as observed for returns on stocks and exchange rates[4]. The empirical distribution of log-price changes on power delivery forward contract are clearly fatter tailed than a normal distribution.

The second result we learned from these tables is that there is no clear relation between the level of the tail-index and the specific market in which the forward delivers. Neither it seems that there is an apparent difference in tail-index values between the base load and peak load contracts or between the left and the right tail of the distribution.

[3]We ignore the α estimate of -42.433 here, which is perhaps due to some estimation error.

[4]See for instance Jansen and de Vries [1991], Koedijk and Kool [1994], Kearns and Pagan [1997], and Huisman et al. [2001].

Table 3.2: **Tail fatness estimates for EEX and NPX forward base returns.**

	2009		2010		2011	
	EEX	**NPX**	**EEX**	**NPX**	**EEX**	**NPX**
γ	0.267	0.281	0.151	0.089	0.402	0.258
	(0.118)	(3.027)	(0.021)	(0.012)	(0.008)	(0.029)
α	3.748	3.559	6.609	11.185	2.489	3.882
γl	0.286	0.406	-0.024	0.083	0.544	0.166
	(0.051)	(0.014)	(0.003)	(0.023)	(0.007)	(0.017)
α	3.491	2.461	- 42.433	12.040	1.837	6.025
γr	0.386	0.284	0.275	0.122	0.284	0.359
	(0.016)	(0.115)	(0.443)	(0.119)	(0.058)	(0.022)
α	2.593	3.521	3.635	8.182	3.527	2.781

Notes: Standard errors are in parenthesis. γ reflects the tail-index for both tails; γl for the left tail, γr for the right tail; α is calculated as $1/\gamma$.

Table 3.3: **Tail fatness estimates for EEX and NPX forward peak returns.**

	2009		2010		2011	
	EEX	**NPX**	**EEX**	**NPX**	**EEX**	**NPX**
γ	0.343	0.173	0.242	0.300	0.370	0.119
	(0.015)	(0.022)	(0.099)	(0.073)	(0.011)	(0.014)
α	2.918	5.787	4.139	3.333	2.702	8.436
γl	0.300	0.161	0.164	0.239	0.432	0.181
	(0.197)	(2.433)	(0.070)	(0.209)	(0.010)	(0.018)
α	3.335	6.218	6.102	4.179	2.313	5.514
γr	0.357	0.161	0.267	0.332	0.156	0.032
	(0.022)	(0.058)	(0.023)	(0.033)	(0.032)	(0.021)
α	2.801	6.207	3.747	3.015	6.399	31.707

Notes: tandard errors are in parenthesis. γ reflects the tail-index for both tails; γl for the left tail, γr for the right tail; α is calculated as $1/\gamma$.

3.6 Discussion and concluding remarks

In this chapter, we have shown that the empirical distributions of log-price changes (or returns) of power forward prices exhibit significant fat tails. This implies that extreme price movements (both up and down) occur more frequently than what a normal distribution function would express. This is a result too important to ignore for risk managers, for instance, as they cannot use normal distributions to calculate their risk measures or values for options and other derivative contracts. If they would do so, they would underestimate the level of risk. With this in mind they can improve their estimates of value at risk, the average loss beyond the value at risk measure, or expected maximum losses using extreme value theory. To see this, we briefly discuss in the extreme value theory way of calculating value at risk, based on Huisman [2009]. Suppose a risk manager likes to measure the 99% one-day Value at Risk (VaR) faced on an open position in the 2011 power baseload delivery contract on the EEX. Per definition, the one-day 99% VaR is that price increase that is being exceeded in only 1% of all days. Let r be the one-day percentage return. Then

$$Pr\{r > 99\%VaR\} = 0.01. \tag{3.8}$$

From Eq. (3.3), we can derive

$$Pr\{r > VaR\} = \frac{n_u}{n}(1 + \frac{VaR - u}{\alpha\beta})^{-\alpha} = 0.01. \tag{3.9}$$

Rewriting this yields

$$VaR = u + \beta\alpha((\frac{0.01n}{n_u})^{\frac{-1}{\alpha}} - 1). \tag{3.10}$$

Using the estimates for α we have obtained before and if we choose a proper value for u, we can easily measure VaR using extreme value theory. Hull [2007] suggests to set u equal to the 95% quantile of the distribution function obtained from historical observations, such that $\frac{n_u}{n} = 0.05$. Still, the risk manager has to estimate β. Huisman et al. [1998] show an alternative way of calculating VaR using extreme value theory. They argue that the degrees of freedom ν in a Student-t distribution, which is fat-tailed, equals the tail-index α. They apply extreme value theory to estimate the degrees of freedom ν and then they read off the value at risk from the Student-t distribution. The advantage of this method is that one does not need to estimate β in Eq. (3.10) or to choose a proper value u. They show that their method provides better VaR estimates for stocks and bonds compared to VaR based on the normal distribution.

This chapter shows that the price changes of power delivery forward contracts are fatter tailed than a normal distribution function. A risk manager in the power industry can, therefore, obtain more accurate risk calculations by applying extreme value theory then by applying measures based on normal distributions.

4 | Electricity Futures Prices: Indirect Storability, Expectations, and Risk Premiums

Chapter 4 is based on Huisman and Kiliç [2012].

4.1 Introduction

In this chapter, we focus on the prices of electricity futures contracts. When a buyer and a seller trade an electricity futures contract, the buyer agrees to purchase an amount of electricity during a future delivery period from the seller and to pay a fixed price per MWh. This is called the futures price which is agreed upon at the moment of the trade.

Fama and French [1987] summarise the two views on commodity futures prices. The first is the theory of storage which points out that traders can offset the risk of positions they have in forward contracts by holding a long or short inventory in the underlying commodity. For instance, when a trader sells a forward contract that involves the delivery obligation of some commodity at a future date against a price fixated today, she can purchase the commodity directly on the spot market, store it, and deliver it at the maturity date directly from inventory. Her delivery obligation is then covered and, hence, the prices she quotes for delivery at that future time period depends on the current spot price of the commodity, financing costs (interest), warehousing costs, and a convenience yield that accounts for the expected additional value of inventory. The second theory, the expectations theory, does not explain forward prices from storability. It describes that the forward price of a commodity equals the expected spot price of the underlying commodity during the delivery period plus an expected risk premium that compensates producers for bearing the uncertainty of delivering against fixed prices. Fama and French [1987] argue that the two theories are not mutually exclusive as variation in expected future spot prices or in the expected risk premium under the expectations theory translates into variation in the interest rate, warehousing costs and the convenience yield.

The expectations theory is the starting point for many electricity forward price models. This view is dominant because electricity is not directly storable and it makes therefore sense to start out from the expectations theory instead of the theory of storage. The price of an electricity forward contract is seen to reflect the expected spot price during the delivery period plus or minus a risk premium. The literature focuses therefore on modelling expectations or risk premiums.

Lucia and Schwartz [2002] focus primarily on expectations. They derive a formula for the forward price of electricity by modelling the expected spot price during a future time period. The expected spot price equals the sum of two prices: an equilibrium long-term spot price level and a mean-reverting short-term price. In addition to these expectations, they assume a constant risk premium[1]. They successfully fit their model to NordPool (NPX) electricity futures prices. This approach origins from the factor models introduced by Schwartz [1997] and the later extension into a long-term / short-term price model by Schwartz and Smith [2000].

Others focus more on (variation in) the risk premium instead of expectations. By subtracting average realised spot prices during the delivery periods from historically observed forward prices and assuming that trader expectations are unbiased in the long run, risk premiums can be studied empirically. This approach is applied by Wilkens and Wimschulte [2007] who examine futures prices on the German EEX market. They find positive but highly volatile risk premiums for futures contracts with times to maturity up to six months. Kolos and Ronn [2008] confirm this result as they find positive risk premiums for EEX forward prices as well. Regarding futures prices in the Nordic market, Gjolberg and Johnsen [2001] and Botterud et al. [2002] identify positive risk premiums for futures contracts with a time to maturity up to one year. Lucia and Torró [2008] find significant positive risk premiums in weekly NPX electricity futures contracts. Weron [2008] determines the market price risk in the NPX futures market using stochastic models. The author finds decreasing risk premiums with increasing time to maturity. These

[1] Two risk premiums actually: one for each source of uncertainty (long-term and short-term price uncertainty).

empirical studies shed light on the sign and variability of the risk premiums. Other studies provide insight in factors that explain risk premiums. Benth et al. [2008] provide a framework that explains how the market risk premium depends on the risk preferences of market players and the interaction between buyers and sellers. The authors argue that the risk premium for the EEX forward contracts depends on two factors; the level of risk aversion of buyers and sellers and secondly on the market power of producers, relative that of buyers. Bessembinder and Lemmon [2002] study the electricity forward risk premium by modelling the industry and the demand and supply of forward contracts. Forward prices are biased predictors of future spot prices and the forward risk premium is negatively related to the variance and positively related to the skewness of expected electricity spot prices. Longstaff and Wang [2004] conduct an empirical analysis of the forward risk premium by using hourly prices. They state that the risk premiums are time-varying and directly related to economic risk factors, such as the volatility of unexpected changes in demand, spot prices, total revenues and the risk that the electricity transmission system reaches its capacity limit. These findings are consistent with Bessembinder and Lemmon [2002]. The results of Cartea and Villaplana [2008] are also in agreement with the model of Bessembinder and Lemmon [2002]. Interestingly, Cartea and Villaplana [2008] find negative risk premiums, indicating backwardation, in the American PJM, English and Welsh and Nordic NPX markets. Bühler and Müller-Mehrbach [2009] develop a dynamic generalisation of the static model by Bessembinder and Lemmon [2002]. In the empirical analysis end-user demand is included and the cost function depends on the water reservoir level. The authors find for the NPX market on average, positive risk premiums for week futures and negative risk premiums for block futures. Besides Bessembinder and Lemmon [2002], Routledge et al. [2001] also consider an equilibrium pricing model with rational expectations for electricity prices. In particular, they observe that the potential storability of electricity in the form of fuels has stimulated the exploration of the relationship between electricity and fuel prices. Douglas and Popova [2008] and van Treslong and Huisman [2010] relate empirically forward risk premiums to indirect storability as they show that higher natural gas inventory levels reduce the forward risk premium in the PJM market, especially during extremely warm and cold periods. Redl and Bunn [2011] conduct a multi-factor analysis to study how the risk in spot price formation induces a counteracting premium in electricity forward contracts. The authors show that the forward premium in electricity is a rather complex function of fundamental, behavioural, dynamic, market conduct and shock components. The main findings are that the market price of risk in electricity is actually that of its underlying fuel commodity gas and that increased oil price volatility also increases the forward premium. From this we can conclude that indirect storability of power influences forward risk premiums.

All these studies model electricity futures prices as a combination of an expected spot price and a risk premium, the two components suggested by the expectations theory. Either the expected spot prices are explicitly modelled or the risk premiums. From literature it is obvious that electricity futures prices contain expected risk premiums or have power to forecast spot prices, however it is unclear whether this might be dependent on the type of electricity supply. This is the goal of this chapter. We follow the method proposed by Fama and French [1987] and Fama [1984] and examine whether we find evidence for forecasting power and/or expected risk premiums in electricity futures prices with a difference in marginal fuel. According to the generation stack function the price is set at the marginal cost of the last unit called when all demand is satisfied. The marginal fuel will eventually determine the price, because in perfect markets prices equal marginal production costs.

In order to examine the relation between the type of power supply in a market and the extent to which futures prices contain forecasts and/or premiums, we distinguish between two types of electricity supply. The motivation from this comes from the theory of storage. Electricity is not (yet) directly storable, but at least it is indirectly storable in the sense that (fossil) fuels can be stored and evidence that traders use this to value electricity forward prices is found by Douglas and Popova [2008] and van Treslong and Huisman [2010]. This holds for fossil fuels such as natural gas, coal, and heating oil. These fuels are storable and can be traded in relatively liquid spot and futures markets. Traders use these characteristics to their discretion. For instance, when an electricity producer sells a futures contract on electricity, she can directly fulfil to the delivery agreement by purchasing the amount of fuels needed in the spot market and store it until the delivery period, during which she converts the stored fuel into electricity with a power plant. Equivalently, she can purchase a futures contract on the underlying fuel instead of storing it[2]. These characteristics are different for renewable energy supply such as wind, solar, and hydro. A wind power producer that sells an electricity futures contract, cannot store the wind needed on beforehand to produce electricity at a later date nor can she trade in a wind futures contract. There is more flexibility in hydro power since water can be stored in basins, however capacity in the long run depends on unexpected weather conditions such as rainfall. Run of the river can also generate hydro power, however with this type even considerably smaller water storage or none is used to supply a power station. Futures contracts

[2] In fact, storing the underlying fuel is then likely undertaken by the seller of that futures contract.

on water are also absent.

When traders sell a forward contract they anticipate on the expected level of water in the basins and therefore on expected rainfall and such. It is more difficult for them to hold an exact inventory of water needed to fuel their power obligations. We therefore distinguish between two types of indirect storability in the electricity market, perfect indirect storability when the underlying fuel can be stored and futures on the underlying fuels can be traded and imperfect indirect storability when the underlying fuel capacity depends on expectations (such as windspeed, solar output and rainfall) and futures contracts on the fuels are not traded (at least not in a relatively liquid market).

We expect that the extent to which electricity futures prices contain expected risk premiums and/or forecasts of expected future spot prices differs between electricity futures prices in case of perfect indirect storability and imperfect indirect storability. In order to examine this, we analyse prices from two markets: the Netherlands and NordPool[3].The Netherlands is a case of almost perfect indirect storability as power is mostly produced by fossil fuels with natural gas being the marginal fuel in most hours (57 percent of the supplied power was fuelled by gas in 2007)[4]. NordPool is the case of almost imperfect indirect storability as NordPool relies heavily (53 percent of total production in 2007)[5] on Norwegian and Swedish hydropower plants which are connected with mountain reservoirs.

Our results show clear differences between the futures prices of both markets. We find evidence for reliable forecasting power in futures prices from both markets. We find evidence for time-varying risk premiums in the Dutch market, at least for delivery up to three months ahead, but not in the NordPool market. Furthermore, we find that the variance of expected future price changes is higher than the variance of risk premiums in both markets but the variance of expected future price changes is higher relative to the variance in risk premiums in NordPool than in the Netherlands. These results are important. The extent to which futures prices contain information about expected future spot prices and/or risk premiums depend on the storability of the type of fuel used in the market wherein the futures contract delivers. Furthermore, time-varying risk premiums exist in markets with perfect storability, but not in

[3] The energy market for Norway, Denmark, Sweden and Finland.

[4] International Energy Agency, Electricity information rapport 2009.

[5] International Energy Agency, Electricity information rapport 2009.

markets with imperfect storability. These findings provide insight in the applicability of forward price models; one cannot apply the same model to all electricity markets. Forward models for markets with imperfect storability should depend heavily on price expectations and should include time-varying risk premiums for markets with perfect storability.

The chapter proceeds as follows. Section 4.2 discusses the methodology that we apply. Section 4.3 summarises the data we use. Section 4.4 presents the results and section 4.5 concludes.

4.2 Methodology

In this part, we start by summarising the methodology as applied by Fama and French [1987] as we will follow their approach in this chapter. Let $F_{t,T}$ be the price per MWh of a forward contract, quoted at time t, for the delivery of 1 MW of electricity in each hour during the delivery period T $(t < T)$. S_t is the day-ahead price per MWh quoted on day t for delivery of 1 MW of electricity in each hour of the day $t + 1$[6]. The future expected spot price $E_t(S_T)$ is the at time t expected average day-ahead price of electricity during the future delivery period T, subject to the information available to market participants at time t. $P_{t,T}$ is the expected to be realised risk premium per MWh charged at time t for the delivery of electricity in period T. From the expectations theory, we know that the forward price equals the expected spot price plus an expected risk premium:

$$F_{t,T} = E_t(S_T) + P_{t,T}. \tag{4.1}$$

Fama and French [1987] proceed with subtracting the current spot price from both sides in the previous equation:

$$F_{t,T} - S_t = E_t(S_T) - S_t + P_{t,T}. \tag{4.2}$$

Equation (4.2) shows that the forward basis, $F_{t,T} - S_t$ contains information about the expected change in the spot price between t and T and the expected to be realised risk

[6]We therefore implicitly assume that the day-ahead price is the best proxy for the spot price. This is not necessarily true as several countries have almost real-time markets in which electricity can be traded on the same day as it is delivered. These markets are less liquid, however, due to the fact that only the most flexible power plants can reschedule their production volume flexible enough to purchase and sell on the real-time market. To circumvent this liquidity issue, we have chosen for the day-ahead price as a proxy for the spot price.

premium. Under the assumption that traders make on rational forecasts (i.e. forecasts errors are random with zero mean), Fama and French [1987] propose to estimate the parameters in the following regression equations:

$$S_T - S_t = \alpha_f + \beta_f(F_{t,T} - S_t) + \sigma_f \epsilon_{f,t}, \tag{4.3}$$

and

$$F_{t,T} - S_T = \alpha_p + \beta_p(F_{t,T} - S_t) + \sigma_p \epsilon_{p,t}. \tag{4.4}$$

The left-hand-side of Eq. (4.4), $F_{t,T} - S_T$, is the realised risk premium and under the assumption of rational forecast it proxies for the expected risk premium $P_{t,T}$ which equals $F_{t,T} - E_t(S_T)$ as can be seen from Eq. (4.1). As Eq. (4.3) and (4.4) are derived from Eq. (4.2), the α's and β's add up to respectively zero and one.

Fama and French [1987] show estimates for β_f and β_p for different commodities (no energy commodities however). Their results show that the basis contains reliable information about future changes in the spot price, i.e. a positive estimate β_f for eight commodities: broilers, eggs, hogs, cattle, and pork bellies (animal products, whose bulk and perishability imply high storage costs) and oats, soy beans, and soy meal which have high storage costs relative to value. For gold and platinum, whose storage costs are low relative to value, forward prices do not exhibit forecast power since β_f is not significantly different from zero. Commodities, such as lumber, soy oil, cocoa, corn, and wheat, have significant expected risk premiums, i.e. their estimates for β_p are significantly different from zero, indicating that storability is used in pricing forward contracts on these commodities. Forward prices from orange juice and plywood exhibit both forecasting power and risk premiums.

As discussed in section 4.1, our goal is to estimate the parameters in Eq. (4.3) and (4.4). Significant estimates for β_f imply that the basis contains information about expected future spot prices. In case we find significant estimates for β_p, the basis contains information about to be time-varying risk premiums. As discussed we estimate these parameters for Dutch and NordPool futures contracts in order to infer how the type of electricity supply and storability influences the parameter estimates.

4.3 Data

The primary data for this study consists of futures prices obtained from the Amsterdam Power Exchange / Endex and Eltermin forward contract prices provided by the Nordic Power Exchange (NordPool). Our data set consists of the futures and forward contract prices that involve the delivery of base load[7] power in calendar months. We shall distinguish between contracts that deliver next month, which is referred to as the M1 contract, the month thereafter (M2) through six months to maturity (M6). The minimum contract size of the month future and forward is 1 MW. The fulfilment of the NordPool month forward contracts is due to cash settlement and takes place during the delivery period. At expiry date, the Dutch month future contracts are settled physically. According to Wimschulte [2010] the price differentials between future and forward contract prices at the Nordic Power Exchange are not statistically significant, therefore we will use the Eltermin forward contract prices in our analysis. The prices we use are the closing prices of these contracts on the first trading day of each month, because we assume that the contracts mature on the first trading day of the delivery month.[8] The sample period for the Dutch and NordPool is from 4 April 2005 through 1 December 2010, having 69 monthly futures price observations. For both markets, we use the day-ahead prices as a proxy for the spot price of electricity for the same delivery periods. The day-ahead base load prices for the Dutch and NordPool markets are calculated as arithmetic averages of the 24 hourly market prices. For the Netherlands, we shall also use (for a robustness check later in this chapter) the natural gas day-ahead prices from the Dutch Title Transfer Facility (TTF) traded at the APX from 4 April 2005 through 1 December 2010. For the Nordic market the natural gas day-ahead prices from 4 April 2008 through 1 December 2010 are obtained from NordPool gas (NPgas).

Liquidity plays a crucial role in the pricing of financial electricity contracts. The market resilience, which indicates the price impact of a supplementary order, and tightness are characteristics of liquidity Newbery et al. [2003]. To measure the level of liquidity for futures or forward contracts the bid-ask spread and the trading volume indicators can be used. The bid-ask spread reflects the difference between the amount active buyers are willing to pay and what active sellers are willing to receive for the security. The trading volume is the quantity of electricity traded in a give time period. The higher the volume, the greater is the extent of liquidity and thus more competitive the market is. The average bid-ask spread for the Eltermin

[7]Base load contracts are delivered Mon-Sun, 00:00 – 24:00 during the length of the contract.
[8]We thereby follow Fama and French [1987].

M1 contract is 0.62 percent (0.26 euro/MWh) and for M6 is 3.3 percent (1.42 euro/MWh). The average bid-ask spread for the Dutch M1 is 0.93 percent (0.49 euro/MWh) and for M6 is is 0.95 percent (0.54 euro/MWh). This indicates that the NordPool market is more liquid then the Dutch market, however the trading activity for NordPool is more concentrated in the front contract and diminishing for longer maturities. In 2010 the total trade at NordPool (Eltermin) was 1286.7 TWh (OMX [2010]), which is around 31 percent of the total consumption of electricity in the Nordic countries. For the Dutch market the total trading volume in 2010 was 280 TWh (Endex [2010]), which is around 41 percent of the total electricity consumption in the Netherlands. All data is obtained from the Bloomberg and Thomson Reuters Datastream database. All prices are converted in natural logs.

4.4 Results

Table 4.1 reports the OLS estimation results of the slope parameters in Eq. (4.3) and (4.4) for the M1 through M6 electricity futures contracts in the Netherlands and NordPool. Let us consider the estimates for the NordPool market. The estimates for β_f range between 0.83 (M3) and 0.94 (M2) and all are significantly different from zero and not significantly different from one. All estimates for β_p are not significantly different from zero (between 0.06 and 0.17). Clearly, the forward basis on the NordPool market contains significant forecasting power and no evidence for time-varying risk premiums. Comparing with the outcomes of Fama and French [1987], these estimates are in line with estimates on prices of futures contracts on those commodities whose bulk and perishability imply high storage costs (broilers, eggs, hogs, cattle, and pork bellies) or that have high storage costs relative to price (oats, soy beans, and soy meal).

Table 4.1: **Estimates for the parameters in Eq. (4.3) and (4.4).**

M1	β_f	β_p	R_f^2	R_p^2	n
The Netherlands	0.61	0.39	0.26	0.12	69
	(4.75)	(3.05)			
NordPool	0.90	0.10	0.23	0.00	69
	(4.72)	(0.55)			
M2	β_f	β_p	R_f^2	R_p^2	n
The Netherlands	0.55	0.45	0.20	0.14	69
	(2.87)	(2.36)			
NordPool	0.94	0.06	0.27	0.00	69
	(4.88)	(0.30)			
M3	β_f	β_p	R_f^2	R_p^2	n
The Netherlands	0.59	0.41	0.24	0.13	69
	(2.85)	(1.99)			
NordPool	0.83	0.17	0.25	0.00	69
	(5.23)	(1.09)			
M4	β_f	β_p	R_f^2	R_p^2	n
The Netherlands	0.69	0.31	0.29	0.06	69
	(3.41)	(1.51)			
NordPool	0.87	0.13	0.29	0.00	69
	(7.23)	(1.10)			
M5	β_f	β_p	R_f^2	R_p^2	n
The Netherlands	0.73	0.27	0.30	0.04	69
	(4.16)	(1.55)			
NordPool	0.86	0.14	0.29	0.00	69
	(7.74)	(1.23)			
M6	β_f	β_p	R_f^2	R_p^2	n
The Netherlands	0.78	0.22	0.30	0.02	69
	(4.71)	(1.31)			
NordPool	0.87	0.13	0.30	0.00	69
	(7.00)	(1.02)			

Notes: The t-statistics reported in parentheses reflect the tests for β's being different from zero and are based on heteroskedastic and autocorrelation consistent estimates of the variances(Newey and West [1987])

The results are different for the Dutch market. The β_f estimates, which are close to one in the NordPool market, range between 0.55 (M2) and 0.78 (M6); all are significantly different from zero. For M1 through M3 delivery, the estimates are significantly different from one.[9] The estimates for β_p range between 0.22 and 0.45 and are significantly different from zero, except for M4, M5, and M6. Futures prices on the Dutch market exhibit both forecasting power and time-varying risk premiums for M1 through M3, similar to estimates for orange juice and plywood in Fama and French [1987].

Apparently, the forward basis in Dutch futures (up to month 3) contains evidence for time-varying risk premiums in addition to forecasting power. These time-varying risk premiums cannot be observed on the NordPool market. When time to maturity increases, the difference disappears in the sense that there is not evidence for time-varying risk premiums in futures prices from both markets from delivery four months ahead and farther away.

We attribute this to the difference in the storability of the underlying (marginal) fuels (hydro versus natural gas) between the markets. As discussed before, a seller of a futures contract in the Netherlands can limit her risk by purchasing natural gas (or a natural gas futures contract), store it and convert it into power during the delivery period. Seen from this perspective, the definition of the basis that we apply $((F_{t,T} - S_t))$ in Eq. (4.3) and (4.4) is questionable. If traders indeed limit their risk by trading in natural gas, then they would focus more on a basis defined as the difference between the electricity futures price and the spot price of natural gas instead of the difference between the the electricity futures price and the current spot price of electricity. To examine the robustness of the results in Table 4.1, we change Eq. (4.2) where we subtract the current spot price from both sides of Eq. (4.1). Instead, we propose to subtract h times the spot price of natural gas, S_t^g, from both sides in Eq. (4.1), where h is the heat rate being the number of gas contracts needed to produce one unit of electricity. To calculate a proper gas spot price for electricity, we assume a heat rate of 49.13% (so $h = \frac{1}{0.4913}$) obtained from Bloomberg, which is the efficiency that power plants convert fuel into electricity.

[9]The OLS t-statistic for H0:$\beta_f = 0$ is equal to the negative t-statistic of H0:$\beta_p = 1$, because $\beta_f + \beta_p = 1$ therefore the residual sum of squares (RSS) for Eq. (4.3) and (4.4) are identical $(RSS_f = y_f'(1 - x(x'x) - 1x')y_f = (x - y_p)'(1 - x(x'x) - 1x')(x - y_p) = y_p'(1 - x(x'x) - 1x')y_p = RRS_p)$ thus the standard errors of β_f and β_p are similar.

We then can rewrite Eq. (4.2) into:

$$F_{t,T} - hS_t^g = E_t(S_T) - hS_t^g + P_{t,T}, \tag{4.5}$$

and Eq. (4.3) and (4.4) into:

$$S_T - hS_t^g = \alpha_f + \beta_f(F_{t,T} - hS_t^g) + \sigma_f\epsilon_{f,t}, \tag{4.6}$$

and

$$F_{t,T} - S_T = \alpha_p + \beta_p(F_{t,T} - hS_t^g) + \sigma_p\epsilon_{p,t}. \tag{4.7}$$

Table 4.2: **Estimates for the parameters in Eq. (4.6) and (4.7).**

M1	β_f	β_p	R_f^2	R_p^2	n
The Netherlands	0.64	0.36	0.29	0.10	69
	(3.82)	(2.12)			
M2	β_f	β_p	R_f^2	R_p^2	n
The Netherlands	0.56	0.44	0.23	0.15	69
	(3.21)	(2.51)			
M3	β_f	β_p	R_f^2	R_p^2	n
The Netherlands	0.63	0.37	0.28	0.11	69
	(3.41)	(2.00)			
M4	β_f	β_p	R_f^2	R_p^2	n
The Netherlands	0.74	0.26	0.33	0.05	69
	(3.99)	(1.44)			
M5	β_f	β_p	R_f^2	R_p^2	n
The Netherlands	0.75	0.25	0.30	0.04	69
	(3.73)	(1.27)			
M6	β_f	β_p	R_f^2	R_p^2	n
The Netherlands	0.77	0.23	0.28	0.02	69
	(3.62)	(1.11)			

Notes: The t-statistics reported in parentheses reflect the tests for β's being different from zero and are based on heteroskedastic and autocorrelation consistent estimates of the variances(Newey and West [1987])

Table 4.2 shows the estimates for Eq. (4.6) and (4.7) for futures prices from the Dutch market. We obtain almost the same results as in Table 4.1. That is, whether we use day-ahead electricity prices or gas prices as a proxy for the spot price S_t, we obtain for the Dutch market that the forward basis contains both reliable information about future prices changes and time-varying risk premiums up three months ahead delivery and only forecasts for longer maturities.

To emphasize the results for the Dutch market we conduct the same analysis for the NordPool market to see whether the results will change if we use day-ahead natural gas prices as a proxy for the spot price S_t. The estimates are reported in Table 4.3.[10] From this table it is clear that the estimation results of Eq. (4.3) and (4.4) with day-ahead electricity prices are almost similar to the estimates of Eq. (4.6) and (4.7) with day-ahead natural gas prices. We also notice that especially for the M1 contract, using day-ahead natural gas prices, increases the R_f^2. The standard deviation of the day-ahead natural gas prices (0.357) is higher then the standard deviation of the day-ahead electricity prices (0.274) for the same period. This evolves into a higher R_f^2 for the estimation with S_t^g, because adding highly volatile data in Eq. (4.6) will increase the standard deviation of the dependent and independent variables, which increases the covariance and therefore will results in a higher R_f^2.

[10]NPgas day-ahead prices are available from 4 April 2008 through 1 December 2010, therefore the same analysis is conducted for Eq. (4.3) and (4.4) with the same time period

Table 4.3: **Estimates for the parameters in Eq. (4.3), (4.4), (4.6) and (4.7).**

M1	β_f	β_p	R_f^2	R_p^2	n
NordPool-E	1.15	-0.15	0.31	-0.02	33
	(5.95)	(-0.76)			
NordPool-G	1.04	-0.04	0.70	-0.03	33
	(8.03)	(-0.33)			
M2	β_f	β_p	R_f^2	R_p^2	n
NordPool-E	1.13	-0.13	0.34	-0.02	33
	(6.27)	(-0.72)			
NordPool-G	1.00	0.00	0.56	-0.03	33
	(4.65)	(0.02)			
M3	β_f	β_p	R_f^2	R_p^2	n
NordPool-E	0.98	0.02	0.33	-0.03	33
	(5.31)	(0.09)			
NordPool-G	0.97	0.03	0.46	-0.03	33
	(4.27)	(0.12)			
M4	β_f	β_p	R_f^2	R_p^2	n
NordPool-E	0.98	0.02	0.36	-0.03	33
	(4.61)	(0.09)			
NordPool-G	1.04	-0.04	0.44	-0.03	33
	(4.68)	(-0.17)			
M5	β_f	β_p	R_f^2	R_p^2	n
NordPool-E	0.89	0.11	0.35	-0.23	33
	(4.28)	(0.51)			
NordPool-G	1.16	-0.16	0.49	-0.01	33
	(5.85)	(-0.80)			
M6	β_f	β_p	R_f^2	R_p^2	n
NordPool-E	0.84	0.16	0.34	-0.01	33
	(3.80)	(0.73)			
NordPool-G	1.35	-0.35	0.59	0.06	33
	(8.57)	(-2.24)			

Notes: The t-statistics reported in parentheses reflect the tests for β's being different from zero and are based on heteroskedastic and autocorrelation consistent estimates of the variances (Newey and West [1987])

To explain the fact that the similarity of the estimates for NordPool reported in Table 4.3 and the higher R_f^2 are not significant for the main conclusion of this chapter we can rewrite Eq. (4.3) and (4.6) into:

$$S_T = \alpha_f + \beta_{f1} F_{t,T} + \beta_{f2} S_t^e + \sigma_f \epsilon_{f,t}, \tag{4.8}$$

$$S_T = \alpha_f + \beta_{f1} F_{t,T} + \beta_{f2} h S_t^g + \sigma_f \epsilon_{f,t}, \tag{4.9}$$

Eq. (4.8) and (4.9) show the relationship between the future expected spot price, the forward price and day-ahead natural gas or electricity prices. These equations are estimated by OLS and the results are reported in Table 4.4. The regression coefficient of the day-ahead natural gas and electricity price (β_{f_2}) for the Dutch market is positive and significant, however for the Nordic market it is negative and not significant. Meaning that the day-ahead natural gas and electricity prices do not influence the future expected spot price in the NordPool market.

Table 4.4: **Estimates for the parameters in Eq. and (4.8) and (4.9).**

	β_{f_1}	β_{f_2}	n
The Netherlands-E	0.41	0.32	69
	(3.15)	(2.66)	
The Netherlands-G	0.40	0.31	69
	(2.27)	(2.13)	
	β_{f_1}	β_{f_2}	n
The Netherlands-E	0.95	-0.14	33
	(4.04)	(-0.70)	
The Netherlands-G	0.87	-0.06	33
	(5.74)	(-0.47)	

Notes: Robust t-statistics are in parentheses.

What can explain the fact that time-varying risk premiums are observed in electricity futures prices from the Dutch market (up to M3) and not in futures prices from the NordPool market?

To shed some light on this, we follow Fama [1984]. The estimate for β_f in Eq. (4.3) can be written as:

$$\begin{aligned}\beta_f &= \frac{cov(S_T - S_t, F_{t,T} - S_t)}{var(F_{t,T} - S_t)} \\ &= \frac{var(E_t(S_T - S_t)) + cov(P_{t,T}, E_t(S_T - S_t))}{var(F_{t,T} - S_t)}\end{aligned} \tag{4.10}$$

and for β_p as

$$\begin{aligned}\beta_p &= \frac{cov(F_{t,T} - S_T, F_{t,T} - S_t)}{var(F_{t,T} - S_t)} \\ &= \frac{var(P_{t,T}) + cov(P_{t,T}, E_t(S_T - S_t))}{var(F_{t,T} - S_t)},\end{aligned} \tag{4.11}$$

where cov stands for covariance and var is variance in the above equations. If we subtract β_p from β_f we obtain

$$\beta_f - \beta_p = \frac{var(E_t(S_T - S_t)) - var(P_{t,T})}{var(F_{t,T} - S_t)}. \tag{4.12}$$

This relation helps us to understand better the results we have found. Table 4.4 contains the estimates for $\beta_f - \beta_p$, based on the outcomes in Table 4.1.

Table 4.5: **Estimates for $\beta_f - \beta_p$.**

	M1	**M2**	**M3**
The Netherlands	0.22	0.10	0.18
	(0.85)	(0.25)	(0.43)
NordPool	0.80	0.88	0.66
	(2.08)	(2.29)	(2.07)
	M4	**M5**	**M6**
The Netherlands	0.38	0.46	0.56
	(0.95)	(1.31)	(1.70)
NordPool	0.74	0.72	0.74
	(3.06)	(3.25)	(2.99)

Notes: Robust t-statistics are in parentheses.

Table 4.5 shows that all values for $\beta_f - \beta_p$ are positive. Eq. (4.12) shows that the difference between β_f and β_p can only be positive if the variance of the expected price change exceeds the variance of the expected risk premium. However, the differences between the parameters estimates are significantly different from zero for futures prices from the NordPool market but not for the Dutch market and the differences are larger in magnitude for NordPool than for the Dutch. Apparently, the variance of expected price changes is significantly larger than the variance of the expected risk premiums in the NordPool market and not for the Dutch market. This makes sense as spot electricity prices in the NordPool markets exhibit strong seasonal influences (we refer to Lucia and Schwartz [2002] for the characteristics of NordPool day-ahead prices) due to changes in weather conditions over the year. These seasonalities are not as such observable in day-ahead prices in the Dutch market (see Huisman [2008] among others) which is at least partly due to the indirect storability possibilities in this market. Hence, the imperfect indirect storability of the NordPool market makes day-ahead prices seasonal and therefore results in a relatively high variance of expected changes in spot prices (relative to perfect indirect storability markets as the Dutch) which makes the difference between β_f and β_p significantly positive. From this argument we conclude that the difference in the parameter estimates can be attributed to the difference in indirect storability between the markets. Futures prices from markets in which electricity is predominantly produced by imperfectly storable fuels such as hydro, wind and solar contain information about expected changes in the spot price of electricity, whereas futures prices from markets in which electricity is predominantly produced with perfectly storable fuels contain information about both expected price changes and time-varying risk premiums.

4.5 Concluding remarks

The goal of this chapter is to examine to what extent electricity futures prices contain expected risk premiums or have power to forecast spot prices and whether this might be dependent on the type of electricity supply. We analyse futures prices from the Dutch market, a market in which power is produced with storable fossil fuels, and futures prices from the NordPool market, where electricity is mostly produced by hydropower. We show that futures prices from markets in which electricity is predominantly produced by imperfectly storable fuels such as hydro, wind and solar contain information about expected changes in the spot price of electricity, whereas futures prices from markets in which electricity is predominantly produced with perfectly storable fuels contain information about both expected price changes and time-varying risk premiums. These findings provide insight in the applicability of forward price models; one cannot apply the same model to all electricity markets. Forward models for markets with imperfect indirect storability should depend heavily on price expectations and models should include time-varying risk premiums for markets with perfect indirect storability.

5 | Price Dynamics between Power and Fossil Fuel Futures

Joint with R. Huisman.

5.1 Introduction

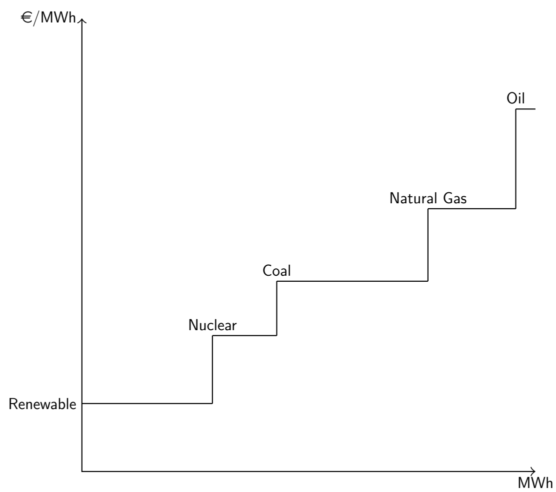
After the liberalisation of the European electricity markets a key point in electricity price formation is that prices are driven by fundamental factors that influence supply and demand. It is not economically feasible to store electricity, therefore the power supply depends directly on the input fuel sources. Basically electricity is a conversion product and therefore the owner of a power plant needs to hold the underlying fuel and generate power when needed. One of the options of the power producer is to sell power on the day-ahead market. Specific features of day-ahead power prices are extreme volatility and large price spikes[1], which gives the power plant owner the option to sell power on the futures market to hedge his risk against this price uncertainty. The power generator who sells power futures contracts also needs to offset his risk against price uncertainty of underlying fuels, that is why the producer can buy and store the fuel needed for electricity generation or can make his position risk free by purchasing a coal or natural gas futures contract equivalent to the amount of sold power futures and convert it into power during the delivery period. In Europe a high percentage of the produced electricity is being generated using fossil fuels as in coal and natural gas. Therefore the above mentioned implies a relationship between the future prices of electricity and fossil fuels.

The power forward price depends on the level of supply and demand, therefore the price is set at the marginal cost of production of the last unit called in the supply curve when all

[1] For an overview of the characteristics of electricity price dynamics and a summary of the literature we refer to Eydeland and Wolyniec [2003], Pilipovic [2007], and Huisman [2009].

demand is satisfied. If we look at the composition of the total electricity supply, renewables [2] and nuclear are assumed to be the cheapest production means to generate electricity, followed by coal and then natural gas. A power plant will only produce with a certain fuel when the price is above its operating cost. When demand is less than the total capacity of the generators, which for example use coal to produce power, the price is determined by the marginal cost of coal, and only firms with lower fuel costs will produce power. If demand exceeds the generation capacity of the coal-fired power plants the electricity price gets decoupled from the marginal costs of coal 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.5.1.

Figure 5.1: **A hypothetical power supply curve**.



To produce electricity fuels need to be converted, therefore we expect that price changes of electricity generation inputs, such as coal and natural gas should be observed in power prices. This interrelationship between electric power supply chains and other energy markets is acknowledged by previous literature on cointegration, however research on the connection between electricity and fossil fuel prices show variations in the strength of relationships and causality for various countries.

Several studies have been conducted in order to investigate the cointegration behaviour between electricity spot relative to fossil fuel prices. Especially a clear relationship is found between electricity and natural gas prices. Emery and Liu [2002] examine this relation between gas futures and electricity futures prices, which are actually the day-ahead prices. In

[2]For example: wind, photovoltaic or hydro.

their research 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 is used. By applying the augmented Engle and Granger [1987] test to determine whether the time series show cointegration, they conclude that the time series of gas and electricity futures prices are indeed cointegrated. In addition 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. As gas is the marginal fuel used for generating electricity in California-Oregon Border (COB) and Palo Verde (PV), Emery and Liu [2002] expect that 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, the asymmetric response can be explained.

One of the main findings of Moutinho et al. [2011] by applying a cointegration analysis is that the price of electricity in Spain from 2002 to 2005 is explained by the evolution of the natural gas price series. Ferkingstad et al. [2011] studied Nordic, German, and UK electricity prices in contemporaneous and lagged time series models with oil, coal, gas, wind, and water reservoir levels and also found a clear linkage between electricity and natural gas prices. de Jong and Schneider [2009] combine the UK (NBP), Belgian (Zeebrugge) and the Dutch (TTF) natural gas markets with the Dutch electricity spot prices (APX) and use cointegration analysis to capture the joint dynamics of multiple energy prices. Clear evidence of cointegration is detected between the gas spot prices and the APX spot market, but this is only in the forward time scale. For electricity and natural gas spot prices a clear relationship is found, however Asche et al. [2006] observed cointegration among natural gas, crude oil, and electricity prices with a leading indicator role of crude oil in UK from January 1995 to June 1998. This leading role is explained by the fact that there is a global market for oil while this is not the case for electricity and natural gas. Bosco et al. [2006] use a multivariate dynamic analysis to show a commonality of trend, a presence of strong integration among European electricity prices and a long-term equilibrium relationship of this trend with oil prices. Gjölberg [2001] and Bencivenga et al. [2010] investigate the short and long-run relationship between crude oil, natural gas and electricity prices and find cointegration relationships between the spot prices of each pair of commodities. In general natural gas and power spot prices are closely related.

Long-term electricity forward contract prices are also being influenced by fundamental factors such as fuel costs. Routledge et al. [2001] use a model to link cross-commodity prices and physical conversion of fuels to electricity. The authors show that a change occurs between the correlation of electricity with the fuels used to generate power due to an exogenous demand and endogenous storage level of the fuels. The changing correlations of electricity and fuel prices are a natural consequence of the option to decide which fuel (or fuels) to use to generate the marginal unit of electricity. Redl et al. [2009] examine the relation between the German EEX and the Nord Pool forward contracts with the fuel markets. In this model they 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 an function of primary fuel costs (gas or coal) and the costs for CO2 emission rights. The correlation between EEX electricity prices with gas and coal are higher than the Nord Pool electricity prices. The authors explain this by stating that in the German market gas and coal are more often the marginal fuels for generating electricity then they are for NordPool where electricity is mainly generated by hydro power. Povh and Fleten [2009] used a cointegration analysis to model the relationship between long-term forward contract prices on fuels (such as oil, coal and natural gas), the price of emission allowances, imported electricity and the long-term price of electricity forwards for the NordPool market. The authors find a long-run relationship between all variables except for natural gas. Furió and Chuliá [2012] find cointegration among one-month-ahead natural gas, electricity and also Brent crude oil forward contract prices in the Spanish market with causality, both in price and volatility, running from the fossil fuels to the electricity market.

According to our expectation electricity forward prices should have a long-term association with the fossil fuels coal or natural gas futures prices, however the dynamics in power demand and the merit order curve could influence this relationship. Hence investigating the interrelationship between power and fossil fuel futures prices to identify to what extent power futures price formations are driven by fundamentals, based on fuel prices, is the objective of this chapter. For this we examined the power futures prices, using one-month and one-year-ahead futures contracts, for the Dutch and German market in which the power production is mainly based on the fossil fuels coal and natural gas. Analysis is performed by testing for cointegration using the augmented Engle and Granger [1987]. After establishing a cointegration relationship an error-correction model is used to determine how forward prices react on deviation from the long-term equilibrium price level.

The chapter proceeds as follows. Section 5.2 summarises the data we use. Section 5.3 discusses the methodology that we apply and presents the results and section 5.4 concludes.

5.2 Data

To assess the interrelationship between electricity, natural gas and coal futures prices the analysis will be performed for the Netherlands and Germany. In both countries a high percentage of fossil fuels, which are being traded on a derivatives market, is being used to produce electrical power. According to Table 5.1 approximately 20.0 percent of the total produced electricity in the Netherlands is being generated by coal and 60.0 percent by natural gas. In Germany a higher percentage of coal approximately 41 percent is being used to generate electricity and natural gas is only being used in approximately 14 percent of the time. In 2012 the electricity production in the Netherlands based on natural gas declined from 60.1 percent to 53 percent and an increase in generation with coal from 18.4 percent to 23.4 percent took place. The cause of this change could be the diminishing power demand due to the economic crises. The German power production shows a substantial increase in renewable power from 15.9 percent to 21.9 percent and a decrease in nuclear power.

Table 5.1: **Electricity production by source %˙**

The Netherlands	**Renewables**	**Nuclear**	**Coal**	**Natural gas**	**Oil**	**Other**
2008	8.8	3.9	20.8	59.7	0.2	6.6
2009	9.5	3.7	20.6	60.3	0.0	5.7
2010	9.5	3.4	18.5	62.3	0.0	6.3
2011	10.9	3.7	18.4	60.1	0.0	6.8
2012	12.2	3.9	23.4	53.0	0.1	7.4
Germany	**Renewables**	**Nuclear**	**Coal**	**Natural gas**	**Oil**	**Other**
2008	15.9	22.2	39.8	15.0	1.3	5.9
2009	17.1	21.5	39.2	14.8	1.5	6.0
2010	16.4	22.4	41.8	13.8	1.3	4.3
2011	20.3	17.7	42.9	13.6	1.1	4.2
2012	21.9	16.0	44.8	11.3	1.6	4.4

Source: CBS statistics Netherlands (StatLine), Eurelectric and Energy Information Administration (EIA).

The data set for this study consists of daily electricity futures prices for the Dutch ENDEX and the European Energy Exchange (EEX) for Germany that involves the delivery of base load[3] and peak load[4] power. For the analysis we distinguish between peak and off peak[5] contract prices, because they differ in level of power demand. In general during off peak hours power demand will be lower than during peak hours. The implied off peak power prices are calculated by (24*base load-12*peak load)/12. The one-month-ahead (M1), which delivers next month and the one-year ahead (Y1) that delivers next year will be used, because of their high liquidity. The minimum contract size of the monthly and yearly future is 1 MW.

According to expectation at the end of a trading period of a certain power futures contract the 'to be hedged' capacity of the generation plants with the lowest marginal costs are already sold. At that moment the fuel with the highest marginal cost, with respect to the level of total power demand during the delivery period, should set the price of the power futures contract. For instance natural gas is on the right of the merit order curve and in the Netherlands a high percentage of natural gas fired power plant capacity is available. Therefore for peak futures contracts near expiration, where demand is at it highest level, we would expect a clear relationship with natural gas. In Germany during off peak hours, with lower power demand, we would expect that coal fired power plants are the marginal producers who set the price for the off peak power forward contract. That is why we analyze the M1 and the Y1 contract to identify more evident relationships between power and fossil fuel futures prices. Nevertheless this all depends on the merit order curve and the dynamics in power demand.

For the Netherlands the natural gas price in €/MWh is obtained by using Title Transfer Facility (TTF) futures contracts traded at the ENDEX exchange. For coal, the prices in $/1000 metric tonnes are acquired from Rotterdam coal futures traded at the Inter Continental Exchange (ICE). For Germany the natural gas price in €/MWh is obtained by the NetConnect Germany (NCG) futures contract and the coal prices in $/1000 metric tonnes are obtained by the Amsterdam-Rotterdam-Antwerp (ARA) coal forward contract traded at the European Energy Exchange (EEX). For the analysis in this chapter the coal futures prices are converted into €/MWh. A conversion factor of 8.14 is used to convert metric tonnes into MWh. The currency conversion is made by using the exchange rate provided by Reuters. The sample period for the

[3]Delivering 1MW of power from Monday to Sunday from 12am to 12pm during the delivery period.

[4]Delivering 1MW of power from Monday to Friday between 8am to 8pm during the delivery period.

[5]Delivering 1MW of power from Monday to Friday between from 12am to 8am and from 8pm to 12am as well as from 12am to 12pm from Saturday to Sunday during the delivery period.

analysis is from 2 January 2008 through 30 December 2012, having approximately 1268 and 1260 daily futures price observations for Germany and the Netherlands, respectively. All prices are converted in natural logs and obtained from Bloomberg and Thomson Reuters Datastream.

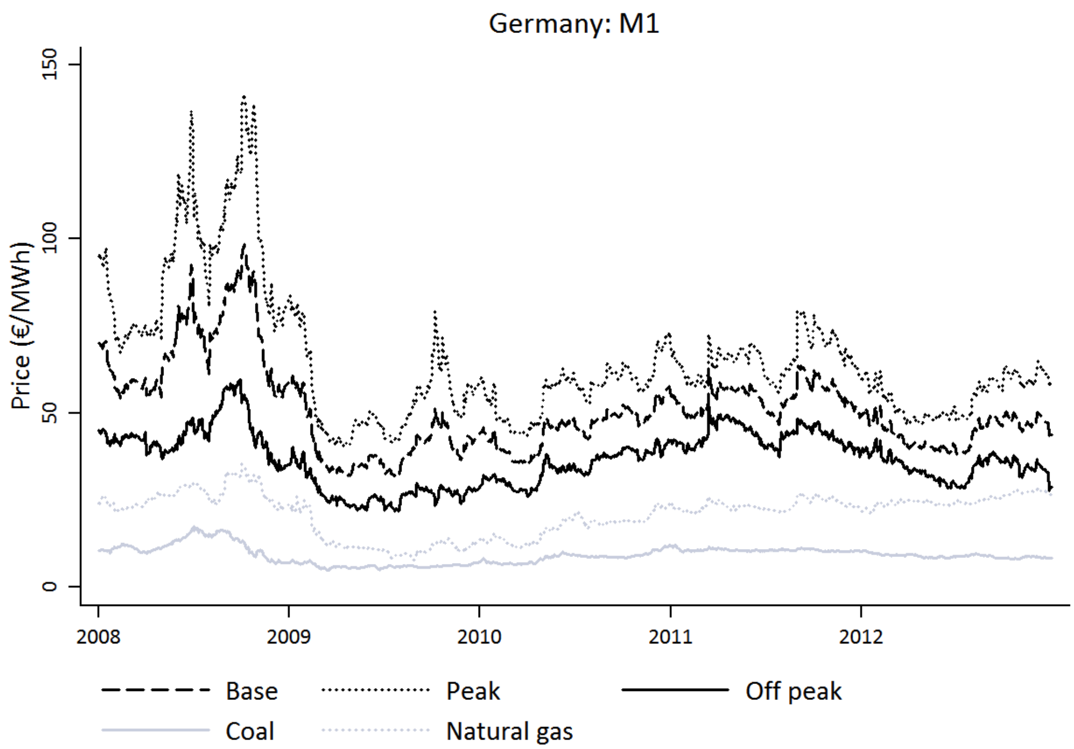
Table 5.2 presents the descriptive statistics for the price return series, computed as the log-differences in daily prices. First of all the peak load, off peak load and natural gas returns for the Dutch M1 contract and off peak load and natural gas log returns for the Dutch Y1 contract exhibit the highest difference between the maximum and minimum, which are also more volatile, as indicated by the higher standard deviation. For the German M1 contract we observe high volatility for the same price series, however the Dutch log returns are more volatile. Comparable result are noted for the German Y1 off peak, though coal log returns show a higher standard deviation. Secondly the measures for skewness and kurtosis suggest, as in most power market studies, a rejection of the normality hypothesis. The Jarque-Bera statistic confirms this result. However, the sample size is relatively large, therefore we assume normality.

Table 5.2: **Descriptive statistics for log-price returns.**

	Peak	Off peak	Coal	Natural gas
The Netherlands: M1				
Mean	-0.0003	-0.0001	-0.0002	0.0001
Min.	-0.63	-0.69	-0.11	-0.16
Max.	0.62	0.73	0.10	0.28
Std. dev.	0.04	0.04	0.02	0.03
Skew.	0.26	0.52	-0.71	0.92
Kurt.	156.39	171.04	9.46	17.38
JB	1127384.0	1353077.0	2096.8	10071.0
	[0.00]	[0.00]	[0.00]	[0.00]
The Netherlands: Y1				
Mean	-0.0003	-0.0001	0.0001	0.0001
Min.	-0.08	-0.30	-0.10	-0.16
Max.	0.17	0.41	0.13	0.35
Std. dev.	0.01	0.03	0.02	0.02
Skew.	1.56	0.95	0.24	4.68
Kurt.	26.23	37.76	11.35	91.36
JB	29596.7	65294.6	3767.0	414771.8
	[0.00]	[0.00]	[0.00]	[0.00]
Germany: M1				
Mean	-0.0004	-0.0004	-0.0002	0.0007
Min.	-0.20	-0.18	-0.10	-0.13
Max.	0.24	0.18	0.09	0.28
Std. dev.	0.03	0.03	0.02	0.03
Skew.	1.27	0.34	-0.48	1.292
Kurt.	18.91	11.36	7.54	19.70
JB	13675.4	3709.7	1136.7	15104.7
	[0.00]	[0.00]	[0.00]	[0.00]
Germany: Y1				
Mean	-0.0003	-0.0001	-0.0001	-0.0001
Min.	-0.06	-0.13	-0.10	-0.06
Max.	0.19	0.11	0.17	0.09
Std. dev.	0.01	0.02	0.02	0.01
Skew.	3.55	-0.11	0.45	0.71
Kurt.	57.18	9.33	14.02	7.71
JB	157494.7	2119.8	6445.2	1275.4
	[0.00]	[0.00]	[0.00]	[0.00]

Notes: Descriptive statistics for daily peak and off peak load electricity futures log-price returns and the coal and natural gas futures log-price returns for the period of January 1, 2008 to December 31, 2012. The number of observations is approximately 1260. The Jarque-bera statistic is used to test for normal distribution of the price series, p-values in brackets.

Figure 5.2: **Behaviour of daily electricity forward prices.**



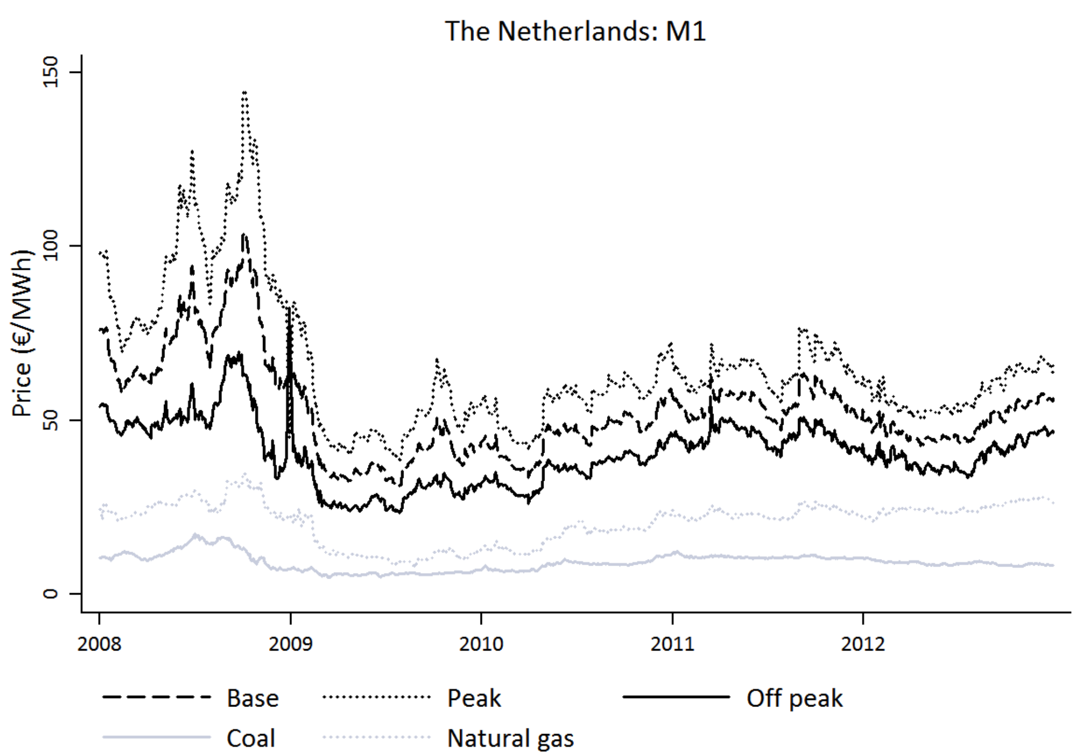
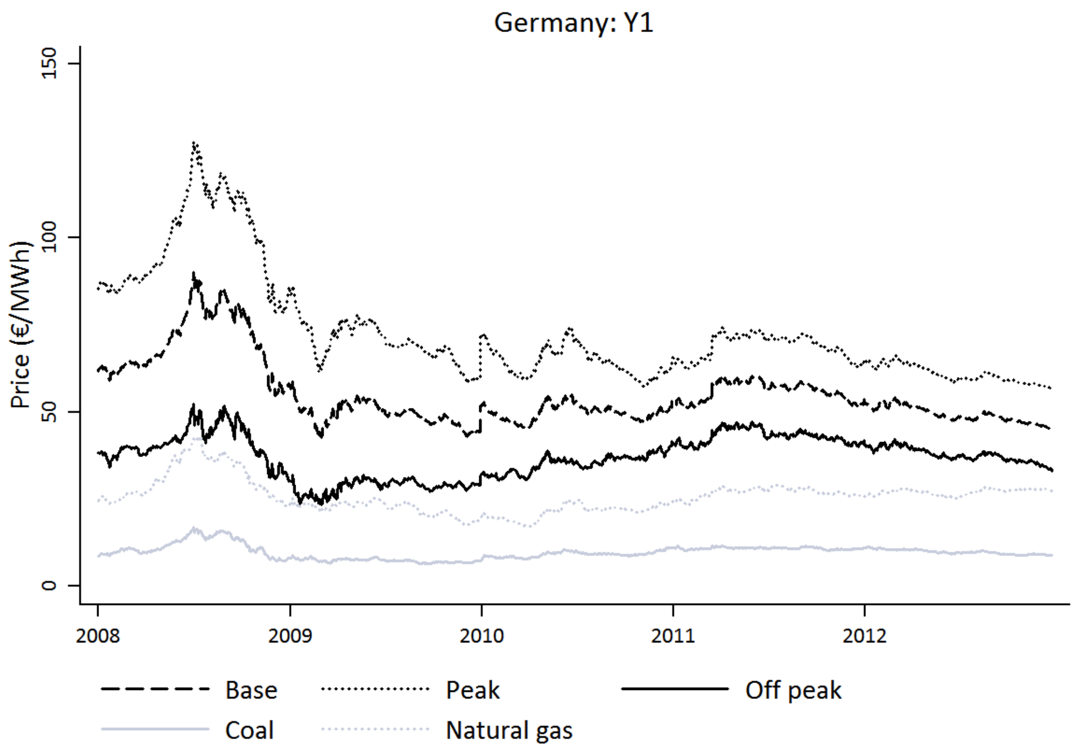
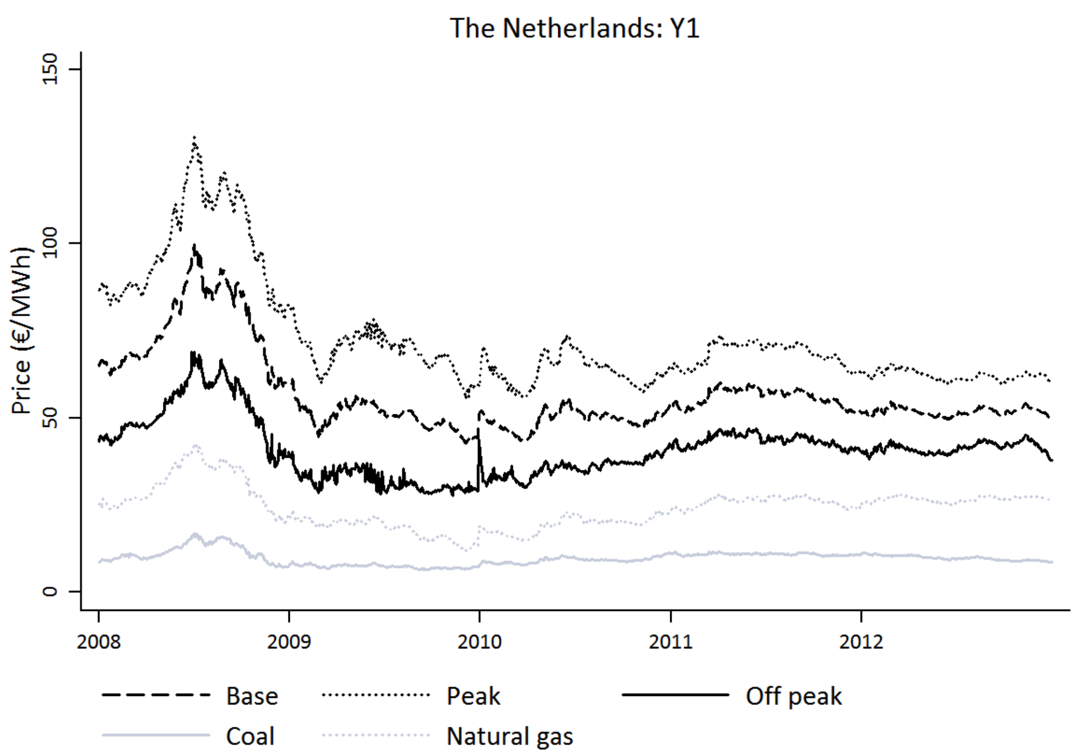


Figure 5.2: **Behaviour of daily electricity forward prices.(cont.)**





As observed in Fig. 5.2 the daily settlement prices overall display a similar pattern. Near the beginning of 2008 we observe a high peak in the price series, which decreases towards the end of 2008. An increasing trend follows and for the Dutch M1 contract at the beginning of 2011 and for the German M1 we observe a decrease in power prices at the end of 2011. Around 2012 the prices show an increasing trend. It is evident that the prices of the commodities tend to move together through time.

5.3 Methodology and results

In this section the long-run equilibrium relationship between the power, natural gas an coal forward prices are analysed for Germany and the Netherlands by employing an cointegration analysis. In order to test for cointegration, the first step is to use the Augmented Dickey-Fuller (1979) test, whether an unit root is present in each of the price series. The following regression Eq. (5.1) can be applied to test for the existence of an unit root:

$$\Delta x_t = \delta_0 + \delta_1 x_{t-1} + \sum_{q=1}^{n} \delta_q \Delta x_{t-(q-1)} + \varepsilon_t \tag{5.1}$$

with x_t as natural gas, coal, peak and off peak electricity futures prices. The ADF test uses the null hypotheses that a series is non-stationary and expects the lagged level of the series (q), δ_1, not to significantly differ from zero, δ_1=0. The results of the Augmented Dickey-Fuller test for stationarity properties of the variables for the Netherlands and Germany are presented in Table 5.3.

The results in Table 5.3 show, based on the ADF test statistics, that the null hypothesis of a unit root for the logarithm prices cannot be rejected whereas the t-statistics for all variables are higher than the critical values at 5 percent level. Meaning that all variables are non-stationary in their level forms.

Table 5.3: **Augmented Dickey-Fuller unit root test.**

	Level		**First differences**	
The Netherlands: M1	δ_1	*t-ratio*	δ_1	*t-ratio*
Peak	-0.010	(-2.44)	-1.195	(-41.22)
Off peak	-0.013	(-2.45)	-1.460	(-23.90)
Coal	-0.004	(-1.55)	-0.886	(-30.18)
Natural gas	-0.004	(-1.47)	-1.023	(-34.64)
The Netherlands: Y1	δ_1	*t-ratio*	δ_1	*t-ratio*
Peak	-0.003	(-1.65)	-0.832	(-12.83)
Off peak	-0.006	(-1.49)	-1.890	(-18.43)
Coal	-0.003	(-1.39)	-1.002	(-35.53)
Natural gas	-0.004	(-1.69)	-0.869	(-31.49)
Germany: M1	δ_1	*t-ratio*	δ_1	*t-ratio*
Peak	-0.008	(-2.46)	-0.900	(-32.12)
Off peak	-0.008	(-2.25)	-1.047	(-37.25)
Coal	-0.003	(-1.53)	-0.832	(-30.00)
Natural gas	-0.003	(-1.28)	-0.935	(-33.34)
Germany: Y1	δ_1	*t-ratio*	δ_1	*t-ratio*
Peak	-0.002	(-1.00)	-0.934	(-33.30)
Off peak	-0.006	(-2.01)	-0.996	(-35.39)
Coal	-0.004	(-1.60)	-0.937	(-33.36)
Natural gas	-0.003	(-1.35)	-0.944	(-33.61)

Notes: The Augmented Dickey-Fuller (ADF) unit root test for peak and off peak load electricity futures logarithm prices and coal and natural gas futures logarithm prices for the period of January 1, 2008 to December 31, 2012. The number of observations is 1268. The critical values at 1% and 5% significance level of MacKinnon (1996) for the ADF (process with intercept) are -3.43 and -2.86, respectively.

The next step is to test whether the differentiated series are stationary. The results of the first differences of the individual time series show that the ADF test statistics for all variables are smaller than the critical values at 1 percent level. Therefore all variables are stationary after differencing once, suggesting that all the variables are integrated of order I(1) and suitable for use in cointegration tests.

The first goal of cointegration analysis is to test whether there are any common stochastic trends in the variables. As electricity is a conversion product for which coal and natural gas is being used, it can be expected that the forward prices of electricity and fossil fuels show long term comovement in prices. If there is a common trend in the set of prices they must have a long term equilibrium relationship. The second goal is to capture this equilibrium in a dynamic correlation analysis. Thus cointegration analysis has two stages. The first stage is to determine whether the time series of electricity and fossil fuels are cointegrated, for this the Augmented Engle-Granger (1987) test is used. The Augmented Engle-Granger (EG) test for cointegration is a two-step residual-based test. The first step is to obtain the residuals. For this the following equation is used:

$$X_{i,t} = \beta_0 + \beta_1 Y_{i,t} + \sum_{j=2}^{12} \beta_j X_j + \varepsilon_t. \tag{5.2}$$

Let $X_{i,t}$, denote the integrated variables of peak load (X_p) and off peak load (X_o) forward prices and $Y_{i,t}$ the fossil fuels coal (Y_c) and natural gas (Y_g) forward prices for the M1 or Y1 contracts. Seasonal variation in electricity prices is a well known characteristic, especially for short term contracts. As one-year- ahead forward contracts deliver the underlying commodities during a whole year continuously for the same price, seasonality will be less than in data using daily settlement prices for one-month-ahead forward contracts. For this reason a seasonal term $\sum_{j=2}^{12} \beta_j X_j$ is added to Eq. (5.2) for the one-month-ahead contract (M1). X_j are month dummies where $X_j = 2$ if the contract month is February and otherwise 0, etc. The residual term ε_t is assumed to be serially independent and will be referred to as the abnormal price of electricity at time t, $Z_{i,t}$.

In the second step to determine whether the time series of electricity and fossil fuels are cointegrated the residuals obtained from Eq. (5.2) are used in the following equation:

$$\Delta Z_{i,t} = \alpha_0 + \alpha_1 Z_{t-1} + \sum_{k=2}^{4} \alpha_k \Delta Z_{t-(k-1)} + \varepsilon_t. \tag{5.3}$$

Table 5.4 presents the results of the Augmented Engle-Granger test for the Netherlands and Germany. If the coefficient of the lagged level of the abnormal price, α_1, is significantly different from zero, the residuals are stationary, meaning that the forward prices are indeed cointegrated.

Analysing the results we observe that there is no clear long term equilibrium relationship between all variables. For the Netherlands we find a cointegration relationship between the one-month-ahead (M1) off peak load and coal prices, which is according to the expectation that the coal-fired power plants are sufficient in meeting the demand for power during off peak hours. This comovement in prices is also present for Germany. For the Netherlands the off peak load prices are also interrelated with the futures prices of the abundant fuel natural gas. For the Dutch one-year-ahead (Y1) we perceive that only off peak prices are interrelated with coal and natural gas futures prices. Analysing the cointegration results established for the German Y1 contract there is only cointegration between off peak load and coal prices. For the Netherlands and Germany there is no sign of cointegration between peak load and fossil fuel forward prices. Meaning that one-month and one-year before expiring the peak load electricity prices do not only depend on one certain fuel, therefore there is no long term equilibrium between the variables present.

Table 5.4: **Augmented Engle-Granger cointegration test.**

	M1		**Y1**	
The Netherlands: Peak	α_1	*t-ratio*	α_1	*t-ratio*
Coal	-0.021	(-3.00)	-0.003	(-1.49)
Natural gas	-0.014	(-2.33)	-0.002	(-0.85)
The Netherlands: Off peak	α_1	*t-ratio*	α_1	*t-ratio*
Coal	-0.080	(-5.29)	-0.038	(-3.90)
Natural gas	-0.043	(-3.96)	-0.036	(-3.49)
Germany: Peak	α_1	*t-ratio*	α_1	*t-ratio*
Coal	-0.014	(-3.08)	-0.002	(-1.18)
Natural gas	-0.008	(-2.27)	-0.002	(-0.76)
Germany: Off peak	α_1	*t-ratio*	α_1	*t-ratio*
Coal	-0.049	(-4.81)	-0.027	(-3.90)
Natural gas	-0.017	(-2.65)	-0.008	(-2.01)

Notes: The augmented Engle-Granger (1987) test for peak and off-peak load electricity futures logarithm prices and coal and natural gas futures logarithm prices for the period of January 1, 2008 to December 31, 2012. The number of observations is 1268. The critical values at 1% and 5% significance level of MacKinnon (1996) for the augmented Engle-Granger are -4.32 and -3.34, respectively.

As shown in Table 5.1 the produced power with different production sources is subject to change due to the level of power demand. We already noted that especially for Germany the power supply has changed over recent years and especially the percentage of production with renewables has increased from 16% in 2008 to 22% in 2012. If we also take into account the variation in power demand it would be difficult to find a clear cointegration relationship for the one-month and one-year-ahead contracts with the underlying fossil fuel futures prices. Primarily because each contract, which will deliver monthly or yearly power, does not require to have a price depending on the same fuel one month or one year before expiration of the contract.

In the second stage of the cointegration analysis, with the existence of cointegration between the logarithm price series, the implementation of the error correction model (ECM) is allowed. The ECM is a dynamic model on the first differences of the integrated variables and is used in modelling the short-term deviations from long-run equilibrium. It is possible that an exogenous shock causes price series with long-term dependence to drift apart in short-term. In order to determine how electricity and fossil fuel prices react to departures in the long-term equilibrium the following equations are used:

$$\Delta X_{i,t} = \alpha_1 + \beta_1 Z_{t-1} + \sum_{k=1}^{m} \gamma_{ik} \Delta X_{i,t-k} + \sum_{k=1}^{m} \delta_{ik} \Delta Y_{j,t-k} + \varepsilon_{i,t}. \tag{5.4}$$

$$\Delta Y_{j,t} = \alpha_2 + \beta_2 Z_{t-1} + \sum_{k=1}^{m} \gamma_{jk} \Delta X_{i,t-k} + \sum_{k=1}^{m} \delta_{jk} \Delta Y_{j,t-k} + \varepsilon_{j,t}. \tag{5.5}$$

where $X_{i,t}$ and $Y_{j,t}$ refer to the electricity and fossil fuel futures logarithm price series, respectively, and Z is the disequilibrium term of Eq. (5.2). β_1 and β_2 are the adjustment parameters to the long-run relationships, the parameters γ_{ik}, γ_{jk}, δ_{ik} and δ_{jk} for $i = p, o$ (peak and off peak load), $j = c, n$ (coal and natural gas) and k=1...m, determines how the return in one market responds to its own lagged returns and to the lagged returns of the other market and, finally, $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ for $i = p, o$ and $j = c, n$ are the Gaussian white noise processes. The coefficients are determined by Ordinary Least Squares (OLS) and the number of lags are determined following the Akaike Information Criteria. The results for Eq. (5.4) and (5.5) are given in Table 5.5 and 5.6.

Table 5.5: **Dynamics between power, coal and natural gas futures prices for the Netherlands.**

The Netherlands: M1	ΔX_o			ΔY_g		
		Value	*t-ratio*		**Value**	*t-ratio*
	α_1	0.000	(-0.18)	α_2	0.000	(0.07)
	β_1	-0.036	(-1.60)	β_2	0.021	(2.48)
	γ_o	-0.264	(-2.01)	γ_o	-0.056	(-1.01)
	δ_g	0.153	(2.17)	δ_g	-0.001	(0.04)
	R^2	0.08		R^2	0.01	
	DW-stat.	2.04		DW-stat.	1.98	
The Netherlands: M1	ΔX_o			ΔY_c		
		Value	*t-ratio*		**Value**	*t-ratio*
	α_1	0.000	(-0.16)	α_2	0.000	(-0.27)
	β_1	-0.091	(-2.90)	β_2	0.003	(0.28)
	γ_o	-0.209	(-1.70)	γ_o	0.018	(0.65)
	δ_c	0.052	(0.83)	δ_c	0.110	(2.29)
	R^2	0.09		R^2	0.01	
	DW-stat.	2.03		DW-stat.	2.01	
The Netherlands: Y1	ΔX_o			ΔY_g		
		Value	*t-ratio*		**Value**	*t-ratio*
	α_1	0.000	(-0.28)	α_2	0.000	(0.07)
	β_1	-0.038	(-3.34)	β_2	0.017	(1.41)
	γ_o	-0.285	(-6.69)	γ_o	-0.001	(-0.04)
	δ_g	0.220	(5.54)	δ_g	-0.005	(-0.10)
	R^2	0.08		R^2	0.00	
	DW-stat.	2.06		DW-stat.	2.00	
The Netherlands: Y1	ΔX_o			ΔY_c		
		Value	*t-ratio*		**Value**	*t-ratio*
	α_1	0.000	(-0.26)	α_2	0.000	(-0.01)
	β_1	-0.051	(-2.90)	β_2	0.006	(0.81)
	γ_o	-0.232	(-3.68)	γ_o	-0.027	(-0.87)
	δ_c	0.216	(3.58)	δ_c	0.149	(3.70)
	R^2	0.08		R^2	0.02	
	DW-stat.	2.10		DW-stat.	1.99	

Notes: $X_{i,t}$ and $Y_{j,t}$ refer to the electricity and fossil fuel futures logarithm price series. β_1 and β_2 are the adjustment parameters to the long-run relationships, the parameters γ_{ik}, γ_{jk}, δ_{ik} and δ_{jk} for $i = p, o$ (peak and off peak load), $j = c, n$ (coal and natural gas) and k=1...m, determines how the return in one market responds to its own lagged returns and to the lagged returns of the other markets and, finally, $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ for $i = p, o$ and $j = c, n$ are the Gaussian white noise processes. The number of lags are determined following the Akaike Information Criteria.Standard errors are in parentheses.

Table 5.6: **Dynamics between power, coal and natural gas futures prices for Germany.**

Germany: M1		ΔX_o			ΔY_c	
		Value	*t-ratio*		**Value**	*t-ratio*
	α_1	0.000	(-0.49)	α_2	0.000	(-0.26)
	β_1	-0.063	(-6.28)	β_2	-0.014	(-2.10)
	γ_o	-0.052	(-1.60)	γ_o	0.041	(1.62)
	δ_c	0.109	(2.28)	δ_c	0.144	(4.07)
	R^2		0.04	R^2	0.03	
	DW-stat.		2.01	DW-stat.	2.00	
Germany: Y1		ΔX_o			ΔY_c	
		Value	*t-ratio*		**Value**	*t-ratio*
	α_1	0.000	(-0.23)	α_2	0.000	(0.04)
	β_1	-0.024	(-2.39)	β_2	0.008	(0.83)
	γ_o	0.015	(0.50)	γ_o	0.095	(2.20)
	δ_c	-0.008	(-0.18)	δ_c	0.008	(0.22)
	R^2	0.00		R^2	0.011	
	DW-stat.	2.00		DW-stat.	2.00	

Notes: $X_{i,t}$ and $Y_{j,t}$ refer to the electricity and fossil fuel futures logarithm price series. β_1 and β_2 are the adjustment parameters to the long-run relationships, the parameters γ_{ik}, γ_{jk}, δ_{ik} and δ_{jk} for $i = p, o$ (peak and off peak load), $j = c, n$ (coal and natural gas) and k=1...m, determines how the return in one market responds to its own lagged returns and to the lagged returns of the other markets and, finally, $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ for $i = p, o$ and $j = c, n$ are the Gaussian white noise processes. The number of lags are determined following the Akaike Information Criteria.Standard errors are in parentheses.

Tables 5.5 and 5.6 represent the adjustment parameters β_1 and β_2, which measures the speed of error correction. The magnitude of the adjustment parameters determines the speed of adjustment back to the long-term equilibrium following an exogenous shock. Large coefficients mean that the adjustment is fast, therefore Z will be highly stationary and reversion to the long-term equilibrium will be rapid. First of all the adjustment parameter for electricity returns, β_1, is negative and significantly different from zero at the 99-percentage confidence level, suggesting that the electricity prices are cointegrated with the fossil fuels, negatively except for M1. Therefore a negative β_1 and a large error correction term Z implies that the electricity futures prices will decrease. Thus electricity prices respond to the price level of the underlying fuels by lowering demand when the underlying fuel prices increase. This is expected since a clear relationship is indicated between the electricity forward prices and forward prices for fossil fuels used to generate electricity. For the Dutch electricity market the β_2 (M1) for natural gas is positive and significant. Consequently we conclude that electricity and natural gas prices respond to a departure from the long-term equilibrium, but coal forward prices do not adjust to a change in the long-term equilibrium. The lagged disequilibrium term has an insignificant effect in the coal (ΔY_c) equation, therefore the error correction mechanism is operating primarily through the adjustment of electricity futures price rather then the coal futures price.

Table 5.6 represents the results for Germany. Similar to the Netherlands the adjustment parameter β_1 is negative and significant for the German electricity forward returns. The off peak futures prices respond to a higher disequilibrium by lowering demand. The parameter β_2 is only negative and significant for M1. Indicating that a shock in the electricity prices in the short-term (M1) results in a negative affect on the coal prices. The reason for this could be that the shock in the electricity price is caused by the dispatchment of the power price with the coal price, which indicates that at that point there is less need for coal in the market and a lower coal price follows. There is strong evidence that the electricity prices seems to adjust to past disequilibria and the fossil fuel prices do not. However in both markets we observe, for the M1, that the abundant fuel does respond to a disequilibria. The asymmetric long-run causality between the fossil fuels and electricity is consistent with the results of Emery and Liu [2002]. Coal and natural gas are important resources for generating electricity, but on the other hand generating power is one of the many uses for coal and natural gas.

The short-run causal relation is measured by γ_{ik}, γ_{jk}, δ_{ik} and δ_{jk}. When analysing the short-run relationship the lagged returns are taken into account. The results of the estimations for causality for the Netherlands are presented in Table 5.5. In the short-run, for the M1 contract a causal relationship is found to run from the natural gas futures prices to the off peak futures prices, at the 5 percent level, while the reverse causality does not exist. Thus, a unidirectional short-run Granger causality exists from natural gas prices to off peak power futures prices. For the Y1 contract the estimated coefficients on past changes in coal and natural gas prices are individually significant for off peak futures prices, suggesting uni-directional short-run causality from coal and natural gas prices to electricity prices. In Table 5.6 the results obtained for Germany from using a vector error correction model suggest a significant short-run univariate causal relationship between off peak and coal futures prices. Coal futures prices affect off peak electricity M1 futures prices, positively. The price of coal futures has a positive short-run response to off peak electricity price shocks for the German Y1 contract.

5.4 Concluding remarks

In this chapter, we analyse the long-run relations and short-run dynamics among one-month and one-year-ahead electricity and the fossil fuels natural gas and coal futures prices for the Dutch and German market. The primary fuel for power generation in the Netherlands is natural gas and in Germany the main production source depends on coal. As it appears there is only a clear equilibrium relationship present between the off peak power and both fossil fuel futures prices for the Netherlands and in the German market the off peak load and coal futures prices are cointegrated. Peak electricity futures prices do not show an apparent dependency on a certain fossil fuel in both markets. We showed that over time the supply stack of the produced power for the Dutch and German market has changed. Especially for Germany an increase in renewable power production is evident. If we also take into account the variation in power demand it would be difficult to find a clear cointegration relationship for the one-month-ahead and the one-year-ahead contracts with the futures prices of a certain underlying fossil fuel, because each contract that delivers monthly or yearly power, does not require to have a price depending on the same fuel one month or one year before expiration of the contract. An impulse response analysis reveals that for both markets, in the longer run, the off peak electricity futures price converge to the price level of the underlying fuels by lowering demand in case of an increase in price. In the short-run the Dutch power futures prices are affected by an exogenous shock in natural gas and coal prices. A causal relationship for the German market is found to run from coal futures prices to the off peak futures prices for M1 and in reverse for Y1. Overall we see that for the peak load futures prices the cointegration analysis is not sufficient enough in capturing the price dynamics depending on fossil fuel prices. Clearly the dynamics in electricity production and demand influences this relationship. Consequently for a better understanding to what extent power futures are fundamentally driven by fossil fuel prices more dynamic models are required.

6 | Electricity Futures Prices: Time Varying Sensitivity to Fundamentals

Joint with S-E Fleten, R. Huisman, H.P.G. Pennings and S. Westgaard.

6.1 Introduction

The owner of a power plant has the option to convert an energy source into electricity at every moment during the lifetime of the power plant. We assume that this lifetime is divided in hours, reflecting the micro structure of many day-ahead markets[1]. During the lifetime of the plant, the power owner has a series of hourly options to convert an energy source into electricity; a plant owner can exercise an option to produce power or not at any hour during the lifetime of the power plant[2]. The timing of the exercise decision depends on the markets in which the plant owner operates and the risk from changes in power prices that he is willing to accept. If he only trades in day-ahead markets, he decides every day how much to produce in every hour tomorrow. He might decide to produce tomorrow between 6pm and 7pm and not between 3am and 4am for instance. The option to produce is not transferable (if the plant does not produce during an hour, that production capacity cannot be stored and used in another hour) and the owner decides to produce or not and he makes this decision for every hour of the day. As a result, the income from the power plant is uncertain as the day-ahead prices and fuel costs are variable and difficult to predict far ahead in the future[3].

[1]This assumption can easily be relaxed and the remaining discussion can be based on half-hourly or fifteen minutes based intervals, depending on the application at hand.

[2]We ignore maintenance periods, during which the power plant is not operational, here for convenience.

[3]There is a huge amount of literature that documents the dynamics of day-ahead power prices such as seasonality, mean reversion, time-varying volatility and sudden price spikes. We refer to Huisman [2009] and Janczura and Weron [2010].

If the owner also trades in forward markets, in addition to day-ahead markets[4], he has an opportunity to make his future income less uncertain, more predictable. He then can sell a forward contract committing to deliver, for instance, a flow of 1 MW against a fixed price in every hour during the delivery period specified in the contract. With the forward contract, the plant owner fixates the selling price of a part of his output during a future delivery period, thereby making his revenues more certain. The uncertainty that remains is the costs of the fuels needed (and emission rights if applicable) since profits decline, on the volume sold against a fixed price, when fuel costs rise. How can the plant owner deal with this situation? This resembles how a market maker in equity forward contracts[5] deals with risk. When the market maker sells a forward contract to deliver a stock against a fixed price at a future moment in time without having the stock in his portfolio, he faces the risk that the stock price rises between the moments of sale and delivery such that, as a consequence, he has to purchase to stock against a higher price than the forward price. The risk comes from not having the stock in his portfolio and he can easily eliminate the risk by purchasing directly the stock after he has sold the forward contract and hold the stock in his portfolio until delivery. The purchasing costs to eliminate his risk is equal to the stock price plus financing costs. Knowing the costs of the risk eliminating strategy, a risk averse market maker will charge a forward price that is at least higher than the purchasing costs. When the stock market is competitive and perfectly liquid, the market forward price equals the costs of the risk eliminating strategy as a risk free arbitrage opportunity emerges otherwise.

This thinking is based on the theory of storage as originally proposed by Kaldor [1939], Working [1948], Telser [1958] and Brennan [1958]. The theory relates the price of a forward contract on an asset to costs of holding inventories of the asset to eliminate risks (storage and financing costs) and benefits (also called convenience yield) from holding the asset (such as dividends in case of a stock). We apply this thinking to the situation of the plant owner, who sold a forward contract to deliver power against a fixed price during some future time period. Suppose the plant converts a (fossil) fuel into electricity and that forward contracts are traded on this specific fuel for the same delivery period as specified in the sold forward contract. This applies for instance to coal and natural gas fired power plants as relatively liquid futures markets exist for these commodities. The plant owner can almost eliminate his risk

[4]Day-ahead contracts can be seen as one-day forward contracts, but we apply the market convention here to see one-day forwards as day-ahead contracts and to define forward contracts as contracts that deliver into periods farther away than one day.

[5]Or market makers in any other financial liquid assets such as currencies and interest rates products.

from selling an electricity forward by purchasing the appropriate amount of fuel and emission rights contracts. After doing so, the owner is almost free of risk as he sold power against a fixed price, purchased the fuel and emission rights against a fixed price and has the plant to convert the fuel into power during the delivery period. He is not perfectly free of risk as the power plant might break down. This risk, however, is manageable for the plant owner through maintenance. Assuming that the plant owner is risk averse, he will purchase the appropriate amount of fuel and emission rights contracts after selling a power forward contract to eliminate risk. And knowing this strategy, he will charge a price higher than the costs of the fuel and emission rights. If electricity, fuel and emission rights forward markets are liquid and competitive and if we assume that all power plants in the market use the same fuel to convert into power with the same efficiency and that there is no risk of plant failure, the forward price of electricity equals the value of the fuel and emission rights forward contracts needed to eliminate risk, just as in equity forward markets[6]. Based on this argument, one expects a direct relation between the forward price of electricity and the forward prices of the fuel and emission rights.

The comparison of the risk eliminating strategy of an equity market maker and the plant owner in this chapter is done to emphasize the interesting difference between stock and electricity. Every equity market maker has access to exactly the same stock. When equity market makers compete, they can apply the exact same risk eliminating strategy using the exact same stock; the exact same underlying asset that can be stored. In electricity markets, the underlying asset, electricity, cannot be stored (yet in an economically efficient way) and power plants compete in conversion technology. One power plant (a.k.a. market maker) converts natural gas into power. Another converts coal into power. In addition, plants differ in efficiency (the amount of fuel needed to produce one unit of power) and some producers have no fuel costs at all, such as solar and wind power plants[7]. The dynamics of price setting in power forward markets differ from equity and other financial markets for that reason. As a consequence, the forward price of electricity does not directly relate to the price of one specific fuel. This is found in different studies about the relation between electricity forward prices and forwards prices of underlying fuels. Emery and Liu [2002] show evidence for a relation between electricity forward prices and forward prices of fuels in terms of a co-integration relationship between

[6]This reasoning also holds in case there is no futures market for the underlying fuel as long as the fuel can be purchased in spot markets and stored in which case the electricity forward price relate to the value of the fuel needed purchased in the spot market plus storage and financing costs and convenience yields if any.

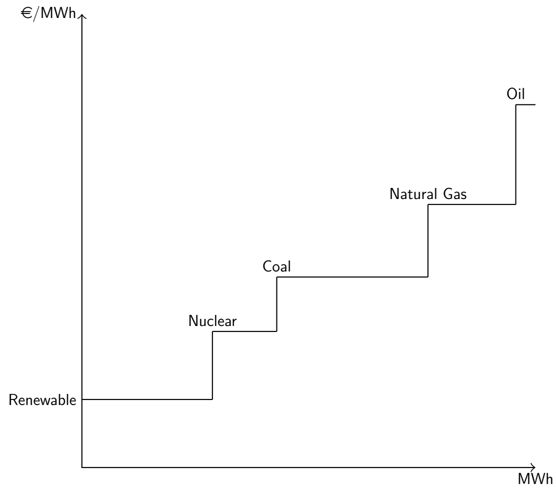
[7]The marginal costs of hydro power depends on the reservoir levels and the option to delay production. See Huisman et al. [2013].

gas and electricity futures prices of the American California-Oregon Border and Palo Verde markets. Mohammadi [2009] examines long-term 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. Similar to 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. Redl et al. [2009] examine the relationship between risk premiums of fuel markets and electricity using the German EEX and the NordPool forward contracts. In this model, the forward price of electricity is a function of primary fuel costs (gas or coal) and the costs for carbon emissions. The EEX electricity prices show higher correlation with gas and coal than the NordPool electricity prices. This can be explained by the fact that gas and coal are more often the marginal fuels for generating electricity than they are for NordPool where electricity is mainly generated by hydro power. This was confirmed by Povh and Fleten [2009]. They modeled the relationship between long-term forward contract prices on fuels (such as oil, coal and natural gas), the price of emission allowances, imported electricity and the long-term price of electricity forwards for the NordPool market. The cointegration analysis reveals a long-run relationship between all variables except for natural gas. The mutual interactions of electricity, gas and carbon prices in the UK were quantified by Fezzi and Bunn [2009]. Energy producers vary in the technology of energy supply and the prices of energy forward contracts relate to the prices of these different technologies.

The literature about pricing electricity forwards contracts develops in two streams. Within the first stream, forward prices are obtained as a stochastic multi-factor process mostly derived from the Schwartz [1997] stochastic models for commodity prices. Lucia and Schwartz [2002] is a direct application to power forward prices (among others). Forward prices are stochastic in this stream, consisting of different stochastic factors such as long and short term price developments and convenience yields. Prices do not directly relate to underlying fundamentals such as fuels or the market structure although the stochastic processes reflect these fundamentals somehow. We focus in this chapter on the second stream. Within this stream forward electricity prices relate to fundamentals. Deng [2000] relate fuel and electricity prices to model the value of electricity generating and transmission assets. Carmona et al. [2013] propose a structural model for spot and derivative electricity prices using a stochastic model of the bid stack. The model has a multi-fuel setting such that each fuel can set the market price and become the marginal fuel. Dong and Liu [2007] use storable fuels (natural gas and coal) in their model for electricity spot prices and forward prices are derived through a Nash bargaining process. According to Falbo et al. [2010] the value of a forward contract is equal to the sum of the expected marginal production cost and the spread option embedded in spot selling. Pirrong and Jermakyan [1999] and Pirrong and Jermakyan [2008] model the equilibrium price as a function of two state variables, electricity demand and the futures price of the marginal fuel. Routledge et al. [2001] derive the equilibrium forward prices by explicitly considering the conversion option of gas and other fuels to electricity (the model is in fact the Routledge et al. [2000] approach for pricing commodity forward contracts adapted to deal with electricity market specifics). Bessembinder and Lemmon [2002]'s equilibrium model implies that the relationship between forward power price and the future spot price is a function of both expected demand and demand variance. As a consequence, the forward price will generally be a biased forecast of the future spot price, with the forward premium positively related to the skewness of the wholesale price and negatively related to the variance of the wholesale price. Suenaga and Williams [2005] extent the Bessembinder and Lemmon [2002] model with fuel prices.

All these studies price electricity forwards by seeing forward prices as a biased predictor of future spot prices, or assume that the supply stack during the trading period of a forward contract is constant or assume that all producers have the same supply function. These are all assumptions needed to derive forward price models. The objective of this chapter is not to derive electricity forward price formulas but to examine the price formation process during the lifetime of an electricity forward contract seen from the risk eliminating strategies of power producers. We focus on the relation between the power forward price and prices of fuel and emission forwards assuming that different power producers use different technologies. We use the German power market to demonstrate our thoughts as a significant supply change occurred recently in this market; an event that we analyze in more detail later. Consider the hypothetical supply curve that loosely mimics the German market in Fig. 6.1. Power is supplied from renewable sources such as wind and solar with low marginal costs (hence they are on the left of the curve) and the fossil fuel sources nuclear, coal, gas and oil. The lines reflect the marginal costs of producing power for each technology.

Figure 6.1: **A hypothetical power supply curve.**



Consider a forward contract that has not been traded before. The forward contract specifies the delivery of 1 MW of power in every hour during a period T, somewhere in the future. For instance a calendar year 20XX base load forward contract that specifies the delivery of power during every hour in the year 20XX. Assume that no power producer has committed to deliver power yet during period T, i.e. none of the producers has sold power forward for that delivery period. Now a buyer, for the first time ever, enters the market willing to purchase that forward contract. The buyer will receive offers from the different power producers. Assuming a competitive market, offers from the renewable producers will be lowest; their price will be just below the marginal costs of the nuclear producers (we ignore competition effects among renewable producers for simplicity here but relax that later). The forward price of power (for that delivery period) relates to the marginal costs of nuclear production. When more and more buyers enter the market for the forward contract over time, the renewable suppliers will be sold out when the total demand for the forward contract from buyers exceeds the amount of capacity that the renewable producers are willing to sell forward. When the renewable producers are sold out, the market for the forward contract consists of less players, only the nuclear, coal, gas and oil plants. A buyer who now enters the market for the forward contract asking for quotes will obtain the lowest offer from the nuclear plants as they now have the lowest marginal costs. Their price will be just below the marginal costs of the coal plant. At this moment, the forward price of power relates to the marginal costs of coal. When the nuclear plants are sold out, the coal plants will offer the best prices. They will sell against a price just below the marginal costs of gas producers and manage their risks by purchasing the right amount of coal forward and emission rights contracts needed to produce power during the delivery period. Here, the forward price of electricity reflects the marginal costs of gas producers. This discussion about how demand for a forward contract meets supply from an agents point of view shows that the forward price relates to different fuels over time. It relates to the costs of nuclear production when the cumulative demand for the forward is lower than the amount that the renewable producers are willing to sell. The forward price of power relates to the marginal costs of coal (and emission rights) when the cumulative demand for the forward contracts is higher than the amount supplied by renewable producers but lower than the sum of volume willing to be supplied by renewable and nuclear suppliers. Considering the price of a forward contract during the lifetime of the contract[8], we expect that the price of the forward first correlates with nuclear prices, then with coal prices, then with gas prices and so forth. The price of the forward will also correlate with emission rights during its lifetime depending on the amount of emission rights needed for each technology. When we therefore analyze the relations between power forward prices and the prices of underlying fuels and emission rights, we expect that the relations should change over time; they are time-varying. This is in line with observations from Karakatsani and Bunn [2008] as they show, for the British market, that a model explains changes in day-ahead electricity prices with market fundamentals and time-varying coefficients exhibits the best predictive performance.

We want to examine the time-variation in the relation between changes in the price of an electricity forward contract and underlying fuels and emission rights during the lifetime of that forward contract. We also expect that the time-variation can be explained by the place of each technology in the supply curve. Before we ignored competition between producers with the same technology, but if we do assume them to act in a competitive setting, then we expect the - in the market of Fig. 6.1 - that in the beginning there is a relation with nuclear prices and that it steadily increases until all renewable producers are sold out, then no relation with nuclear prices and increasing relation with coal prices until the nuclear plant are sold out and then no relation with nuclear and coal and increasing relation with gas prices until they are sold out. This is most clear when there are sellers or investors taking short positions in the markets, but if we assume that consumption of power is positive over time, we expect such behaviour.

[8] The lifetime of a forward contract is from the moment of the first transaction in the contract until expiry.

The change in supply capacity in Germany between 2007 and 2012 is summarised in the following tables.

Table 6.1: **Electricity production by source (%).**

Year	Renewables	Nuclear	Coal	Natural Gas	Oil	Other
2007	15.16	20.96	42.98	13.28	1.35	6.26
2008	15.86	22.16	39.77	15.04	1.31	5.86
2009	17.05	21.53	39.21	14.76	1.47	5.99
2010	16.40	22.40	41.80	13.80	1.30	4.30
2011	20.30	17.70	42.90	13.60	1.10	4.20
2012	21.90	16.00	44.80	11.30	1.60	4.40

Source: Eurelectric and Energy Information Administration (EIA).

Table 6.2: **Electricity generation capacity by source (%).**

Year	Renewables	Nuclear	Coal	Natural Gas	Oil
2007	28.78	14.19	33.34	19.36	4.34
2008	30.91	13.75	32.44	18.79	4.11
2009	33.50	13.14	30.93	18.54	3.90
2010	37.38	12.31	29.01	17.83	3.48
2011	43.02	8.65	30.57	15.93	1.83
2012	46.02	7.79	28.32	16.19	1.68

Source: Eurelectric and European Energy Exchange.

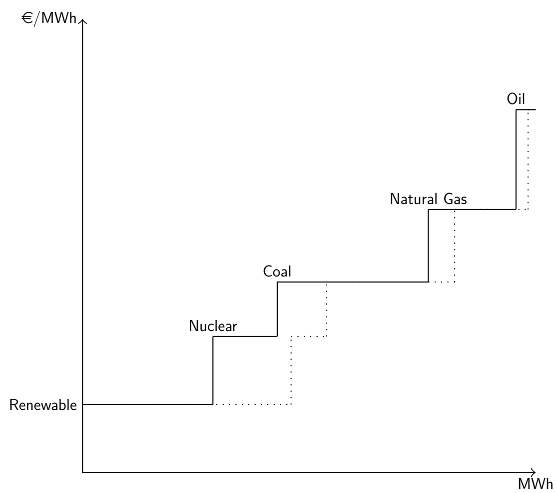
Table 6.3: **Electricity generation capacity of renewables (%).**

Year	Photovoltaic	Wind	Rest renewables
2007	2.68	15.45	10.65
2008	4.00	16.06	10.84
2009	6.18	16.53	10.79
2010	10.51	16.35	10.52
2011	14.14	19.72	9.16
2012	18.18	19.37	8.46

Source: Eurelectric and European Energy Exchange.

The structure of time-variation can differ in case of a substantial change in the supply curve. Figure 6.2 shows what happened in the German power market between 2007 and 2008. The new hypothetical supply curve after the supply change is shown as the dotted line.

Figure 6.2: **The German power supply curve shift between 2007 and 2012.**



Notes: Straight line 2007 and dotted line 2012.

The change in the supply curve comes from a substantial increase in solar capacity and a sharp reduction in nuclear capacity (as a result of Fukushima). As the share of nuclear decreased and the share of renewable increased the competitive setting of the market changed. If we examine the price of a forward contract with delivery after this period, but that was traded during this period, we should observe differences in the relations between forward prices and underlying fuels as a result of this. This brings us to the goal of this chapter. Our aim is to shed more light on the time-varying relation between electricity forward prices and the prices of underlying fuels and emission rights by studying the prices of a forward contract during its lifetime. We do so by studying a German contract that was traded between 2007 and 2012 such that we can analyze the impact of the changes in the supply curve in the market.

6.2 Methodology and data

We choose a time varying parameter model with a state space representation estimated with the Kalman Filter to examine how the relation between the price of an electricity forward contract and underlying fuels (fundamentals) vary over time. Let y_t, be the price of an electricity forward contract on day t, measured per MWh. The vector X_t contains time-varying explanatory variables. The main power sources in the German market that we study are renewables, nuclear, coal, and natural gas. Forward and futures contracts on the latter two fuels are actively traded in markets and we limit our study to examine the time-varying relation between the electricity forward price and forward / futures prices of the underlying fuels coal and natural gas. To calculate the marginal costs of power production, we assume an 'average' coal producer with an efficiency rate of 0.38 (one unit of fuel generates 0.38 units of power) and who emits 0.971 tonnes of CO_2 (net)[9]. When this coal producer prices an electricity forward contract, the minimum price he wants to offer is:

$$X_{c,t} = ((F_{c,t}/29.31)/0.2777) * (1/0.38) + 0.971 * F_{e,t}. \tag{6.1}$$

The variable $X_{c,t}$ is the marginal production cost that the coal producer can lock in today when he sells the power forward contract. It equals the market value of the number of coal forward contracts $F_{c,t}$ and emission rights $F_{e,t}$, which both deliver during the same period as the power forward contract, needed to produce the power that the (average) coal producer commits to sell through the power forward contract; i.e. the exact number of contracts needed to eliminate risk. The numbers 29.31 and 0.2777 convert the coal futures contract measured in tonnes to MW. For an average natural gas firing power producer, the marginal cost of producing one MWh of power is:

$$X_{g,t} = 2 * F_{g,t} + 0.404 * F_{e,t}. \tag{6.2}$$

The average natural gas plant produces power with 0.5 efficiency (hence, 2 gas forward contracts are needed) and emits 0.404 tonnes of CO_2 to produce 1 MWh of power. The variable $F_{g,t}$ is the price (measured per MWh) of a forward contract at time t from which natural gas is delivered during the same period as the power forward contract. The variables $X_{c,t}$ and $X_{g,t}$ are the fundamentals that we examine as they represent the marginal costs of producing power from coal and gas (for average efficient plants) based on the forward prices of coal and gas; i.e. the costs they pay to make themselves risk-free. We refer to these costs as the forward marginal costs of producing power as the costs are derived from forward prices. Let X_t be the (1×2) vector containing the marginal costs of both fuels: $X_t = (X_{c,t}, X_{g,t})$. Let β_t be a (2×1) vector with the time-varying coefficients that linearly relate the coal and gas marginal costs to the power forward prices. The model that linearly relates the forward marginal costs of producing power to the forward price of electricity is:

$$y_t = \mu + X_t\beta_t + \epsilon_t, \tag{6.3}$$

[9]We obtained the efficiency rates and number of emission rights needed for an average coal and gas plant from Bloomberg.

where μ is a constant and ϵ_t is a normally distributed error term with mean 0 and variance σ^2_ϵ. This model makes it possible to track the relation between the marginal fuel costs and the forward price of electricity over time by examining the behavior of the coefficient vector β_t. To do so, we need to specify how we allow β_t to vary over time. We choose a simple random walk specification:

$$\beta_t = \beta_{t-1} + \tau_t, \tag{6.4}$$

where τ_t is the (2×1) vector with normally distributed error terms $\tau_{c,t}$ in row 1 and $\tau_{g,t}$ in row 2 that both have mean 0 and variances $\sigma^2_{\tau,c}$ and $\sigma^2_{\tau,g}$ respectively. We assume that all the errors ϵ_t, $\tau_{c,t}$ and $\tau_{g,t}$ are independent.

Equation (6.3) and (6.4) encompass the model that we use to examine the time variation in the β parameters that relate the forward marginal costs of coal and natural gas production to the forward price of electricity. The β coefficients are not standard regression coefficients but are latent, stochastic variables that follow a random walk. The β parameters can be estimated by a Kalman Filter (Kim and Nelson [1999]). In state-space formulation, Eq. (6.3) is the measurement and Eq. (6.4) is the transition equation (Durbin and Koopman [2012]).In order to obtain all parameter estimates, we apply maximum likelihood in combination with the Kalman Filter[10].

To estimate the parameters and to observe whether the latent β coefficients move in line with what we expect from our discussion, we use the complete history of prices of the German (EEX market) calendar year 2013 base load[11] and peak load [12] contracts[13]. The delivery period of the base load contract overlaps the delivery period of the peak contract as peak delivery takes place during the peak part of the day and base delivery is for the whole day. We use the base load and peak load price to calculate the implied off peak price to observe the price of two non-overlapping delivery periods (peak and off peak), consistent with market practice. The implied off peak prices [14] are calculated as (24 * base load price - 12 * peak load price) / 12. We examine the peak and off peak prices in this chapter, not the base prices as base

[10]Implementation of the unobservable component model is performed by using $STAMP8.0^{TM}$

[11]Delivering 1MW of power in any hour of the day.

[12]Delivering 1MW of power from Monday to Friday between 8 am and 8 pm.

[13]The calendar year 2013 contract is chosen since the whole trading period for the electricity forward contract matches with coal, natural gas and emission rights forward contracts.

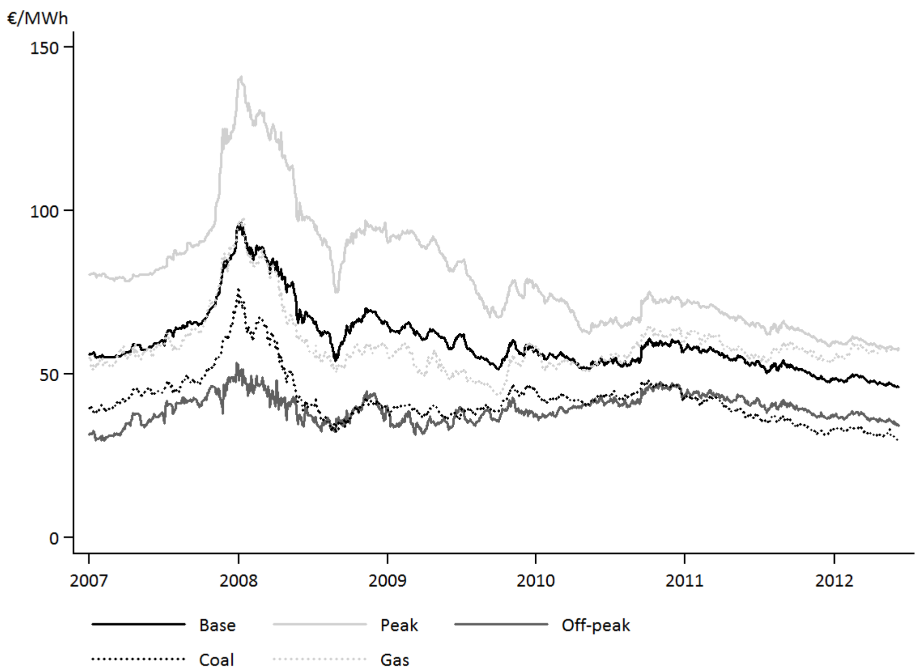
[14]Delivering 1MW of power from Monday to Friday outside the 8 am and 8pm period.

overlap off-peak and peak delivery and is therefore redundant when we examine the separate peak and off peak prices.

The EEX calendar year futures contract starts trading approximately six years before delivery. The sample period for the calendar year 2013 contracts that we examine is from 2 July 2007 through 5 December 2012, yielding 1369 daily closing price observations. The natural gas forward prices in €/MWh are the NetConnect Germany (NCG) forward contract traded on the EEX. The coal prices in $/1000 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. The currency conversion is made by using the exchange rate provided by Reuters. All data is obtained from Bloomberg, Thomson Reuters Datastream and Montel database. Figure 6.3 shows the price history of the forward marginal costs of producing power using coal and gas (as in Eq. (6.1) and (6.2)) and the forward prices of 2013 delivery base, peak and off peak power.

From Fig. 6.3 it is evident that prices of the electricity forward contract follow the pattern of the forward marginal costs of producing power. The forward marginal costs went up before 2008 and went down thereafter. The same trends are apparent in the power base, peak and off peak contracts. The price of the power calendar year 2013 off peak contract follows the forward marginal costs of producing power with coal in a pattern that is consistent with the way of reasoning in the introducing section. The off peak price is lower than the forward marginal costs of producing with coal in the beginning of the life of the contract as renewable and nuclear producers most likely offer lower forward marginal costs than coal producers. After the renewables and nuclear plants were sold out, the off peak price follows almost exactly the forward marginal costs of coal production between mid 2008 until the beginning of 2011.

Figure 6.3: **The German Cal-2013 commodity prices**.



Thereafter, the off peak price exceeds the forward marginal costs of coal production as more expensive plants than the average coal plant that we model here set the off peak forward price. These more expensive plant might be less efficient coal fired plants or gas plants being the next fuel in the merit order. Peak prices were the highest reflecting the higher demand for power during peak hours. The peak power forward prices exceed the forward marginal costs of producing power with gas for the whole lifetime, but peak prices converges to the forward marginal costs of producing with gas at the end of the lifetime. The likely causes of the peak prices first being higher and later almost equal to the forward marginal costs of power production are the economic crisis that materialized throughout this period resulting in end-consumers of power selling futures contracts as expected demand for power in 2013 reduced due to the crisis and secondly the change in the merit order after 2008 with a substantial increase in solar power capacity that deliver during day time (peak) hours and the close of nuclear plants after Fukushima.

Table 6.4 shows summary statistics of the calendar year 2013 power forward prices and the forward marginal costs of producing power with coal and gas.

Table 6.4: **Descriptive statistics for power price and marginal production costs (€/MWh).**

	Peak	Off-peak	Coal	Natural Gas
Mean	80.350	39.431	42.313	58.905
St.dev	18.350	4.177	7.993	9.208
Observations	1384	1384	1384	1384

Notes: Descriptive statistics of daily peak and off-peak calendar year 2013 power prices and the forward marginal costs of producing power in 2013 with coal and gas between July 2007 and December 2012. electricity futures prices.

To emphasize this influence of the two different marginal fuel costs on the electricity forward price over the lifetime of a yearly contract we use the following two-factor model:

$$X^e_{t,T} = \alpha + \beta_C X^c_{t,T} + \beta_G X^g_{t,T} + \varepsilon \tag{6.5}$$

where $X^e_{t,T}$, $X^c_{t,T}$ and $X^g_{t,T}$ refer to electricity, coal and natural gas forward prices, respectively[15]. The data set consists of forward prices comprising the delivery of peak and off peak power in calendar years. We shall distinguish between contracts delivering next year, referred to as the Y1 contract, through three years to maturity (Y3). The sample period is from 1 January 2008 through 31 December 2012, having approximately 1267 daily forward price observations. The prices are converted in natural logs. For the Y1, Y2 and Y3 price series a significantly positive ($\rho \approx 0.6$) correlation between $X^c_{t,T}$ and $X^g_{t,T}$ is found, reflecting a sensible fundamental relationship. Coal and natural gas are substitute fuels used in the production of electricity. Therefore the estimated coefficients from Eq. (6.5) might be distorted by the dual role the proxies are playing. This nonessential collinearity in the regression can be eliminated by orthogonalizing one of the independent variables. The orthogonalization creates a new measurement of $X^g_{t,T}$ variable that is uncorrelated with $X^c_{t,T}$ variable. [16]In Table 6.5 the peak* and off peak* are the parameter estimates with orthogonalized $X^g_{t,T}$ in Eq. (6.5).

[15]The coal $X^c_{t,T}$ and natural gas $X^g_{t,T}$ forward prices are the marginal production costs of producing 1MW of power converted through Eq. (6.1) and Eq. (6.2)

[16]Orthogonalization can be explained as a process of finding the residual of the interaction term. Given the structure of this new measurement, the coefficient of the revised coal variable has a different interpretation. It serves as an unbiased estimate of the sensitivity of forward electricity price to the forward natural gas price after considering forward natural gas price sensitivity to forward coal prices. The variable replaced by residuals is the dependent variable in the auxiliary regression. Here $X^g_{t,T}$, is regressed on $X^c_{t,T}$, the residuals replace $X^g_{t,T}$ in Eq. (6.5).

Consistent to our expectation we observe in Table 6.5, for off peak* prices that the estimates for β_G are higher for the one-year-ahead (Y1), than Y2 and Y3, which are not significantly different from zero. Closer to delivery it shows that the off peak prices are indeed getting related to natural gas prices. The coefficient β_C is around the 0.8 for peak* and 0.6 for off peak* prices, which is lower than expected. The peak prices show a higher β_G this indicates that the natural gas forward price has more influence in the formation of the forward electricity price than in off peak prices. These results confirm that the electricity forward prices are influenced by fossil fuel forward prices, however these results do not show a clear changing sensitivity of the power prices to the merit order through the lifetime of a contract.

Table 6.5: **Estimates for the parameters in Eq. (6.5)**

		Peak		**Peak***		**Off peak**		**Off peak***	
(a)Coefficients		**Value**	*t-ratio*	**Value**	*t-ratio*	**Value**	*t-ratio*	**Value**	*t-ratio*
β_C	Y1	0.542	(8.52)	0.767	(20.69)	0.365	(6.46)	0.603	(13.57)
	Y2	0.494	(15.87)	0.759	(5.01)	0.530	(6.21)	0.569	(11.51)
	Y3	0.519	(3.72)	0.783	(12.52)	0.664	(9.09)	0.570	(12.49)
β_G	Y1	0.334	(5.07)	0.334	(5.07)	0.353	(6.59)	0.353	(6.59)
	Y2	0.377	(3.76)	0.377	(3.76)	0.060	(0.71)	0.060	(0.71)
	Y3	0.343	(2.45)	0.343	(2.45)	-0.122	(-1.42)	-0.122	(-1.42)
(b) Test statistics		**Value**				**Value**			
R^2	Y1	0.70				0.58			
	Y2	0.56				0.42			
	Y3	0.45				0.43			
n	Y1	1267				1267			
	Y2	1269				1269			
	Y3	1268				1268			

Notes: The peak* and off peak* are the parameter estimates with orthogonalized $X^g_{t,T}$ in Eq. (6.5). The t-statistics are based on robust Newey-West Heteroskedasticity and Autocorrelation (HAC) standard errors and are in parentheses. R^2 is the coefficient of determination for the coal and natural gas regressions, respectively. n is the number of observations in a regression.

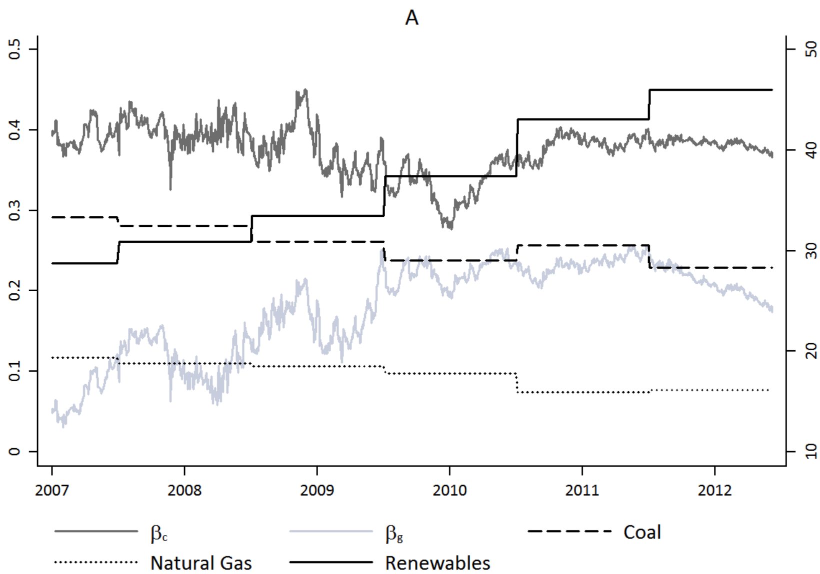
6.3 Results

Our goal is to examine the relationship between the forward marginal costs of producing power and the power forward price (2013 delivery) over time. We expect these to be time varying following the merit order. Figure 6.4 shows the evolution of the β parameters in Eq (6.4) over the lifetime of the 2013 off peak and peak delivery contracts.

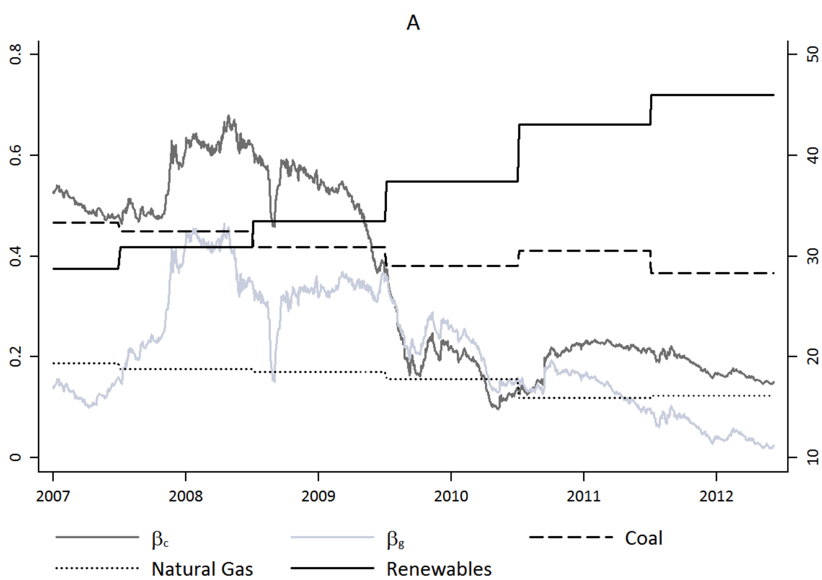
The top graph in Fig. 6.4 shows that the coefficient for coal (β_c) hovers around 0.4 over time for the off peak contract and that the coefficient for gas (β_g) increases, consistent with our discussion. Coal fired power plants are the marginal producers in most off peak hours and hence those producers are likely to set the price for the off peak power forward contract during its lifetime. When time progresses and more and more coal plants sell out for 2013 delivery, gas fired plants will become competitive too, hence the increase in the (β_g) coefficient. The decline of the coefficient at the end of the life of the contract can be explained by sales of the 2013 contract as companies lowered demand expectations for 2013 power due to the economic crisis.

The bottom graph of Fig. 6.4 shows the huge impact of the substantial increase of renewable energy capacity, in particular solar power, on peak power prices. The peak power forward related to the forward marginal costs of producing power with coal and gas before mid 2009 with the influence of gas increasing between 2007 and 2008 being consistent with the discussion in the introduction. After 2009, the increase in renewables had its impact on peak power prices as both the coal and gas coefficients declined. In 2007, 33.3 percent of the electricity generation capacity depended on coal and 19.4 percent on natural gas. Renewable generation capacity increased from 28.8 percent in 2007 to 42.3 percent in 2012. This is mainly triggered by the reconsideration of the nuclear policy and abandoning nuclear power and investing in renewable energy sources. The electricity generation capacity dependent on coal and natural gas decreased to 28.3 percent and 16.2 percent, respectively. A second cause for the decline in the coefficients for coal and gas is likely the economic crises resulting in especially a decline in peak demand due to lower industrial demand for power.

Figure 6.4: **Time-varying coefficients for the calendar year 2013 and the evolution of generation capacity (%) over time. Model A**



Off peak



Peak

Table 6.6: **Estimates for the parameters in Eq. (6.3), (6.4) and (6.6).**

		Peak model A		**Peak model B**	
Variances		**Value**	[q-ratio]	**Value**	[q-ratio]
Irregular	σ^2_ϵ	0.00002E-2	[0.000]	0.00002E-2	[0.000]
Coal	$\sigma^2_{\tau,c}$	0.00010	[1.000]	0.00010	[1.000]
Natural gas	$\sigma^2_{\tau,g}$	0.00008	[0.794]	0.00008	[0.794]
Coefficients		**Value**	*t-ratio*	**Value**	*t-ratio*
Level	μ	52.022	(30.856)	68.855	(22.030)
climate spread	γ			-0.029	(-6.360)
Test statistics		**Value**		**Value**	
St. error		0.014		0.013	
H(460)		0.164		0.140	
r(1)		-0.074		-0.103	
r(37)		-0.009		-0.007	
Q		97.161		98.101	
AIC		-8.582		-8.639	
		Off Peak model A		**Off Peak model B**	
Variances		**Value**	[q-ratio]	**Value**	[q-ratio]
Irregular	σ^2_ϵ	0.00765	[1.000]	0.02102	[1.000]
Coal	$\sigma^2_{\tau,c}$	0.00013	[0.017]	0.00026	[0.012]
Natural gas	$\sigma^2_{\tau,g}$	0.00008	[0.011]	0.00001	[0.001]
Coefficients	**Value**	*t-ratio*	**Value**	*t-ratio*	
Level	μ	13.230	(7.353)	18.590	(5.771)
climate spread	γ			-0.009	(-1.944)
Test statistics		**Value**		**Value**	
St. error		0.095		0.157	
H(460)		0.132		0.134	
r(1)		-0.183		-0.168	
r(37)		0.085		0.085	
Q		112.970		105.100	
AIC		-4.703		-3.697	

Notes: In the table, H(460) is a basic non-parametric test of heteroscedasticity, being a two-sided $F_{k,k}$ test centered around unity. The critical value for this test at the 5 % level is approximately equal to 1.00. For independence the individual autocorrelations of the residuals for lag 1 up to lag 37 are significant. The residuals are statistically independent if the value does not exceed $\pm$ 1.96/$\sqrt{n}$ according to a confidence interval of 95 %. Q is the Box-Ljung statistic, a test for residual autocorrelations and serial tested, which is based on the first 37 residual autocorrelations and tested against a chi-square distribution with 35 degrees of freedom. The critical value for this test at the 5 % level is approximately 49.8. The fit of different models can be compared by using the Akaike information criterion (AIC). The q-ratios are the ratios of the associated variance to the highest variance.

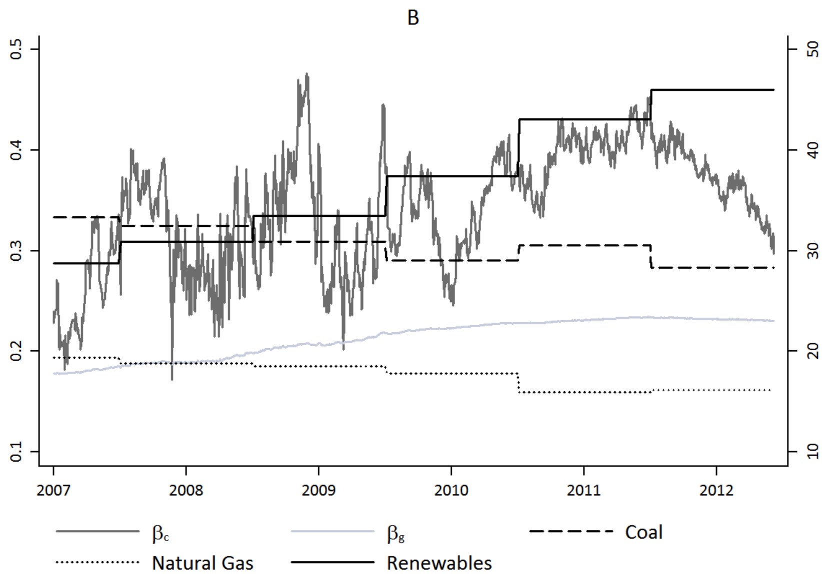
Table 6.6 contains information about the estimates for the parameters in Eq. (6.3) and (6.4). The parameter estimates are headed model A (model B will be introduced later). The q-ratio, which are the ratios of each variance to the largest, will give us useful information for the process. For peak prices, most of the model variation is explained by coal, as implied by the q-ratio being equal to one, however natural gas also has significant explanatory power. The variance of the irregular component for the off peak prices is equal to one and consequently less variation is explained by the explanatory variables. The results of the diagnostic test for the residuals of the analysis show that for peak and off peak prices the test for homoscedasticity and independence at lag 1 are satisfactory. The H-statistic is smaller than the critical value of $F_{460,460;0.025} \approx 1.00$. The autocorrelations at lag 1 are well within the 95-percentage confidence limits however, the overall Q-statistic for the first 37 autocorrelations confirms the high amount of dependency between the residuals.

The graphs show that the coefficients vary over time in a way related to the merit order and changes in the supply curve. High carbon costs and lower natural gas prices can establish that less CO2-intensive gas-fired power plants become more profitable than coal-fired power plants. The competitiveness of power plants have changed after the introduction of carbon costs through emission certificates, and this effect might influence our view as we did not include this in our analysis. We introduce the variable X_t^3 that we call the climate spread, which is the difference between the clean spark spread and the clean dark spread. The clean spark spread represents the net revenue from power sales after gas and emissions allowance costs, and the clean dark spread is the analogous spread for coal-fired generation plants. We change the measurement Eq. (6.3) into:

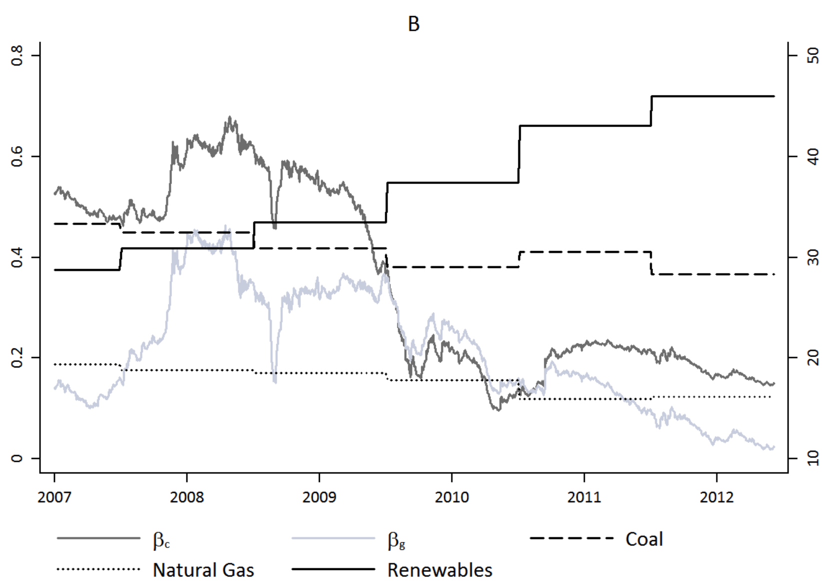
$$y_t = \mu + X_t\beta_t + \gamma X_t^3\epsilon_t, \tag{6.6}$$

where the parameter γ is a fixed variable that allows to control for the climate spread influence on the price of the power forward contract. We refer to this model as model B and the estimates of the parameters are in Table 6.6 under the header model B. The estimates for γ are negative and significant for both off peak and peak delivery contracts. The negative estimates indicate that a higher climate spread results in lower power forward prices. This results is consistent with Emery and Liu [2002] who show that electricity prices respond negatively with increasing spark spreads, because an increase in fuel prices will induce a decline in power demand. A higher climate spread can be caused by an increasing natural gas price. This increases the spark spread, therefore the negative estimates between the climate spread and power prices are conform with the results found in literature.

Figure 6.5: **Time-varying coefficients for the calendar year 2013 and the evolution of generation capacity (%) over time. Model B**



Off peak



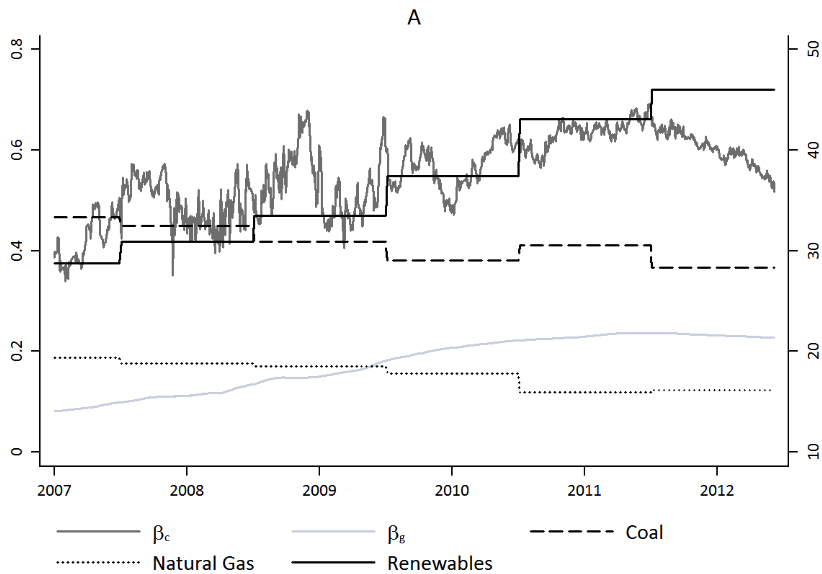
Peak

In Fig. 6.2 we observe that the marginal cost of producing power with natural gas was decreasing and in the first months of 2010 the price was almost equal to the marginal costs of producing power with coal. Lower natural gas prices will result in a smaller climate spread and this has an increasing effect on the forward electricity prices because of an increase in demand for power futures. The time-varying β coefficients for coal and gas are in Fig. 6.5. The graphs shows a similar patterns as in the results without including the climate spread; adding this control variable does not change the results that the parameters are time varying and importantly behave as in line with our discussion.

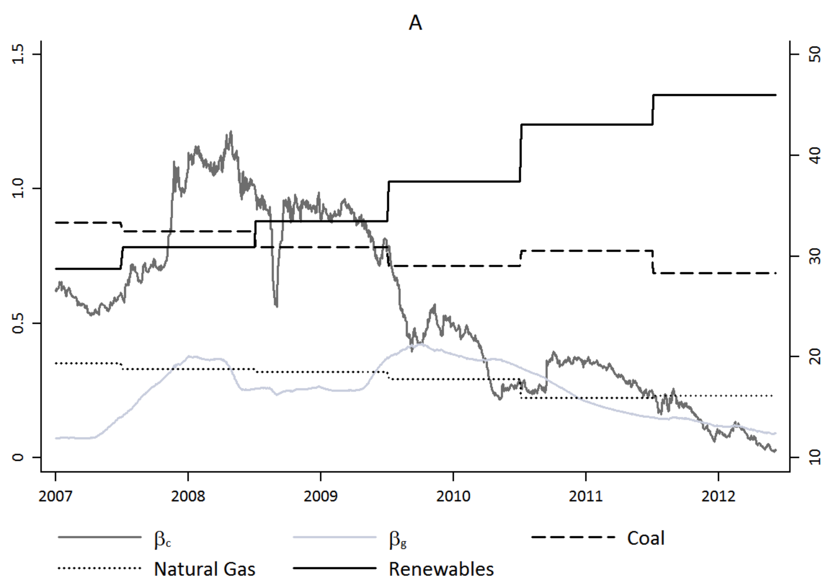
As a final point we note that, as mentioned in the methodology and data section, the marginal production cost of power based on the fossil fuels coal and natural gas experience a significantly high correlation between the price series ($\rho \approx 0.8$), because of the similarity in usage. We apply orthogonalization to eliminate nonessential collinearity between $X_{c,t}$ and $X_{g,t}$. We orthogonalize $X_{g,t}$ and therefore $X_{c,t}$ and $X^*_{g,t}$ will be mutually independent. $X^*_{g,t}$ will replace $X_{g,t}$ in Eq. (6.3) and Eq. (6.6).

Table 6.7 (A) contains information about the estimates for the parameters in Eq. (6.3), (6.4) and (6.6) with $X^*_{g,t}$. The parameter estimates are headed model A* and model B*. We do not observe any clear difference in the parameter estimates compared to the results of the estimates for the parameters in Eq. (6.3), (6.4) and (6.6) with $X_{g,t}$. The graphs show the same results as without orthogonalizing $X_{g,t}$ as in time varying sensitivities, however for peak the coefficient for coal (β_c) is clearly higher and even reaches 1.0 at the beginning of the trading period after which it starts to decline. β_c for off peak also exhibits an increasing trend from 0.4 to 0.7 near expiration. Therefore we can state that orthogonalizing does not change our main conclusion, nonetheless the time-varying sensitivity to coal seems to be more apparent.

Figure 6.6: **Time-varying coefficients for the calendar year 2013 and the evolution of generation capacity (%) over time. Model A***

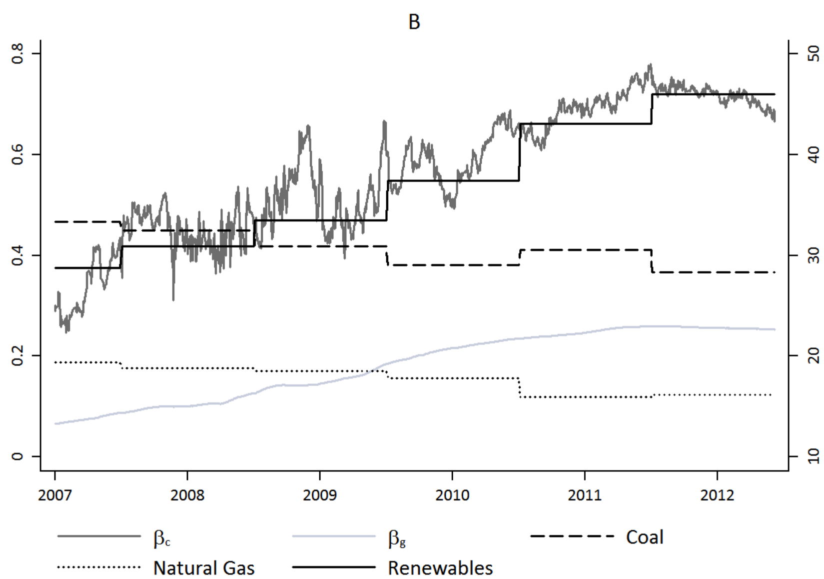


Off peak

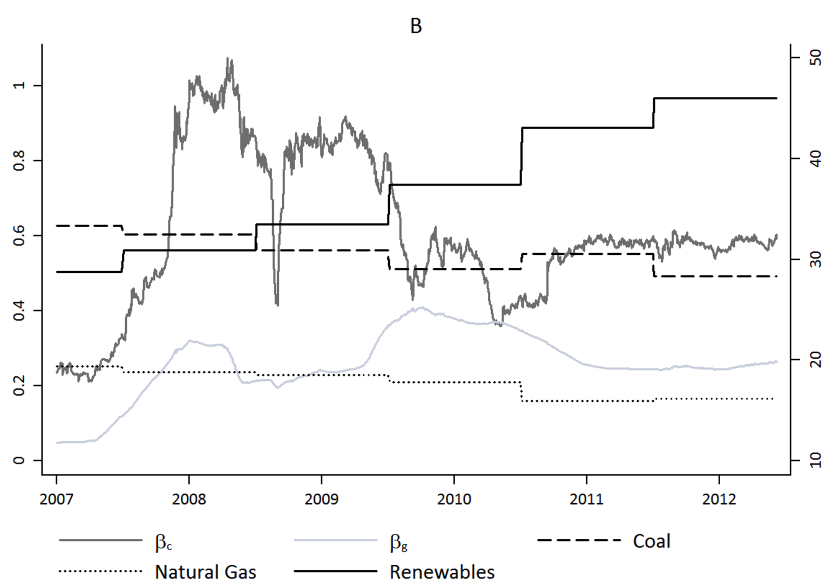


Peak

Figure 6.7: **Time-varying coefficients for the calendar year 2013 and the evolution of generation capacity (%) over time. Model B***



Off peak



Peak

6.4 Conclusion

This chapter analyses the time varying sensitivity of underlying fossil fuels, such as coal and natural gas, as well as carbon emission allowance futures prices on the price formation of an electricity future calendar contact throughout the trading period. To capture the dynamics in the price formation we apply the univariate unobservable component model, where the explanatory variables are functions of time and the parameters are time varying. We observe that the sensitivities of long term electricity futures prices to explanatory variables coal and natural gas vary over time in a sense that the forward power price is highly influenced by the marginal production costs based on forward fuel prices. The time-varying link between electricity forward prices and the forward marginal costs of electricity production, time varying due to (changes in) the merit order of fuels, support the need for theories and models that link electricity forward prices to their fundamentals and suggest that purely stochastic models likely do not suffice.

6.5 Appendix

Table 6.7: **Estimates for the parameters in Eq. (6.3), (6.4) and (6.6).**

		Peak model A*		Peak model B*	
Variances		**Value**	[q-ratio]	**Value**	[q-ratio]
Irregular	σ^2_ϵ	0.00004E-3	[0.000]	0.00004E-3	[0.000]
Coal	$\sigma^2_{\tau,c}$	0.00027	[1.000]	0.00026	[1.000]
Natural gas	$\sigma^2_{\tau,g}$	0.00014	[0.519]	0.00008	[0.308]
Coefficients		**Value**	*t-ratio*	**Value**	*t-ratio*
Level	μ	55.995	(38.19)	71.254	(25.97)
climate spread	γ			-0.029	(-6.36)
Test statistics		**Value**		**Value**	
St. error		0.020		0.019	
H(460)		0.179		0.143	
r(1)		-0.090		-0.112	
r(37)		-0.009		-0.010	
Q		100.26		104.78	
AIC		-7.80		-7.88	
		Off Peak model A*		**Off Peak model B***	
Variances		**Value**	[q-ratio]	**Value**	[q-ratio]
Irregular	σ^2_ϵ	0.02456	[1.000]	0.02301	[1.000]
Coal	$\sigma^2_{\tau,c}$	0.00027	[0.011]	0.00027	[0.011]
Natural gas	$\sigma^2_{\tau,g}$	0.00001	[0.001]	0.00002	[0.001]
Coefficients	**Value**	*t-ratio*	**Value**	*t-ratio*	
Level	μ	16.281	(10.56)	20.135	(6.93)
climate spread	γ			-0.006	(-1.56)
Test statistics		**Value**		**Value**	
St. error		0.165		0.160	
H(460)		0.138		0.135	
r(1)		-0.163		-0.168	
r(37)		0.084		0.085	
Q		104.04		105.01	
AIC		-3.59		-3.65	

Notes: The peak* and off peak* are the parameter estimates with orthogonalized $X^g_{t,T}$ in Eq. (6.3) and Eq. (6.6). In the table, H(460) is a basic non-parametric test of heteroscedasticity, being a two-sided $F_{k,k}$ test centered around unity. The critical value for this test at the 5 % level is approximately equal to 1.00. For independence the individual autocorrelations of the residuals for lag 1 up to lag 37 are significant. The residuals are statistically independent if the value does not exceed $\pm$ 1.96/$\sqrt{n}$ according to a confidence interval of 95 %. Q is the Box-Ljung statistic, a test for residual autocorrelations and serial tested, which is based on the first 37 residual autocorrelations and tested against a chi-square distribution with 35 degrees of freedom. The critical value for this test at the 5 % level is approximately 49.8. The fit of different models can be compared by using the Akaike information criterion (AIC). The q-ratios are the ratios of the associated variance to the highest variance.

7 | Conclusion

Characterising price drivers is important when it concerns power futures contracts. Futures contracts serve as financial instruments to hedge against price risk. Besides the specific characteristics of electricity as a commodity and the complexity of the electricity market other risks in terms of pricing emerge. Empirical studies show for instance that demand, generation capacity and fuel prices influence the power forward prices (see Barlow [2002]; Cartea and Villaplana [2008]; Pirrong and Jermakyan [2008]; Howison and Coulon [2009] among others)

This thesis contributes to the literature on forward pricing by analyzing the electricity power derivative prices with respect to their fundamentals. The first part of this thesis, chapter 2 and 3, analyses the behaviour of short-term and long-term electricity prices stochastically with respect to price risk, which depends on demand and supply side factors. The second part of this thesis, chapters 4, 5 and 6 presents that difference on the supply side regarding the storability of power generation influences the forward price formation. In this final chapter, I summarize the main findings and present the conclusions from the five studies.

According to literature electricity day-ahead prices experience seasonality, high volatility, mean-reversion and extreme price spikes. The findings in chapter 2 indicate that according to expectation increased connectivity, which yields additional supply in the short-term, reduces the impact of price spikes. We show that next to the decreased impact of price spikes and volatility over time, prices tend to behave more random, and that parameter estimates between various connected markets seem to have converged between the Belgian, Dutch, French, German, and Nordic day-ahead markets over the years 2003 through 2010.

The behaviour of long-term forward prices concerning the occurrence of extreme price changes are analyzed in chapter 3. Essentially in the forward prices extreme price movements (both up and down) occur more frequently than what a normal distribution function would express. This is a result too important to ignore for risk managers, for instance, as they cannot use normal distributions to calculate their risk measures or values for options and other derivative contracts. If they would do so, they would underestimate the level of risk. Therefore risk managers in the power industry can obtain better insight in the amount of risk their companies face by applying extreme value theory. This higher price risk relates to the non-storability feature of electricity and as a consequence power futures prices have to be valued according to the expectation theory and reflect expectations and risk premiums (see Fama and French [1987]; Lucia and Schwartz [2002]; Eydeland and Wolyniec [2003]; Huisman [2009] among others).

In chapter 4 we analysed futures prices from the Dutch market, a market in which power is produced with storable fossil fuels, and futures prices from the NordPool market, where electricity is mostly produced by hydropower to examine to what extent electricity futures prices contain expected risk premiums or have power to forecast spot prices and whether this might be dependent on the type of electricity supply. We show that futures prices from markets in which electricity is predominantly produced by imperfectly storable fuels such as hydro, wind and solar contain information about expected changes in the spot price of electricity, whereas futures prices from markets in which electricity is predominantly produced with perfectly storable fuels contain information about both expected price changes and time-varying risk premiums. These findings provide insight in the applicability of forward price models; one cannot apply the same model to all electricity markets. Forward models for markets with imperfect indirect storability should depend heavily on price expectations and models should include time-varying risk premiums for markets with perfect indirect storability.

The findings reported in chapter 4 highlight an important point: the characteristics of the underlying abundant fuel influences the forward price formation. Therefore in chapter 5 the long-run relations and short-run dynamics between electricity and fossil fuel futures prices are analysed to identify if power futures price formations are driven by fundamentals, based on fuel prices. Our results show that in the Netherlands both fossil fuel futures prices play a role in the price formation of off peak prices and in Germany the off peak futures prices are cointegrated with coal futures only. Peak electricity futures prices do not show an apparent dependency on a certain fossil fuel in both markets. We showed that over time the supply stack of the produced power for the Dutch and German market has changed. Especially for Germany an increase in renewable power production is evident. If we also take into account the variation in power demand it would be difficult to find a clear cointegration relation between the one-month-ahead or one-year-ahead contracts with the futures prices of a specific underlying fossil fuel, because each contract that delivers monthly or yearly power, does not require to have a price depending on the same fuel one month or one year before expiration of the contract. Furthermore, we observe a causal relationship between the off peak power and fossil fuel futures prices for both markets. Overall we see that for the peak load futures prices the cointegration analysis is not sufficient enough in capturing the price dynamics depending on fossil fuel prices. Clearly the dynamics in electricity production and demand influences this relationship. Consequently for a better understanding to what extent power futures are fundamentally driven by fossil fuel prices more dynamic models are required.

This non existing interrelationship between peak load futures prices with a specific fossil fuel gave indications to examine the time-variation in the relation between changes in the price of an electricity forward contract, underlying fuels and emission rights during the lifetime of a forward contract in chapter 6. We observed that the sensitivities of long-term electricity futures prices to explanatory variables coal and natural gas vary over time according to the merit order. To meet the demand power plants are added in the order of the increasing marginal costs; the cheapest producers first, then stacking the more expensive until the demand is met. Therefore the time-variation can be explained by the place of each technology in the supply curve and the evolution of the power demand. Specifically we find that the change in the merit order, caused by the increase of renewable energy capacity has a great impact on the time varying sensitivities of fossil fuels in peak power prices. This behaviour of power prices has clear implications for the valuation and hedging of forward contracts during the trading period. For this reason, electricity price forming processes cannot be detached from the prices of the fuels used for power generation.

7.1 Discussion

Financial models cannot directly be copied into the world of electricity prices. For modelling forward commodity prices reduced-form models based on Schwartz [1997] derive forward prices assuming that they depend on several factors such as the spot price, the convenience yield and the interest rate. These factors, including the convenience yield, are defined as a stochastic process. This dependence of the convenience yield on time expresses the fact that it varies inversely with the level of inventories of a commodity. Based on the Schwartz [1997] model Lucia and Schwartz [2002] propose a two-factor model which they apply to electricity futures prices. The power prices are modeled according to non-observable state variables that account for the short-term movements and long-term trends in electricity prices. Most papers build upon these stochastic factor models to describe the dynamics of electricity forward prices, introducing concepts such as convenience yields into electricity. However, the research performed in this thesis gave me a different view concerning this fact. Those papers basically treat electricity as a regular commodity, but they ignore the fact that electricity is a conversion commodity; coal converted into power, gas converted into power. In chapter 6, I show that there is a clear dependency between the futures prices of fossil fuels and power. Therefore the price of a power forward contract can be seen as the price of the marginal fuel and some conversion costs. How can we interpret the convenience yield embedded in these models when we know that the convenience yield is nothing more then the expectation of the amount of profit that can be derived out of having the physical good in store over having a contract. A power plant has a capacity to convert a fuel or wind into power. Capacity that is not used now, cannot be used later in time; conversion units as such cannot be stored. Therefore the power producer does not have the opportunity to create an inventory of conversion units. In my opinion, convenience yields for electricity will only exist when electricity becomes efficiently storable. "The convenience yield" captured by these models is nothing more than the convenience yield of the underlying fuels (except for wind and solar) used for power generation and should be modeled as such. The convenience yield embedded in the coal futures are clearly different from the convenience yield in gas futures prices. Due to the price setting dynamics, which clearly depends on the supply stack function, the sensitivity to the different fuels are time-varying, therefore this convenience yield is also expected to be time-varying. Altogether this questions whether these stochastic factor models for electricity forwards are methodologically correct. Clearly we need to rethink pricing models for power futures.

Samenvatting (Summary in Dutch)

Transformaties zijn heersende fenomenen in de energiemarkt. In 1990 is de elektriciteitsmarkt overgegaan van een gereguleerde naar een geliberaliseerde markt. Dit is geïnitieerd door de Europese Unie met het doel om een enkele Europese elektriciteitsmarkt te creëren. Een van de gewenste resultaten van de deregulering, beëindiging van monopolies en inefficiënties was het verlagen van de prijzen voor eindgebruikers, terwijl de Europese Unie een verbeterde concurrentiepositie verkreeg ten aanzien van elektriciteit voor de toekomst. Met de deregulering zijn er markten voor financiële contracten op elektriciteit ontstaan en hierdoor werd elektriciteit een verhandelbaar goed. Elektriciteit werd verhandeld op de energiebeurzen door de nieuwe spelers, die in de geherstructureerde elektriciteitsmarkt verschenen: de producenten, de retailers en de eindgebruikers. De beursgenoteerde marktprijs in de geliberaliseerde elektriciteitsmarkt wordt bepaald door de vrije marktwerking tussen vraag en aanbod. Deze prijsbepalende factoren zijn onderhevig aan veranderingen, waardoor nieuwe onzekerheden op de markt worden geïntroduceerd. Het identificeren van de fundamenten die van invloed zijn op de prijsvorming van termijncontracten zijn waardevol voor het begrijpen en managen van risico's.

In Europa was het Verenigd Koninkrijk het eerste land dat zijn elektriciteitsmarkt in 1990 met de Elektriciteitswet herstructureerde (Mork [2001]). Kort na het Verenigd Koninkrijk begon Noorwegen aan zijn transformatie. Het land nam in 1990 de Noorse Elektriciteitswet aan, waardoor een progressief aantal consumenten vrij waren in hun keuze van elektriciteitsleverancier. Twee jaar later kwam in Noorwegen een officiële spotmarkt voor elektriciteit tot stand, terwijl de handel in futures en forwards in 1996 pas begon. Het was deze energiebeurs die uitgroeide tot de Nord Pool markt[1], die nu ook Noorwegen, Finland, Zweden en Denemarken omvat

[1] Voor 1 november 2010 was de financiële energiemarkt NASDAQ OMX Commodities Europa bekend onder de naam Nord Pool

(Mork [2001]). Meer landen volgden, de APX (Nederland) werd in 1999 opgericht, Powernext (Frankrijk) in 2001 en de EEX (Duitsland) in 2002. De liberalisering van de elektriciteitsmarkt heeft bijkomende risico's en nieuwe uitdagingen voor de marktspelers gecreëerd. Voornamelijk het feit dat elektriciteit niet op grote schaal kan worden opgeslagen heeft het gevolg dat vraag en aanbod te allen tijde in evenwicht moeten zijn. Het is niet mogelijk onbalans via fysieke voorraden te corrigeren. Het gebrek aan opslaanbaarheid, in combinatie met de volatiele vraag naar elektriciteit en de convexe productie curve, heeft gevolgen voor de prijsstelling en handel van elektriciteit op de energiebeurs. Een fysieke onbalans in vraag en aanbod resulteert in hoge prijsvolatiliteit en frequente pieken in de prijzen. Spotprijzen vertonen ook sterke seizoenspatronen, zoals dag-, week -en seizoensgebonden cycli, en aangezien elektriciteit wordt gedreven door het evenwicht tussen vraag en aanbod neigen de prijzen terug te keren naar het gemiddelde (mean reversion). De specifieke kenmerken van de elektriciteitprijs leidt tot uitdagingen in het modelleren van de spotprijsdynamiek. Beginnend met traditionele stochastische grondstof prijsmodellen worden de specifieke kenmerken van de elektriciteitsprijzen geïdentificeerd en via mean reversion door een- of twee - factor -modellen vastgelegd (Lucia and Schwartz [2002]). Historische data is hierbij noodzakelijk voor de schatting van de belangrijkste stochastische parameters, bijvoorbeeld gemiddelde en volatiliteit. Jump diffusion proces (bv. Deng [2000]) en of regime - switching aanpak (bv. Ethier and Mount [1999], Huisman and Mahieu [2003] o.a.) zijn opgenomen om de gestileerde feiten van elektriciteit spotprijsdynamiek in het model op te nemen. Echter elektriciteitsprijzen worden sterk beïnvloed door exogene factoren. Daarom kan de spotpijsdynamiek ook door fundamentele factoren worden opgevat door, zoal vraag of schaarste in aanbod (Karakatsani and Bunn [2008]). De invloed van schommelingen van fysieke variabelen zoals temperatuur, regenval, instroom in waterreservoirs en verschillende factoren aan de vraagzijde op de elektriciteitsprijzen zijn ook door verschillende auteurs bestudeerd (bv. Huisman [2008]; Vehviläinen and Pyykkönen [2005]; Fleten et al. [2002]).

Deze hoge volatiliteit en de pieken in de spotprijzen maakt het gebruik van elektriciteitsderivaten, zoals lange termijncontracten meer toepasselijk voor risicoafdekking. Risicomijdende hedgers die elektriciteit produceren of consumeren kunnen spotprijs risico's afdekken door in termijncontracten te handelen en kunnen hun toekomstige kasstromen hiermee stabiliseren. Met een termijncontract wordt voor een specifieke periode in de toekomst overeengekomen een hoeveelheid energie tegen een vooraf bepaalde prijs per eenheid te leveren. Voor elke periode, beoordelen afnemers vooraf de vraag en gaan contracten aan met producenten voor de gegeven hoeveelheid elektriciteit. Gedurende de overeengekomen periode wordt van de producent verwacht dat de gecontracteerde hoeveelheid elektriciteit wordt geproduceerd en geleverd en van de afnemer wordt verwacht dat zij deze hoeveelheid afneemt. In de meeste elektriciteitsmarkten zijn contracten beschikbaar voor de periode van een maand, kwartaal, halfjaar en jaar. De expectations theorie is het beginpunt voor vele elektriciteit-termijncontract prijsmodellen. Het is economisch nog niet haalbaar om elektriciteit op te slaan met als gevolg dat elektriciteitstermijncontractprijzen verwachtingen en risicopremies bevatten (zie Fama and French [1987]; Lucia and Schwartz [2002]; Eydeland and Wolyniec [2003], en Huisman [2009] o.a.). De prijs van een elektriciteits-termijncontract weerspiegelt de verwachte spotprijs in de leveringsperiode plus of min een risicopremie. Echter elektriciteits-termijncontractprijzen hoeven niet altijd afhankelijk te zijn van de spotprijs en hierdoor zou de prijsdynamiek ook gemodelleerd kunnen worden als een alleenstaand proces. Het onderzoek is grofweg verdeeld in fundamentele en non-fundamentele modellen die elektriciteits-termijncontracten waarderen. Lucia and Schwartz [2002] is een belangrijk voorbeeld die elektriciteits-termijncontracten stochastisch waarderen. Lucia and Schwartz [2002] richten zich primair op de verwachtingen. Door het modelleren van de verwachte spotprijs gedurende een toekomstige tijdsperiode leiden ze een formule af voor de prijs van een termijncontract op elektriciteit. De verwachte spotprijs is gelijk aan de som van twee prijzen: een lange termijn evenwichtsspotprijs en een prijs die op korte termijn terugkeert naar het gemiddelde. In aanvulling op deze verwachtingen gaan ze uit van een constante risicopremie [2]. Maar zoals bij het modelleren van spotprijzen is het essentieel om bij het waarderen van grondstofderivaten de fundamentele kenmerken en risicofactoren die de termijncontract prijsdynamiek beïnvloeden te identificeren. In fundamentele prijsmodellen worden variabelen die de aanbod of vraag beïnvloeden ook meegenomen bij het modelleren van de verwachtingen of risicopremies die in de termijncontractprijzen zijn ingebed (bv. Bessembinder and Lemmon [2002], Routledge et al. [2001] en Douglas and Popova [2008]). Een specifiek kenmerk van elektriciteit is de homogeniteit ook al wordt het opgewekt uit verschillende bronnen, zoals hernieuwbare energiebronnen (bv. wind, zon en waterkracht), kernenergie of fossiele brandstoffen zoals kolen, gas en olie. Al deze middelen van elektriciteitsproductie hebben verschillende kenmerken en kosten. Met name vanwege de niet opslaanbaarheid van elektriciteit is er een nauwer verband met de fundamentele onderliggende factoren die de prijs beïnvloeden (vooral brandstofprijzen, vraag en productiecapaciteit) dan in andere markten.

Dit proefschrift draagt bij aan de literatuur over termijncontractprijzen door de elektriciteitsprijzen van derivaten te analyseren met betrekking tot hun fundamenten. Het eerste deel van

[2] Twee risicopremies: Een voor elke bron van onzekerheid (lange-termijn en korte-termijn prijsonzekerheid)

dit proefschrift, hoofdstuk 2 en 3, analyseert de prijsgedraging van korte- en lange termijncontracten stochastisch met betrekking tot prijsrisico, dat afhankelijk is van vraag en aanbod factoren. Het tweede deel van dit proefschrift, hoofdstukken 4, 5 en 6 presenteert dat het verschil aan de aanbodzijde ten aanzien van opslaanbaarheid van elektriciteitsproductie de prijsvorming van het termijncontract beïnvloedt.

In hoofdstuk 2 onderzoeken we voor vijf Europese markten, die over de afgelopen jaren steeds meer gekoppeld zijn, de ontwikkeling van de day-ahead prijzen. Waar eerdere studies de convergentie op prijsniveaus over tijd onderzochten, richten wij ons op patronen in de parameter schattingen van een regime-switching model. Dit maakt het mogelijk om onderscheid te maken tussen de prijzen onder normale marktomstandigheden en onder non-normale marktomstandigheden, welke marktomstandigheden zijn die extreme prijspieken kunnen veroorzaken. De bevindingen in hoofdstuk 2 geven aan dat volgens verwachting de toegenomen connectiviteit, wat op de korte termijn voor extra aanbod zorgt, het effect van de prijspieken vermindert. We laten zien dat de prijzen naast de verminderde impact van pieken en volatiliteit over tijd ook de neiging hebben zich meer willekeurig te gedragen. Tussen de verschillende gekoppelde day-ahead markten, zoals België, Nederland, Frankrijk, Duitsland en Scandinavië over de jaren 2003 tot en met 2010 lijken de parameter schattingen ook te zijn geconvergeerd.

Hoofdstuk 3 van dit proefschrift richt zich op het prijsrisico in de elektriciteits-termijn contractprijs. We analyseren het optreden van extreme prijsveranderingen in elektriciteits- termijncontracten door te onderzoeken in hoeverre veranderingen in de elektriciteits-termijncontractprijzen gemodelleerd kunnen worden met behulp van een normale verdeling of dat een andere methode zou moeten worden toegepast. We passen de extreme waarde theorie toe om de grootte van dikstaartigheid te beoordelen, i.e. de frequentie waarmee extreme prijzen voorkomen, zodanig dat we kunnen waarnemen of deze prijswijzigingen met behulp van een normale verdeling gemodelleerd kunnen worden of niet. Hoofdzakelijk in de termijncontractprijzen komen extreme prijsbewegingen (zowel omhoog als omlaag) vaker voor dan wat volgens een normale verdelingsfunctie zou moeten. Dit is een belangrijk gevolg voor risicomanagers om te negeren, bijvoorbeeld ze kunnen normale verdelingen niet gebruiken om hun risico maatregelen of waarden voor opties en andere derivaten te berekenen. Indien ze dat zouden doen, dan zouden ze het risico onderschatten. Daarom kunnen risicomanagers in de energie-industrie door het toepassen van extreme waarde theorie beter inzicht verkrijgen in de hoeveelheid risico waar hun bedrijven mee worden geconfronteerd. Dit hogere prijsrisico heeft betrekking op de niet opslaanbaarheid van elektriciteit met als gevolg dat de elektriciteits-termijncontractprijzen gewaardeerd moeten worden volgens de expectations theorie en zodoende verwachtingen en risicopremies bevatten (zie Fama and French [1987]; Lucia and Schwartz [2002]; Eydeland and Wolyniec [2003]; Huisman [2009] o.a.).

Het tweede deel van dit proefschrift omvat een empirisch onderzoek die derivaatprijzen met betrekking tot de fundamenten analyseert. Hoofdstuk 4 onderzoekt in hoeverre elektriciteits-termijncontractprijzen verwachte risicopremies bevatten en of macht hebben om spotprijzen te voorspellen en ofwel dit afhankelijk is van het type elektriciteitsaanbod. Deze analyse wordt uitgevoerd volgens het expectations theorie, die de termijncontractprijs van een grondstof gelijk stelt aan de verwachte spotprijs van de onderliggende grondstof gedurende de leveringsperiode plus een verwachte risicopremie die producenten compenseert voor het dragen van de onzekerheid die het leveren tegen vaste prijzen met zich meebrengt. We analyseren termijncontractprijzen voor de Nederlandse markt, waarin elektriciteit wordt opgewekt met fossiele brandstoffen die over een opslagmogelijkheid beschikken, en de termijncontractprijzen voor de Nord Pool markt, waar elektriciteit voornamelijk wordt geproduceerd door waterkracht. We laten zien dat termijncontractprijzen voor markten waarop elektriciteit voornamelijk wordt geproduceerd door imperfect opslaanbare brandstoffen, zoals waterkracht, wind-en zonne-energie informatie bevatten over de verwachte veranderingen in de spotprijs van elektriciteit. Terwijl termijncontractprijzen voor markten waar elektriciteit voornamelijk geproduceerd wordt met perfecte opslaanbare brandstoffen informatie bevatten over zowel de verwachte prijsveranderingen en tijdsafhankelijke risicopremies. Deze bevindingen bieden inzicht in de toepasbaarheid van termijncontract prijsmodellen; het is niet mogelijk hetzelfde model toe te passen op alle elektriciteitsmarkten. Termijncontract modellen voor elektriciteitsmarkten met imperfecte indirecte opslag moeten sterk afhankelijk zijn van de prijs verwachtingen en modellen voor elektriciteitsmarkten met perfecte indirecte opslag moeten tijdsafhankelijke risicopremies bevatten.

De bevindingen gerapporteerd in hoofdstuk 4 markeren een belangrijk punt: de karakteristieken van de onderliggende overvloedige brandstof beïnvloedt de prijsvorming van het termijncontract. Daarom wordt in hoofdstuk 5 de lange-termijn relaties en korte-termijn dynamiek tussen termijncontractprijzen van elektriciteit en fossiele brandstoffen geanalyseerd om te bepalen in welke mate de elektriciteitsprijs formaties gedreven worden door fundamenten, welke gebaseerd zijn op brandstofprijzen. Deze analyse wordt uitgevoerd voor de Nederlandse en Duitse markt, waar elektriciteit voornamelijk wordt opgewekt door fossiele brandstoffen voor de een- maand en de een- jaar voor levering piek en dal termijncontracten. Om voor cointegratie tussen elektriciteit, steenkool en aardgas termijncontractprijzen te testen worden de augmented Engle - Granger (1987) test en de error correction model gebruikt. Onze resultaten laten zien dat in Nederland zowel het termijncontractprijs van fossiele brandstoffen in de prijsvorming van het daluur prijs een rol spelen en in Duitsland is het dal termijncontractprijs met enkel de steenkool-termijncontractprijs gecointegreerd. In beide markten zijn de piek termijncontract prijzen duidelijk niet afhankelijkheid van een bepaalde fossiele brandstof. We tonen aan dat voor de Nederlandse en Duitse markt de aanbodcurve van het geproduceerde elektriciteit na verloop van tijd is veranderd. Vooral voor Duitsland is een toename van hernieuwbare energie productie evident. Als we ook rekening houden met de variatie in de elektriciteitsvraag dan bemoeilijkt dit om een duidelijke cointegratie relatie tussen de prijzen van elektriciteits-termijncontracten die een- maand of een- jaar voor levering verhandeld worden en de onderliggende fossiele brandstoffen te vinden, omdat de prijs van elk verschillend contract die maandelijks of jaarlijks elektriciteit levert, niet afhankelijk hoeft te zijn van dezelfde brandstof een maand of een jaar voor het verstrijken van het contract. Over het algemeen zien we dat voor de piek termijncontractprijs de cointegratie analyse niet voldoende is om de prijsdynamiek, afhankelijk van fossiele brandstofprijzen op te pakken. Het is duidelijk dat de dynamiek in elektriciteitsproductie en vraag deze relatie beïnvloedt. Meer dynamische modellen zijn benodigd voor het ontwikkelen van een beter begrip met betrekking tot in hoeverre de elektriciteits-termijncontractprijs wezenlijk gedreven wordt door fossiele brandstof prijzen.

Hoofdstuk 6 analyseert de tijd variërende invloed van termijncontractprijzen van de onderliggende fossiele brandstoffen, zoals steenkool en aardgas, alsmede emissierechten op de formatie van elektriciteits-termijncontractprijzen over de gehele handelsperiode van een kalendercontract. Om de dynamiek in de prijsvorming vast te leggen passen we een univariate unobservable component model toe waarbij de verklarende variabelen functies zijn van tijd en de parameters tijd variërend zijn. We verwachten dat aan het begin van de handelsperiode van een elektriciteits-termijncontract de prijs wordt bepaald door de prijs van de termijncontract van de marginale brandstof met de laagste kosten en wanneer de capaciteit van de centrales met de laagste marginale kosten bijna vergeven zijn, zal de volgende marginale brandstof de termijncontractprijs bepalen. Voor dit onderzoek hebben we de Duitse EEX, waar de stroomproductie hoofdzakelijk gebaseerd is op de fossiele brandstoffen steenkool en aardgas, piek en daluur termijncontract prijzen van de kalender 2013 contract gebruikt. We observeren dat de relatie van de elektriciteits-termijncontractprijs tot de verklarende variabelen steenkool en aardgas, afhankelijk van de merit order, door de tijd heen variëren. Om de vraag tegemoet te komen worden centrales toegevoegd in de volgorde van toenemende marginale kosten, de goedkoopste producenten eerst, dan de duurdere totdat aan de vraag wordt voldaan. Daarom kan de tijdsvariatie worden verklaard door de plaats van elke technologie in de aanbodcurve en de evolutie van het gevraagde vermogen. Specifiek vinden we dat de verandering in de merit order, veroorzaakt door de toename van de capaciteit voor hernieuwbare energie, een grote impact heeft op de tijd variërende relatie van fossiele brandstoffen op piek elektriciteitsprijzen. Dit gedrag van elektriciteitsprijzen heeft duidelijke gevolgen voor de waardering en hedging van termijncontracten tijdens de verhandelingsperiode. Om deze reden kunnen elektriciteitsprijsvormende processen niet onlosmakelijk gezien worden van de prijzen van brandstoffen die voor energieopwekking wordt gebruikt.

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