Mai Thi Nguyen

Modeling the Nord Pool System Price: A Quantile Regression Approach

Master's thesis in Financial Economics

Trondheim, June 2015

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NTNU
Norwegian University of Science and Technology
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Abstract

This thesis contributes to the area of research on electricity price formation by studying how fundamental factors influence different quantiles of the distribution of the Nord Pool system price. Using quantile regression, a model for the electricity price in the off-peak period 04 (03:00-04:00) and the peak period 11 (10:00-11:00) is proposed. Generally, results show positive impact of adaptive behavior, demand, fossil fuel prices, CO_2 emissions allowance price and electricity certificate price, while water reservoir level and wind power have negative impact on the electricity price. The effect of price volatility is negative in lower quantiles and positive in upper quantiles. Furthermore, results suggest that the influence of fundamentals vary non-linearly across quantiles, as well as between trading periods.

Preface

This master thesis in Financial Economics has been carried out at the Norwegian University of Science and Technology (NTNU) – Department of Economics. The thesis is the final work of a 2-year Master's Degree.

I would like to thank my supervisor Doctoral Fellow Lars Ivar Hagfors for great guidance with the thesis during these 5 months. He has at all times been available for advice, provided helpful comments and proofread the thesis. At the top, he has shown great interest in my progress, which in turn has given me huge motivation.

I would also like to thank Statkraft and Glenn Frode Grøtheim for taking the time to have an informative meeting with me. I am grateful for all the guidance and kindness the staff at the Department of Economics has shown me during my 5 years at Dragvoll Campus. Last, but not least, I would like to thank Kjetil Ones and Phuong Nguyen for valuable support.

Mai Thi Nguyen

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Abbreviations

ARIMAX	Auto Regressive Integrated Moving Average with Exogenous Input
BTU	British Thermal Unit
CAViaR	Conditional Autoregressive Value-at-Risk
CO_2	Carbon Dioxide
CET	Central European Time
GWh	Gigawatt hours
EU	European Union
EUA	European Union Allowance
EU ETS	European Union Emissions Trading System
GARCH	Generalized Auto Regressive Conditional Heteroscedasticity
IGARCH	Integrated Generalized Auto Regressive Conditional Heteroscedasticity
ln	The Natural Logarithm
MWh	Megawatt hours
OLS	Ordinary Least Squares

P04	Price in period 04
P11	Price in period 11
TWh	Terrawatt hours
VaR	Value-at-Risk

1 Introduction

In the course of time, electricity has obtained an important position in most economies. The choices of use are many for both industry and private households, ranging from essential applications of light, heat and power to consumption purely in order to make living more comfortable. In fact, virtually all fields of the society have become reliant on electricity. This has led to a broad literature trying to understand the development of the electricity price. However, despite the attention, the price formation remains only partially understood.

Complications related to electricity price are induced by the uniqueness of electricity as a commodity. Firstly, the non-storability requires that demand equals supply at all times. Secondly, it is reliant on a transmission grid, making electricity bound to a more regional market than other commodities. These restrictions make the electricity price highly volatile. Furthermore, the electricity market is closely connected to other energy markets. Electricity is produced by converting other energy sources. Fossil fuels like coal, natural gas and oil, renewable energy sources like hydro and wind, and nuclear, are all sources utilized in electricity generation. Price formation is, thus, affected by input fuel prices, or availability regarding renewables, as they are a part of the production costs.

The main goal of this thesis is to contribute to a deeper understanding of how fundamental factors influence different quantiles of the distribution of the Nord Pool system price, which is the market-clearing price in the day-ahead market. The choice of the Nordic area and the accompanying exchange, Nord Pool, is motivated by eagerness to learn more about my "home electricity market". The problem is motivated by the fact that modeling the electricity price has proved to be challenging, yet crucial and is hence of great current interest. For agents involved in electricity exchange activities, including producers, suppliers, consumers, traders and distributors, it is of highly importance to understand the spot price formation across the whole distribution in different delivery hours. Modeling and forecasting electricity prices with a reasonable accuracy give market participants the opportunity to adjust their production or consumption schedule together with their bidding strategy in the day-ahead market in order to maximize income or minimize cost. Especially for risk management purposes, modeling the tails of price distributions are more useful than modeling central expectations (Bunn et al., 2016, p. 2). However, tail distributions are difficult to model due to the sparseness of data. The semi-parametric quantile regression is advantageous in this respect for many reasons, which is why I have chosen this methodology.

First introduced by Koenker and Bassett Jr. (1978), quantile regression offers desirable features in modeling the electricity price. It gives the opportunity to capture any position of the price distribution by examining several quantiles, allowing for investigation of price formation beyond the central location, including the tails. Quantile regression accounts for non-linear relationships between the electricity price and fundamental factors as coefficients can vary across quantiles, giving insights in exogenous drivers' impact on price under different market conditions. Hence, this framework offers a deeper understanding of the price series compared to only modeling the mean. Moreover, the semi-parametric formulation is appropriate in this context due to electricity price characteristics of high volatility, spikes and positive skewness. Application of this framework to prices can be found for instance in Bunn et al. (2016) and Hammoudeh et al. (2014).

In order to achieve the thesis' goal, the main contribution is the proposition of a linear quantile regression model for the system price at Nord Pool Spot. Focus is situated on two different periods: the off-peak period 04 (03:00-04:00) and the peak period 11 (10:00-11:00). These periods are chosen because they represent hours of lowest and highest demand in the data set in use, respectively. In the previous literature, a wide range of both fundamental and statistical models for the spot price are suggested. This thesis takes a fundamental approach. Fundamental market models link supply and demand to market variables in order to derive estimations of electricity prices (Burger et al., 2014, p. 301). Demand is a main influence on prices and is therefore included. Since the Nordic market is heavily reliant on hydropower, hydro reservoir level is included to capture available capacity. In order to examine the influence of renewable energy, wind power is included. The CO_2 emissions allowance price and electricity certificate price are included with the aim to investigate whether the environmentally friendly generation policy in the area has any influence on the electricity price. Agent learning due to repeated auctions is considered by including lagged prices. Also, a historical volatility term is included in order to soak up additional uncertainty. Results generally show changing coefficients of the explanatory variables across quantiles for both the hourly system prices explored, suggesting a non-linear influence of fundamentals on the electricity price.

As a demonstration of the usefulness of the quantile regression framework to electricity price modeling, I next perform 1-day-ahead Value-at-Risk (VaR) calculations for both long and short trading positions, which is valuable for agents concerned with short-term risk management. VaR is a commonly used method for market risk quantification. Following the deregulation of electricity markets, competition has led to a strong need for market surveillance. For agents concerned with managing and assessing risk, price models which are accurate in forecasting tail risk is thus vital. Quantile regression models the conditional quantiles directly. Another utilization of quantile regression is, hence, in VaR calculations, as they are nothing more than conditional quantile functions. The findings suggest that the quantile regression approach provides accurate forecasts and the correct percentage of violations, but seems to suffer from clustering of exceedances.

This thesis has several contributions. As previously explained, I propose a linear quantile regression model for the Nord Pool system price. I very much follow in the spirit of Bunn et al. (2016). As far as I know, however, a similar methodology has not yet been applied to the Nordic market. Second, time series data spans over nine years including recent observations, from January 2006 to December 2014, which will give new insights. Third, there is a rich selection of fundamental variables, allowing for careful investigation of the price formation. Fourth, studying different trading hours instead of daily average prices gives the opportunity to examine intra-day variations of the influence of fundamentals on the electricity price. Fifth, by estimating nine quantiles for each trading period investigated, ranging from the 1% quantile to the 99% quantile, the whole price distribution is covered. Thus, a deeper understanding of the non-linear impact of fundamentals on different price levels is offered. Finally, I perform 1-day-ahead Value-at-Risk calculations for both long and short trading positions.

The rest of this paper proceeds as follows: Section 2 briefly reviews earlier literature concerning electricity price modeling. Section 3 presents the background of the Nordic electricity market. In Section 4, fundamental factors are introduced. Section 5 describes the data used in the analysis, while Section 6 describes the methodology in use. In Section 7, results and discussion of the analysis are presented. Section 8 contains the VaR application of the model. The conclusion is presented in Section 9. Further presentations of statistics and results can be found in the Appendix.

2 Literature Review

This thesis can be located within several research areas. Four of them are briefly reviewed below.

There is a lot of literature on fundamental models concerning the electricity market. The fundamental approach generates electricity prices from expected demand and production costs, with an attempt to give insight into fundamental price drivers and market mechanisms. Nogales et al. (2002) define a dynamic regression model and a transfer function model with demand as explanatory variable for the Spanish and Californian market, the main conclusion being that the models are accurate in predicting the electricity price in both markets. Torro (2007) estimates an ARIMAX model for the Nordic market with temperature, precipitation, reservoir levels and the difference between the futures price and spot price as explanatory variables. Results show that the model is accurate in forecasting the spot electricity price. Karakatsani and Bunn (2008) examine the electricity spot price in the British market using three different models: a linear regression model, a time-varying parameter regression model of random-walk coefficients and a Markov regime-switching regression model. Lagged prices are included as fundamentals, among others. Findings suggest that the time-varying parameter regression model derives the most accurate forecasts for the electricity price. Huisman et al. (2014) explore the relationship between the natural gas price, CO_2 emission allowance price, reservoir levels and the electricity price in the Nordic market by utilizing a supply and demand model. They demonstrate that regressions on high and low reservoir levels have different parameters, giving evidence of a non-linear relationship between fuel prices and the electricity price. Bunn et al. (2016) investigate the day-ahead electricity price in Great Britain by using quantile regression with prices of gas, coal, carbon emissions, demand forecast, reserve margin forecast and conditional volatility as fundamentals. They find a positive influence of fuel prices and demand forecast, and a negative influence of reserve margin forecast on the electricity price.

The growing focus on environmentally friendly electricity generation has resulted in a broad research stream investigating the impact of renewable energy sources on the electricity price. Hu et al. (2010) show, by studying the relationship between the spot price and wind power generation in western Denmark, that the spot price decreases when wind power penetration increases. Genoese et al. (2010) find that wind power generation is the most important factor explaining the occurrence of negative prices in the German market. Gelabert et al. (2011) demonstrate that a marginal increase in electricity generation coming from renewable energy technologies like wind, solar and biomass decreases the electricity price in the Spanish market by estimating a multivariate regression model. Astaneh et al. (2013), by use of an agent based simulation method, find proof of excessive price reduction and high price volatility in wind dominant electricity markets. Huisman et al. (2013) demonstrate indirectly that an increase in solar and wind power supply leads to lower electricity prices. They do so by studying the hydropower generation at the Nordic market with a supply and demand model. Evidence of substitution from fossil fuels to wind power are found in the study of the German market by Paraschiv et al. (2014) by means of a time-varying regression model.

The Nordic electricity market has been addressed in several studies in addition to those already mentioned. Weron et al. (2004) face the problem of modeling the Nord Pool system price with a statistical approach, in which seeks to model the electricity price dynamics directly. They develop a mean reverting jump diffusion model whose simulated prices turn out to resemble actual prices quite well. Vehviläinen and Pyykkönen (2005) present a bottom-up model for the Nordic system price. First, separate models for consumption, generation and marginal water value are developed. These models are explained by fundamental variables which are described as stochastic factors by using statistical models. Then, they combine these separate models in order to simulate market equilibrium and hence find the system price. A bottom-up price model is also proposed by Fuglerud et al. (2012), who additionally include a separate model of exchange. Haldrup and Nielsen (2006) suggest a Markov regime switching model which takes long memory in different regime states in the Nord Pool system price into account. They demonstrate that price behavior differs significantly between periods with and without transmission congestion.

Value-at-Risk (VaR) predictions for energy commodities have also been devoted much attention. Cabedo and Moya (2003) and Costello et al. (2008) use VaR for oil price risk quantification based on the historical simulation approach. Giot and Laurent (2003) investigate the performance of different parametric VaR models for both long and short trading positions for several energy markets. Aloui (2008) applies GARCH models in the VaR analysis of oil and gas prices. VaR for electricity prices are found in Chan and Gray (2006), in which extreme value theory is assessed. Bunn et al. (2016) also use a semi-parametric approach to VaR for electricity prices, namely the quantile regression framework. They demonstrate that the quantile regression model with exogenous factors performs better than more complicated CAViaR and GARCH formulations regarding 1-day-ahead out-of-sample forecasts.

3 Background

3.1 The Nordic Electricity Market: Nord Pool Spot

The deregulation policy of the Nordic countries in the 1990s led to the establishment of the power exchange Nord Pool Spot. Norway was the first country to open the grids for competition in 1991. In 1993, Nord Pool was founded, and it expanded to include Sweden in a joint electricity market in 1996. Finland and Denmark became members in 1998 and 2000, respectively, resulting in a fully integrated Nordic market. In later years, the Baltic States Estonia, Lithuania and Latvia have joined Nord Pool Spot. By allowing for exchange of electricity between countries, the governments aimed to create more economically efficient markets through free competition. With a total traded volume of 501 TWh in 2014, Nord Pool Spot is Europe's largest electricity wholesale market by volume traded (Nord Pool Spot). The Nordic market is connected to several European markets through submarine power cables or power grid lines.

Nord Pool Spot consists of a day-ahead market, Elspot, and an intra-day market, Elbas. Elspot is the main auction market where the majority of the electricity volume at Nord Pool is traded. The day-ahead market is in focus in this thesis. Here, each day is divided into 24 hourly trading periods. Buyers and suppliers submit bids and offers for every hour the following day. The volume of electricity a participant is willing to buy or sell at specific price levels is listed in the order. When the deadline for submitting orders at 12:00 CET is passed, Elspot calculates the hourly system prices for the next day, which are the market clearing prices.[1] Prices are then announced at 12:42 CET or later. At announcement, trades are also settled. Finally, electricity contracts are physically delivered from 00:00 CET the following day. System prices are theoretical prices in the sense that they are assumed to be identical across all regions in the Nordic market. In reality, bottlenecks in the transmission system may occur, resulting in different area prices. Nevertheless, system prices are important indicators as they are the Nordic reference prices for financial contracts. On the other hand, Elbas is the intra-day market whose main function is to maintain market balance between supply and demand. Market balance is particularly important for the power market since electricity is a flow commodity, which is produced and consumed continuously and instantaneously, rather than a stock commodity (Bunn et al., 2016, p. 6). The cost of supply failure is therefore high. Members can trade volumes up until one hour before delivery, and trading is continuous. As

[1] The system price is also commonly referred to as spot price or day-ahead price.

renewable energy sources such as wind power steadily increase their share of the total electricity production, Elbas becomes more crucial. This is due to the fact that these sources are dependent on weather conditions and, hence, very unpredictable.

3.2 Electricity Generation

Electricity generation technologies differ between the Nordic countries, partly due to various natural and weather conditions. Hydropower dominates the Norwegian supply, whereas hydropower, nuclear power and conventional thermal power are the main technologies in Sweden and Finland. In Denmark conventional thermal power dominates production, but with wind power as a growing generation source.

The production costs of a power plant depend mainly on fuels and technology. Figure 1 illustrates the *merit order curve* at Nord Pool, which describes the relationship between the marginal production costs and volume of electricity produced.[2] It is, hence, a cost-based description of the fundamental aggregated supply curve in the electricity market (Burger et al., 2014, p. 335). Plants running on renewable energy sources like wind and water enters to the very left of the curve. These have nearly zero marginal costs since the fuel used in production virtually comes for free. Nuclear power plants, with their low and stable marginal costs, enter next in line. In order to supply electricity to the lowest cost, hydro- and nuclear power plants run frequently and cover the base load in the Nordic market. These technologies also offer predictable and regulative production, but are somewhat inflexible due to long start-up time. They are, thus, suitable as base load generation.

Fossil fuel-based generation technologies enter at the right end of the curve. Thermal power plants have highest marginal costs because of the price of fuel. Moreover, policy commitments to environmental protection such as electricity certificates and CO_2 emission allowances add to the cost. However, conventional thermal plants exhibit high flexibility due to short start-up time. When demand increases, fossil-fueled plants in Sweden, Finland and Denmark, as well as import of electricity from other European countries in which fossil fuel-based production are the main technology in electricity generation, cover peak demand. The remarkable difference in marginal costs for the various generation units gives a steeply increasing and convex supply curve.

[2] Figure 1 and 2 are reproduced from www.nordpoolspot.com.

Consequently, use of peak load generation has large impact on the market price (Sensfuss et al., 2008, p. 3088).

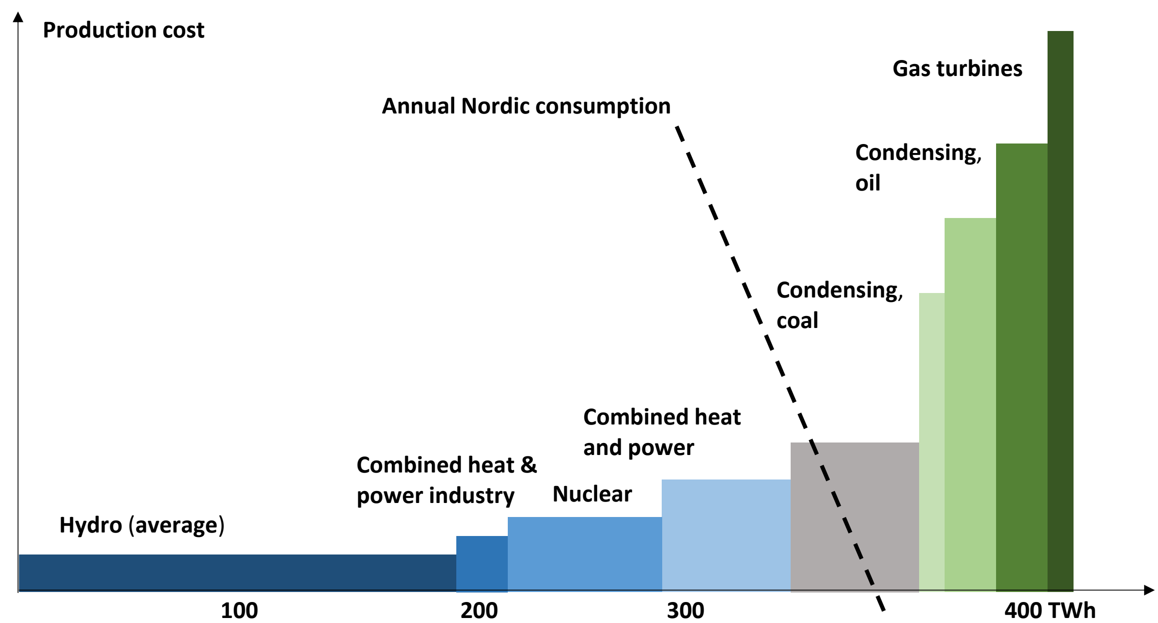

Figure 1: The figure illustrates the merit order curve in the Nordic market. The horizontal axis shows the supply in TWh, while the vertical axis shows the marginal production costs. Marginal costs vary with production technology.

3.3 Theory of Price Formation at Elspot

The day-ahead market is in economic theory close to a market of free competition. In order to win as many auctions as possible, the supplier of electricity sets his offers close to his short-term marginal production costs. Offers lower than short-term marginal costs will not be profitable as income does not cover short-run variable costs of production. On the other hand, offering above short-run marginal costs increases the probability of not winning the auction as the equilibrium price might settle between the supplier's offers and short-run marginal costs. Since the supplier gains from every market price above short-term marginal cost, he therefore prefers to place a bid equal or very close to short-run marginal costs. Hence, each supplier's short-run supply curve equals its short-run marginal cost curve above the average variable cost curve (Begg, 2011, p. 173).

At Elspot, buyers and suppliers submit bids and offers for electricity to buy or supply hour by hour the following day. When the deadline for submitting orders for delivery is passed, all the individual demand and supply curves are aggregated into a market demand and supply curve for each trading period of the next day. The hourly system prices are determined by the intersection of the hourly supply and demand curves, as shown in Figure 2. The hourly equilibrium price is the price that all members have to pay or receive. It represents both the short-run marginal cost of producing 1 MWh of electricity from the most expensive power plant needed to meet demand and the price that consumers are willing to pay for the last MWh demanded, that is, the lowest possible price that leads to market balance.

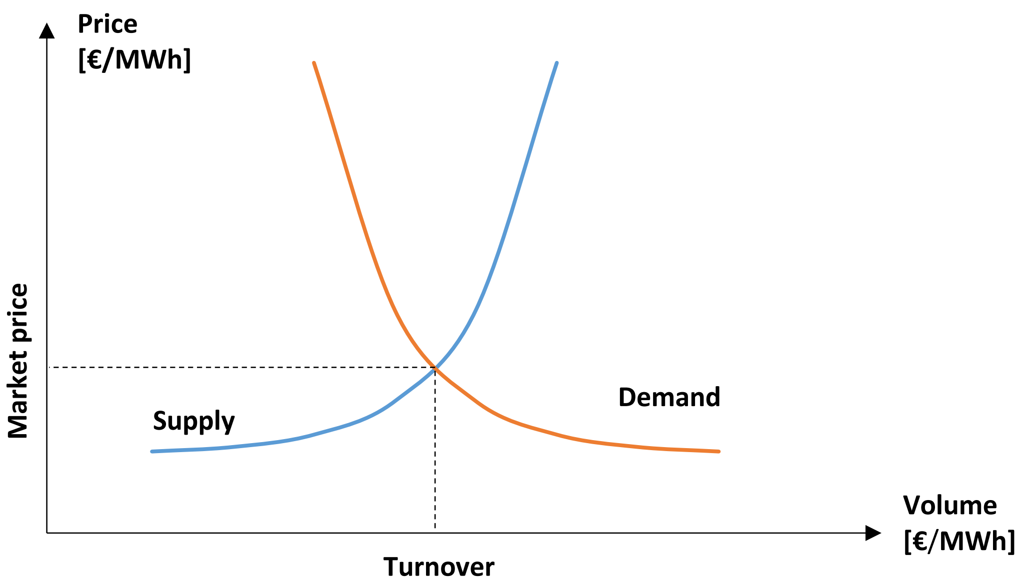

Figure 2: The figure shows the price formation at Nord Pool Spot. The system price for each hour is determined by the equilibrium in the electricity market, where the aggregated supply curve, i.e. the merit order curve, and the aggregated demand curve intersect.

4 Fundamental Factors

This section presents the fundamental factors included as explanatory variables in this study. A discussion of each explanatory variable's relevance for the electricity price is also given. The price formation and shape of the supply curve, studied in the previous section, imply that the impact of fundamentals are likely to be non-linear.

4.1 Adaptive Behavior: Yesterday's Price and Last Week's Price

Price from the same period the previous day, P_{t-1}, and price from the same period the previous week, P_{t-7}, incorporate historic price signals and influence agents' expectations of price when taking part in electricity auctions (Paraschiv et al., 2014, p. 204). Thus, they are likely important in explaining today's price. Yesterday's price and price last week contain different information about price movements. The former represents the price level in which the electricity price is within during a period, whereas the latter represents the variations in price across weekdays.

Bunn et al. (2016) argue that adaptive behavior consists of reinforcing previously successful offers. Hence, I expect that yesterday's price and price last week have a positive influence on today's price across quantiles. Further, I think the influence is weaker in the peak period compared to the off-peak period because offers are likely more complex in high activity periods.

4.2 Demand

Demand for electricity is very inelastic in the short run and vary with consumption patterns of final consumers like industry and households. Demand fluctuations occur on a daily basis; it increases in the early morning hours when business activities peak, it is still high in the evening hours as household consumption increases before it decreases when night approaches. Furthermore, demand depends on time of the year, as it is highly driven by temperature. Cold winter months increases the need for heating, while air conditioning is rare during summer. Also, whether it is weekday or weekend, and whether it is work day or holiday, affects demand due to differences in business activities (Burger et al., 2014, p. 304). Intersection between the demand and supply curve determines the hourly market-clearing price, hence demand is a primary effect on the price formation.

In reality, market members at Elspot have demand prognosis for the future in which they consider when submitting bids and offers. However, I do not have access to data for demand forecasts covering the complete sampling period. Therefore, I choose to use actual consumption data as the best approximation to demand prognosis. Karakatsani and Bunn (2008) state that demand forecasts are generally very accurate. On the basis of this, I believe actual consumption is an acceptable approximation to demand forecasts.

Daily demand is measured relative to the median value in order to capture effects related to demand differing from the normal. Additionally, it might soak up further information about the influence of demand not already expressed by the time dummy variables included.[3] The median is chosen as measure of central location instead of the mean because the distribution of demand is skewed in both period 04 and period 11, as shown in Figure B.1 and Table B.5 in Appendix B. In cases like this, the median is more informative than the mean (Hao and Naiman, 2007, p. 3).

I expect the system price to depend positively on demand because a positive shift in the inelastic demand curve requires more expensive generation plants to be switched on in order to meet demand, increasing the market-clearing price. The effect is likely stronger in period 11 when demand is initially high and base load plants are utilized to a higher degree. Moreover, I expect that prices will be more sensitive to demand at higher quantiles, since a positive shift in demand when prices are already high will increase prices non-linearly due to the steeply increasing and convex merit order curve. Contrary, prices are not sensitive to demand if shifts in demand remain within the flat, left region of the curve.

4.3 Water Reservoir Levels

Hydropower contributes to about 50% of the total power generation at Nord Pool (Huisman et al., 2014, p. 2). Electricity production is driven by water as fuel, which is stored in reservoirs until production is needed to meet demand. Higher levels imply increased production capacity. Consequently, reservoir levels can give information about the available hydropower supply. Reservoir levels depend on water inflow from precipitation and snowmelt. Thus, the available production capacity is normally highest in the summer months and lowest in the winter months.

[3] A presentation of time dummy variables is given in Section 4.9.

Production is relatively easy to regulate. Producers therefore plan electricity generation based on future prospects. Low reservoir levels and high electricity prices give them incentives to delay production, as the opportunity cost of producing now might be large if prices are even higher in the future. Situations in which water has high marginal value are for instance in cold winters and when prices of alternative fuels used in electricity generation, such as coal and gas, are high. On the other hand, high reservoir levels and the belief of lower prices in the future give producers incentives to produce now.

Daily water reservoir levels are measured relative to the median value in order to capture effects related to reservoir levels differing from the normal. Additionally, it might soak up further information about the influence of reservoir levels not already expressed by the time dummy variables included. Like demand, the median is chosen as measure of central location instead of the mean because the distribution of water reservoir levels are non-normal, as presented in Figure B.1 and Table B.5 in Appendix B. Hence, the median is more informative.

I expect the system price to depend negatively on reservoir levels across quantiles. Higher reservoir levels increase the production capacity of low marginal cost technologies, making the flat, left part of the merit order curve longer. Thus, increased reservoir levels and hence production capacity might substitute the use of more expensive generation plants in order to cover demand. Hydropower is the most important source for electricity generation in the Nordic market with half of the total production, and therefore I expect the negative effect to be large in magnitude.

4.4 Wind Power

Wind power contributed to 6% of the total power generation in the Nordic countries in 2013 and the production is increasing with approximately 4 TWh per year (Nordic Energy Regulators, 2014, p. 11). With low marginal costs, wind power is very cheap to produce once the plants are installed. However, wind power generation is unpredictable due to wind's nature. Recent studies prove that wind power does influence electricity prices, indicating it as an increasingly important power generating source. Looking back at the merit order curve, increasing wind power production extends the flat part of the curve on the left end. It thus requires a larger shift in demand in order to raise the electricity price.

I do not have access to data for wind power prognosis covering the complete sample period. Using the same reasoning as with demand, I choose to use actual wind power production as the best approximation to production prognosis.

Although wind power still has a small share of the total electricity generation at Nord Pool, I expect wind power to have a small negative effect on the system price due to its low marginal costs compared to other generation technologies. Moreover, I believe that the price in period 04 will be more sensitive to wind power since demand is low during night hours and additional supply from wind power will drive prices down.

4.5 Fossil Fuel Prices: Gas, Oil and Coal Prices

Due to favorable natural conditions, fossil fuels are not the dominating energy sources at the Nordic market. However, the region is dependent on import from among others Germany, Russia, Netherlands and Poland during peak load, countries in which fossil fuels are important in electricity generation. Usually, peak load occurs when temperatures drop below 0 C° during the winter (Nordic Energy Regulators, 2014, p. 13) or during technical problems in generation plants. For instance, about 40% of the electricity generation in Germany comes from coal-fueled plants, while in Russia about 50% of the electricity comes from gas-fueled plants (International Energy Agency). The Nordic market is strongly dependent on hydropower. Consequently, in dry years resulting in low reservoir levels, the market is vastly dependent on import. For this reason, I believe fossil fuel prices will be relevant in explaining Nord Pool's system price.

Fossil fuel prices are a part of the production cost of electricity. Conventional thermal power plants are in charge of the largest share of electricity generation in Europe (Burger et al., 2014, p. 307). Coal-fired plants are mainly used to cover base load, whereas gas-and oil-fired plants are switched on during periods of high demand due to their short ramp-up time. However, these plants have high marginal costs as fossil fuels are expensive compared to for instance water and wind. Therefore, I expect the system price to depend positively on fuel prices. Furthermore, I expect that the peak period 11 will be more sensitive to fuel prices than the off-peak period 04, as demand is low during night hours and there is available low marginal cost generation capacity. I also expect the sensitivity to increase with higher quantiles for both periods, as high prices reflect moving to peak load due to fully utilized base load plants, which increases the need to import. Hence, a conventional thermal plant is likely to set the electricity price by being the marginal technology.

4.6 CO_2 Emissions Allowance Price

An EU Allowance (EUA) unit gives the owner the right to emit 1 ton of CO_2. The system helps member states to reduce emissions according to the Kyoto Protocol. Since the EU Emissions Trading System (EU ETS), which is a cap-and-trade scheme, was launched in 2005, producers of electricity with fossils as fuel must buy EUAs to cover their total emissions. That is, the EU ETS prices CO_2 and imposes extra costs for polluting producers in order to give incentives to reduce emissions. The EUA price is included as a fundamental factor because it is closely connected to fossil fuel prices.

Coal-fired plants emit most CO_2, followed by gas- and oil-fired plants. Rickels et al. (2007) find, by studying the EUA price in 2005 to 2006, that gas and oil prices have a positive effect on the EUA price, while coal has a negative effect. They explain these results with the *switching effect*. High gas and oil prices make producers switch to coal as fuel in the power generation, leading to higher pollution as coal has highest CO_2 content, higher demand for EUAs and hence higher prices. On the other hand, high coal prices lead to switching to gas and oil, reduced emissions and reduced price on EUAs.

Due to the generally positive relationship between fossil fuel prices and the emissions allowance price, I expect that the system price depends positively on the CO_2 emissions price and that the effect increases with higher quantiles, owing to the fact that high prices imply increased electricity generation by fossil-fueled plants.

4.6.1 Dummy variable for the CO_2 emissions allowance price

Phase 1 of the EU ETS (2005 to 2007) was a pilot phase in which experienced severe price fluctuations. On 25 April 2006, as the first member states of the EU, the Netherlands, Czech Republic, France and Spain reported data of their 2005 CO_2 emissions of their installations, revealing an over-allocation of EUAs (Alberola et al., 2008, p. 790). These news led to a large price drop within few days. Prices stabilized around June 2006, but again dropped on October 2006 when the EU announced news for Phase 2 of the EU ETS, and stayed close to zero for the rest of

Phase 1. A closer examination can be found in Alberola and Chevallier (2009) and Rickels et al. (2007).

I include a dummy variable which equals 1 in the period of structural break in the EUA price from 27 April 2006 to 1 February 2008.[4] I believe the EU ETS is different from other markets due to the period of worthless EUAs and that the structural break must be controlled for. A dummy variable will remove the effect of the huge price drop of EUAs on the electricity price.

4.7 Electricity Certificate Price

Several studies have investigated the theoretical link between the electricity certificate market and the electricity market (e.g. Morthorst (2000) and Jensen and Skytte (2002)). Thus, there are reasons to believe that the price on el-certificates might have an effect on the system price.

The common arrangement of el-certificates for Norway and Sweden was initiated in January 2012 with the objective of integrating the growth of renewable energy technologies into a liberalized electricity market (Morthorst, 2000, p. 1086). The arrangement aims at reaching 26.4 TWh from generation using renewable energy sources in year 2020. To achieve this goal, producers who invest in any renewable power technology receive el-certificates in which they can resell. On the other hand, suppliers of electricity are obliged to buy el-certificates on behalf of the consumers, who pay the additional cost through increased electricity prices. Thus, end-users contribute in financing the growth of renewable energy sources by committing themselves to buy some of the electricity generated from renewable energy plants. The price on el-certificates is determined by supply and demand. In theoretical terms, this price equals the difference between the cost of renewable-based electricity generation and the cost of conventional thermal electricity generation (Jensen and Skytte, 2002, p. 427).

Producers of electricity generated from renewable energy technologies have a two-fold income. They receive income from the sale of electricity to the spot market as well as from the sale of

[3] The EUA price started to decline on 26 April 2006. However, in the data material used in the analysis, this price is lagged with one day in order to ensure exogenous market information for the electricity price formation. This will be further explained in Section 5.1. Therefore, the dummy variable equals 1 in the period 27 April 2006 to 1 February 2008. A closer examination of the theoretical framework concerning the structural break is given in Section 5.4.

electricity certificates to the market of certificates. In this respect, the el-certificates contribute in making renewable energy production desirable by giving producers an additional payment. It will be worthwhile to operate if the marginal income exceeds the short-run marginal cost of production. I expect a negative relationship between the el-certificate price and the electricity price because an increase in the el-certificate price means that a lower electricity price is required in order to ensure that the total income cover marginal costs of renewable production.

4.8 Price Volatility

The system price fluctuates over time, reflecting volatility in the price series. Instability is likely caused by the steeply increasing and convex supply curve, making shifts in demand cause large variations in price. Variations in demand are induced by unpredictable weather conditions, among others. Thus, demand volatility partly causes price volatility (Bunn et al., 2016, p. 7). Volatility is measured by the standard deviation and is related to the total risk in prices, which might influence agents' risk aversion. In an attempt to soak up price uncertainty which is not already encapsulated in the fundamental factors, I include a historical volatility term.

I expect that the electricity price in period 04 depends negatively on volatility since the off-peak period has low demand and relatively low price. On the other hand, I expect the electricity price in period 11 to depend positively on volatility since the peak period has high demand and relatively high prices. The influence in absolute value is expected to increase with extreme quantiles, that is with low quantiles in period 04 and with high quantiles in period 11.

4.9 Time Dummy Variables

Figure A.2 and A.3 in Appendix A shows the historical price variations across weekdays and months, revealing seasonal patterns in electricity prices. This is due to fluctuations in both demand and supply. Prices follow the same path across months for period 04 and period 11.

When it comes to demand, variations across months reflect the high need for heating during the winter, making prices generally higher in these months compared to summer months. The weekend effect with lower consumption on Saturdays and Sundays is also noticeable in Figure A.2, especially for period 11. This is because most workplaces are closed and, hence, do not consume electricity. For period 04, Sundays and Mondays have lower prices than other days, while Saturdays have not. A reasonable explanation might be that people stay up longer on Saturdays, increasing consumption in the night hours compared to Sundays and Mondays, which mark the start of a new working week.

Seasonality in supply is caused by the availability of fuels used in electricity generation. The Nordic market, which is heavily reliant on hydropower, experiences fluctuations in the availability of hydropower production, as hydro reservoir levels depends on precipitation and snowmelt. Since price is determined by the marginal technology used in production in order to meet demand, variations in supply naturally affects the electricity price.

By including time dummy variables, the model controls for seasonality in the electricity price (Wooldridge, 2009, p. 368).

4.9.1 Weekend dummy variable

I include a weekend dummy to control for variations in electricity price within the week. The dummy equals 1 if the day is Saturday or Sunday. The remaining days work as the base period.

4.9.2 Month dummy variables

I include dummies for February to December, which is 11 dummies in total. January works as the base period. Including month dummies makes the model able soak up some of the effect the different months have on the electricity price by being in that particular month.

5 Data

5.1 Data Material

I use data from 2 January 2006 to 31 December 2014, which is a large time series data set suited for empirical analysis. My focus will be on period 04, representing the off-peak hour 03:00-04:00, and period 11, representing the peak hour 10:00-11:00. These periods are chosen because they have the lowest and highest average demand in the data set, respectively, as shown in Figure C.1 in Appendix C. By deriving separate models for period 04 and period 11, the estimation results will give insight in how the fundamental factors influence the system price in different trading periods during a day.

Data are either in an hourly, daily or weekly frequency. Hourly data are applied to the estimation of the model of the corresponding trading hour, while daily and weekly data are applied to the estimation of both models. For missing observations, I have used linear interpolation to make the data set complete.[5] Table 1 gives an overview of data granularity and source in which data are accessed. It is chosen to use a natural logarithmic transformation on the dependent variable and all independent variables because log-transformation has variance-stabilizing properties. Also, all coefficients can be interpreted as elasticities.

In the following, I will present the dependent variable and the fundamental factors used in the analysis. Development of the data series of explanatory variables is shown in Figure 3 to Figure 5. Descriptive statistics are given in Table B.1 in Appendix B.

Elspot system price: I use hourly system prices for period 04 and period 11 from the day-ahead market Elspot as the dependent variable. Prices are quoted in €/MWh.

Yesterday's price: I use hourly system prices for period 04 and period 11 from the day-ahead market lagged by one day.

Last week's price: I use hourly system prices for period 04 and period 11 from the day-ahead market lagged by seven days.

[5] This mostly concerns fuel prices and the EUA price, in which prices on Saturdays and Sundays are not quoted due to closed exchanges.

Table 1: Overview of data granularity and data source of fundamental variables.

Variable	Daily	Hourly	Weekly	Data source
Elspot system price		X		Nord Pool
Demand		X		Montel
Water reservoir level			X	Norwegian Water Resources and Energy Directorate
Wind power		X		Energinet.dk
Gas price	X			Macrobond
Oil price	X			Macrobond
Coal price	X			Macrobond
EUA price	X			Datastream and Macrobond
El-certificate price	X			Macrobond

Demand: I use hourly aggregate consumption in Norway, Sweden, Denmark and Finland for period 04 and period 11, quoted in MWh. Observations are measured relative to the median value in order to capture further information about the influence of demand not already expressed by the time dummy variables.

Water reservoir level: I use weekly reservoir levels in Norway quoted in GWh. Weekly observations are announced every Wednesday. For the sake of obtaining daily observations, for every two Wednesdays, six observations in between (Thursday to Tuesday) are obtained with use of linear interpolation. A similar approach to transforming weekly data into daily data can be found in Huisman et al. (2014). Observations are measured relative to the median value in order to capture further information about the influence of water reservoir level not already expressed by the time dummy variables.

Wind power: I use hourly wind power production in Denmark for period 04 and period 11. Production is quoted in MWh.

Gas price: I use the daily UK Natural Gas Index quoted in GBP/therm. I have converted prices into €/BTU.

Oil price: I use the daily ICE Brent Crude oil spot price quoted in $/barrel. I have converted prices into €/barrel.

Coal price: I use the daily NYMEX coal forward price. Prices are quoted as $/metric ton. I have converted prices into €/metric ton.

CO_2 emissions allowance price: I use the daily ICE EU Allowance forward price quoted in €/metric ton.

Electricity certificate price: I use the daily Swedish electricity certificate volume-weighted average price quoted in SEK/certificate. I have converted prices into €/certificate.

Volatility: I use the standard deviation of the system price, calculated in a 7 days moving window for the same trading period 04 and 11, respectively. Volatility is quoted in €/MWh. Price volatility is defined in a similar way by Karakatsani and Bunn (2008) and Paraschiv et al. (2014).

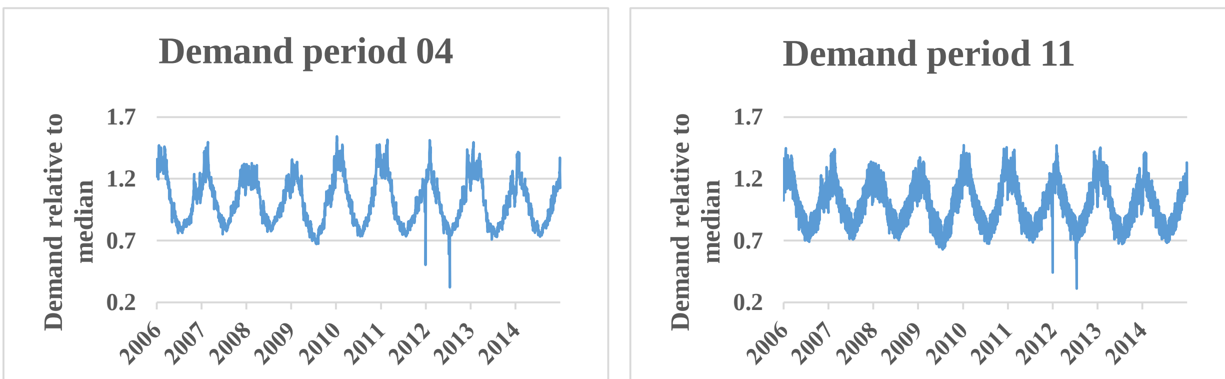

Figure 3: The figure shows the demand series for period 04 and period 11, measured relative to the median. Data spans from 2 January 2006 to 31 December 2014.

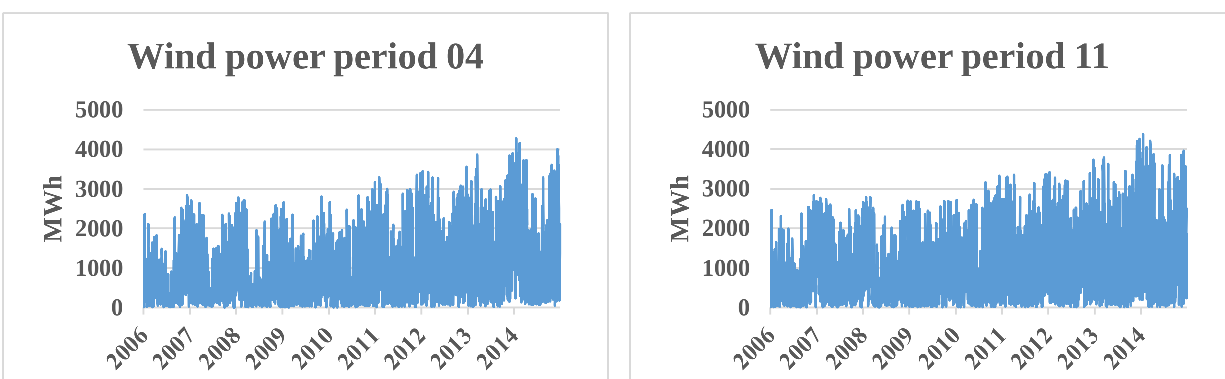

Figure 4: The figure shows the wind power series for period 04 and 11. Data spans from 2 January 2006 to 31 December 2014.

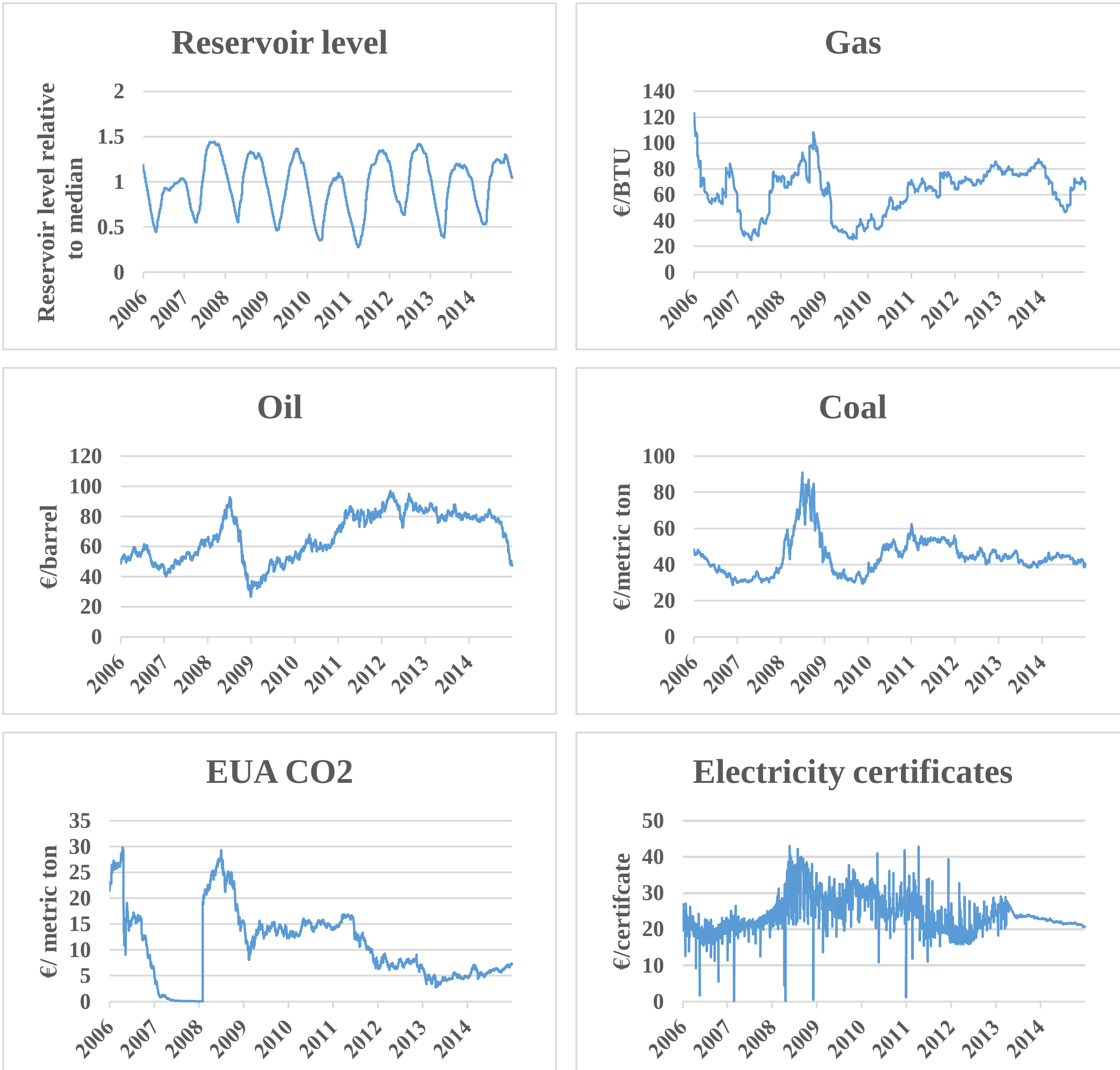

Figure 5: The figure shows the water reservoir level series measured relative to the median, gas price series, oil price series, coal price series, EUA price series and el-certificate price series. Data spans from 2 January 2006 to 31 December 2014.

In order to ensure that information which is relevant for the electricity price formation regarding the fundamentals is known to the market before the power exchange closes for the trading period of interest, fuel prices, CO_2 emissions allowance price, el-certificate price and reservoir level data are lagged by one day. Actual consumption and wind power are used as approximations for demand forecast and wind power forecast made the previous day, respectively, and is therefore not lagged. This secures exogenous explanatory variables.

5.2 Descriptive Statistics of Electricity Prices

Figure 6 shows the non-linear characteristics of peaks, seasonality, mean reversion and volatility of the Nord Pool electricity price in period 04 and period 11. In this section, I will present descriptive statistics and tests supporting the visual evidence of electricity price features.

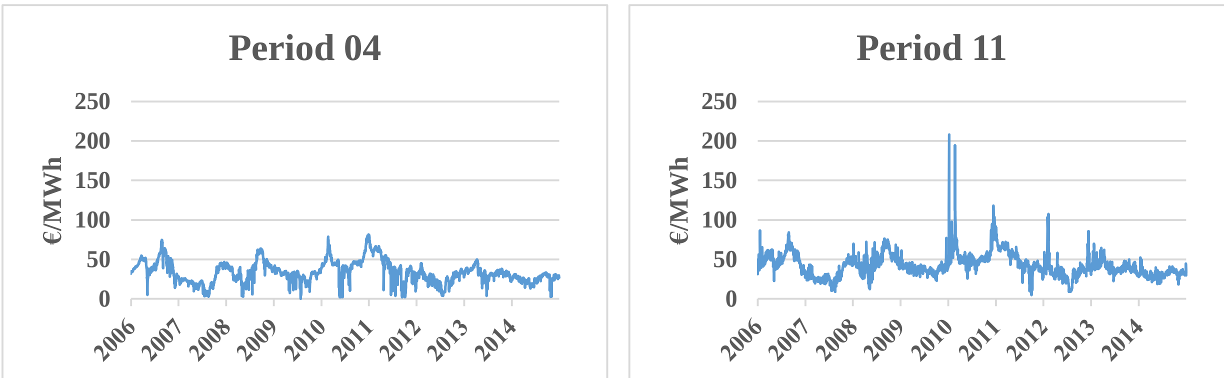

Figure 6: The figure shows the price level series of period 04 and 11, and gives visual evidence of electricity price features. Data spans from 2 January 2006 to 31 December 2014.

Descriptive statistics of electricity prices are presented in Table 2. The statistics reveals high standard deviation, which confirm volatility in prices. Positive skewness and excess kurtosis, especially for the peak period, show that extreme prices often occur. Figure A.1 in Appendix A compares the distribution of prices to a normal distribution, showing these results graphically. Rejection of normality is verified by the Jarque-Bera test presented in Table A.2 in Appendix A.

Table 2: The table shows the mean, median, minimum observation, maximum observation, standard deviation, skewness and kurtosis of the electricity price level series for period 04 and 11.

Variable	Mean	Median	Min	Max	Std dev	Skewness	Kurtosis
P04	33.834	32.505	0.490	81.630	13.695	0.463	3.478
P11	42.693	40.295	5.140	208.160	14.702	1.563	12.604

Table A.1 in Appendix A lists the descriptive statistics for the ln-series. For period 04, log-transformation decreases the standard deviations considerably. However, the skewness becomes negative and the kurtosis increases. For period 11, both standard deviation and kurtosis decreases, while the skewness becomes slightly negative.

5.2.1 Autocorrelation

The autocorrelation function and partial autocorrelation function together with the Ljung-Box test for the 1.difference of price series are presented in Table A.5 to A.6 in Appendix A. They show clear signs of correlation of the electricity price with its own past values, supporting the existence of adaptive behavior among agents. For period 04, the effect of lag 1 is noticeable. For period 11, effects of lag 7 and 14 are noticeable. However, lag 7 and 14 are relatively highly correlated, as shown in Table A.7 to A.8 in Appendix A, revealing that they explain the same effect in prices. On the contrary, lag 1 and 7 are correlated to a much smaller degree, which indicate that they contain different information about the electricity price. Therefore, in order to account for autoregressive effects in the model, lag 1 and 7 are included as explanatory variables.

Note that the autocorrelation is high for all lags in the price level series, presented in Table A.3 to A.4 in Appendix A, due to the fact that hourly prices usually lie within a certain interval over a short time period, causing persistence in prices. Thus, it would be natural to base decisions of lags on the 1.difference series instead.

5.2.2 Stationarity

The Augmented Dickey-Fuller test for stationarity, listed in Table A.9 in Appendix A, rejects the presence of unit roots in the electricity price for both period 04 and period 11. The augmented version of the test is applied to ensure that the error term is white noise, as the test is valid only in this case. Moreover, in order to intercept the dependence on previous prices, 7 lags of prices are included because, according to the discussion in Section 4.1.1, lag 1 and 7 have big influence on today's price. Rejection confirms that the price series are weakly stationary, meaning that the series in both periods are mean reverting. Shocks in prices will, hence, gradually die away.

5.2.3 Empirical quantiles

Table 3: The table shows the empirical 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% and 99% quantiles of the price level series for period 04 and 11.

Variable	1%	5%	10%	25%	50%	75%	90%	95%	99%
P04	3.98	12.75	17.9	25.03	32.505	41.74	51.3	60.71	72.52
P11	12.45	23.64	26.92	33.18	40.295	50.8	61.17	67.89	86.37

The empirical quantiles at the 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% and 99% level for the price series presented in Table 3 confirm large price variations across quantiles. This evidence supports quantile regression as a suitable method for modeling the electricity price. Empirical quantiles for the ln-series are listed in Table A.10 in Appendix A.

5.2.4 Correlation

Table B.2 in Appendix B shows the correlation between the electricity price in period 04 and 11 and their respective fundamental factors. Signs of the pairwise correlations give an indication of the co-movement of the electricity price with fundamentals. Generally, correlations support the expected effects of the fundamentals discussed in Section 4. Demand, gas price, coal price, EUA price and el-certificate price have positive correlation with the electricity price. Wind, reservoir level and oil price have negative correlation with the electricity price. Negative and low correlation with oil might imply that oil is of little importance of the price formation in most quantiles. Volatility has a negative relationship with price in period 04 and a positive relationship with price in period 11.

5.3 Multicollinearity

Multicollinearity is the problem of highly correlated explanatory variables in a model. It could create bias in the result estimates, leading to high standard deviations and insignificant explanatory variables. There is no size of the correlation coefficient that can be cited to conclude that multicollinearity is a problem (Wooldridge, 2009, p. 97). However, as can be seen in Table B.3 to B.4 in Appendix B, all pairwise correlations are below 0.6. Thus, multicollinearity is most likely not a problem in the data set. For correlation between lagged prices, see the discussion in Section 5.2.1.

There are, nonetheless, some pairwise correlations worth mentioning. Fuel prices have pairwise correlation between 0.442 and 0.551. Fossil fuels are substitutes in the electricity generation, as stated in Section 4.6, causing these positive relationships. Moreover, the correlation between the coal price and the EUA price is 0.575, reflecting the high CO_2 density in coal compared to gas and oil.

5.4 More About the CO_2 Emissions Allowance Price

As mentioned previously, a structural break in the EUA prices is taken consideration of by including a dummy variable. This method is used by e.g. Alberola et al. (2008) and Hervé-Mignucci et al. (2011). In the following, I will explain the choice of break dates and the tests done to verify the presence of a break in the data series.[6] For further details, see Appendix D.

5.4.1 Chow test for structural change across time

The purpose of the Chow test is to detect whether there is a structural break in the EUA price series. The dummy variables approach is applied to calculate the test (see e.g. Brooks (2008)). First, a test for a break at 26 April 2006 is performed. Secondly, a test for another break at 1 February 2008 to indicate the end of the structural change is performed. Two different OLS regressions of the ln-series of the EUA price on fuel prices are run. These regressions give grounds to performing the tests. Fossil fuel prices are used as explanatory variables because the EUA price is connected to these by the fact that the demand for EUAs increases with the combustion of fuels. Rejection of the joint restriction under the null hypothesis in both tests lead to the conclusion of the presence of a structural break in the period 26 April 2006 to 31 January 2008.

The Chow test is only valid under homoscedasticity. However, White's test for heteroscedasticity shows that the OLS regressions have heteroscedastic residuals. Fortunately, log-transformation of the variables make heteroscedasticity less severe (Brooks, 2008, p. 138). I use OLS regressions as a benchmark for the Chow test, but I acknowledge the inconvenience of the residual properties.

5.4.2 Choice of date in which the structural break occurs

The Chow test requires that the date of the structural change is known. Following Brooks (2008), choice of these dates are made according to known important historical events. On 25 April 2006, the first 2005 CO_2 emissions data was disclosed. Prices started to decline the following day. Hence, I use 26 April 2006 as the beginning of the structural break. 1 January 2008 marks the start of Phase 2 of the EU ETS. I was, however, not able to access Phase 2 prices for January 2008. Therefore, prices for January 2008 are still close to zero as an extension of the prices in 2007. I am aware of this weakness in my data set. Nevertheless, I choose to still use this data as it is the best I have access to. As a consequence, 1 February 2008 is chosen to mark the end of the structural break.

[6] Tests are performed on the non-lagged EUA price series.

5.5 Omitted Variables

In this section, I will comment on variables in which I considered to include in the model, but yet have been omitted for different reasons.

5.5.1 Nuclear power

Nuclear power is an important electricity generation technology to cover base load in Sweden and Finland. Nuclear plants generally run with constant output and have low marginal costs, but operation and maintenance costs are high. Furthermore, fuel prices, for instance the price of uranium, are stable and make up only a small share of the production costs.

Due to low and stable marginal costs, fluctuations in the electricity price are most likely not linked to the variable costs of nuclear power plants. On the other hand, planned and forced outages of plants reduce the available generation possibilities and will in that respect have a considerable influence on the system price. The available production capacity of nuclear power plants in Sweden and Finland could, hence, add to the list of variables in the model. However, data proved to be difficult to access. Therefore, nuclear power is omitted from the model.

5.5.2 Temperature

Demand is to a high degree driven by temperature, but the connection between temperature and electricity price is not as obvious. The intention was to study if there are other properties with temperature, except its impact on demand, that influence the electricity price. I used a weighted average daily temperature in Oslo, Haugesund, Trondheim, Tromsø and Bergen, each city representing one Elspot area NO1 to NO5 in Norway, respectively.[7] Data was accessed through eKlima.net.[8] Weights were calculated by considering the total consumption in each area relatively to total consumption in the whole country, using data for total consumption in 2013 and 2014.

The correlation between demand and temperature turns out to be -0.936 for period 04 and -0.868 for period 11. A high negative correlation means that high temperatures decrease demand and vice versa. Due to very high co-movement for both period 04 and period 11, it is reasonable to expect that most of the impact of temperature on the electricity price already is taken consideration of by

[7] The day-ahead market is divided into several bidding areas.

[8] eKlima.net is the Norwegian Meteorological Office's database.

including demand as a fundamental factor. Including temperature would therefore cause severe problems related to multicollinearity, as discussed in Section 5.3.

5.5.3 Hours of daylight

Hours of daylight incorporates the same fluctuations every year. In this respect, the variable could have been included to control for seasonality instead of the month dummies.[9] Moreover, daylight is able to soak up seasonality more smoothly because it avoids sharp breaks in every turn of the months. Hours of daylight were calculated by means of the formulas proposed in Kamstra et al. (2003), using the latitude of Oslo as basis.

The coefficient is, however, insignificant in most quantiles. This might be due to the high correlation between demand and hours of daylight (-0.762 for period 04 and -0.751 for period 11), again causing problems related to multicollinearity. Demand is affected by daylight because more hours of daylight requires less need for electrical lighting, among others. Month dummy variables are, thus, preferred.

5.5.4 Precipitation

Precipitation contributes to hydro inflow in water reservoirs. Nevertheless, when temperature is below the freezing point, precipitation does not fill up reservoirs within a short time, but will increase the snow-pack instead. This precipitation will add to the water reservoir levels when it eventually melts. Thus, it give indications about future inflow.

The aim was to study the influence of precipitation on the electricity price beyond its connection to hydropower production. I used a weighted average daily precipitation value for Oslo, Haugesund, Trondheim, Tromsø and Bergen in the same way as with temperature data. Data was accessed through eKlima.net and quoted in millimeters/day. The observations turned out to be unreliable since there were many missing values and few days without any precipitation. Additionally, the correlation with hydro reservoir levels was surprisingly low (0.1898), increasing my suspicion regarding unreliable data. Therefore, I decided to exclude precipitation as a fundamental factor.

[9] I would like to thank Peter Molnar at the Department of Industrial Economics and Technology Management, NTNU, for helpful comments.

6 Models

6.1 Quantile Regression

Quantile regression estimates a set of coefficients corresponding to different quantiles of a dependent variable's conditional distribution. It was first introduced by Koenker and Bassett Jr. (1978) and later described by Hao and Naiman (2007), among others. The method models each quantile separately with a linear regression line, allowing for study of any predetermined position of the distribution. Hence, it is able to give a more complete understanding of the sensitivity of electricity price towards fundamental factors.

Let $q \in (0,1)$ be the 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% or 99% quantile. The linear quantile regression can be formulated as

$$Q^q(\ln P_{i,t} \,|\, \mathbf{X}_{i,t}) = \alpha_i^q + \mathbf{X}_{i,t}\boldsymbol{\beta}_i^q + \varepsilon_{i,t}^q \qquad (1)$$

where Q^q is the conditional q-quantile function of $\ln P_{i,t}$, $\mathbf{X}_{i,t}$ is a 24-dimensional vector of explanatory variables (including dummy variables), α_i^q is a constant at quantile q, $\boldsymbol{\beta}_i^q$ is a vector of coefficients at quantile q, $\varepsilon_{i,t}^q$ is the error term at quantile q and i=4,11 is the period of interest. The value Q^q equals the inverse of the conditional cumulative distribution function F of $\ln P_{i,t}$ at quantile q:

$$Q^q = F^{-1}(q \,|\, \mathbf{X}_{i,t}) . \qquad (2)$$

α_i^q and $\boldsymbol{\beta}_i^q$ is found by solving the minimization problem

$$\min_{\alpha,\boldsymbol{\beta}} \sum_{t=1}^{T} (q - 1_{\ln P_{i,t} \le \alpha_i^q + \mathbf{X}_{i,t}\boldsymbol{\beta}_i^q})(\ln P_{i,t} - (\alpha_i^q + \mathbf{X}_{i,t}\boldsymbol{\beta}_i^q)) \qquad (3)$$

where

$$1_{\ln P_{i,t} \le \alpha_i^q + \mathbf{X}_{i,t}\boldsymbol{\beta}_i^q} = \begin{cases} 1\, if\ \ln P_{i,t} \le \alpha_i^q + \mathbf{X}_{i,t}\boldsymbol{\beta}_i^q \\ 0\ otherwise. \end{cases} \tag{4}$$

Hence, the quantile loss function expresses the loss related to a residual as

$$q - 1_{\ln P_{i,t} \le \alpha_i^q + \mathbf{X}_{i,t}\boldsymbol{\beta}_i^q} \ . \tag{5}$$

Since the indicator function in Equation (4) equals 1 when the residual is negative and equals 0 when the residual is positive, the problem seeks to find coefficients that minimize the weighted sum of absolute residuals, where negative residuals have the weight |*q*-1| and positive residuals have the weight *q*. That is, we minimize the weighted absolute distances from all observed values to its fitted values (Hao and Naiman, 2007, p. 34).

The solution to the minimization problem, $(\hat{\alpha}_i^q, \hat{\boldsymbol{\beta}}_i^q)$, satisfies the sample estimate of the conditional quantile:

$$\hat{Q}^q(\ln P_{i,t} \,|\, \mathbf{X}_{i,t}) = \hat{\alpha}_i^q + \mathbf{X}_{i,t}\hat{\boldsymbol{\beta}}_i^q + \hat{\varepsilon}_{i,t}^q \,. \tag{6}$$

When *q* is small the majority of the observations lie above the regression line, while when *q* is large the majority of the observations lie below the regression line. The estimation of coefficients corresponding to each quantile is hence based on the weighted data of the whole sample (Hao and Naiman, 2007, p. 37). Simple formulas for finding $(\hat{\alpha}_i^q, \hat{\boldsymbol{\beta}}_i^q)$ do not exist. However, Stata, the software package in which I use, is able to solve the optimization problem presented in Equation (3) to (4) with an algorithm.

Quantile-based measure of location instead of the mean, as in the method of Ordinary Least Squares (OLS), gives the opportunity to examine not only the center of the distribution, but all parts including the lower and upper tails, as the regression lines pass through chosen quantiles of the data plot. Quantile regression can, thus, model any position of the price distribution. This opens up for investigation of the influence of fundamental factors on the dependent variable and how the sensitivity towards these factors changes across price levels. With a semi-parametric formulation, quantile regression is also less restrictive than OLS. The coefficients can change across quantiles, permitting non-linear sensitivity towards explanatory variables. It does neither have any distributional assumptions like normality in the response variable nor in the residuals. This is convenient in the study of electricity prices, which has a skewed distribution and excess kurtosis.

6.1.1 Goodness of Fit: Koenker and Machado R-squared

A goodness of fit measure for quantile regression models proposed by Koenker and Machado (1999) concerns to compare the sum of weighted distances in the unrestricted model of interest with the sum of weighted distances in a restricted model containing only a constant term. The measure is formulated as

$$R(q) = 1 - \frac{V^{U}(q)}{V^{R}(q)} \tag{7}$$

where $V^{U}(q) \geq 0$ is the sum of weighted distances for the unrestricted *q*-quantile regression model and $V^{R}(q) \geq 0$ is the sum of weighted distances for the restricted *q*-quantile regression model, respectively. Furthermore, $V^{R}(q) > V^{U}(q)$ because the unrestricted model with explanatory variables is always better fitted than the restricted model. $R(q)$ is greater the better fit the model of interest is, i.e. the lower the last term in (7). Hence, $R(q) \in [0,1]$ where $R(q) = 1$ denotes a perfectly fitted model with minimized sum of weighted distances.

From now on, the Koenker and Machado goodness of fit measure presented above is referred to as R-squared.

6.1.2 Standard error calculation: The Bootstrap approach

Bootstrapping, introduced by Efron (1979), is a non-parametric method for inference. It involves repetitive computations to estimate the shape of the sampling distribution. Bootstrapping does not make any assumptions about the distribution of neither the response variable nor the error term (Hao and Naiman, 2007, p. 47). This approach is therefore preferable over the asymptotic approach, which is dependent on strong parametric assumptions like independent and identically distributed error terms.

6.1.3 Estimation

Estimation is performed with use of the software package Stata. Quantiles in focus are the 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% and 99% quantile. Period 04 and period 11 are examined, which give 18 models in total. The corresponding standard errors are calculated according to the bootstrap procedure with 50 replications, which is considered as a sufficient number of computations (Hao and Naiman, 2007, p. 48). Koenker and Machado (1999) R-squared is also obtained for each model.

7 Results

In this section, I will present and discuss the quantile regression results. Quantile regression coefficients and the associated R-squared are listed in Table 4 for period 04 and Table 5 for period 11. Bold coefficients are significant at either 1%, 5% or 10% level. For a thorough presentation of results and significance level, see Appendix E. The R-squared is in the range of 0.602 to 0.732 for period 04 and 0.664 to 0.746 for period 11, respectively. Regarding a relatively parsimonious model formulation, the goodness of fit is quite good.

Table 4: The table presents quantile regression coefficients and R-squared for period 04. Bold coefficients are significant at either 1%, 5% or 10% level.

	1%	5%	10%	25%	50%	75%	90%	95%	99%
Yesterd.price	**1.004**	**1.004**	**1.005**	**0.922**	**0.848**	**0.703**	**0.611**	**0.511**	**0.362**
Last w. price	**0.247**	0.142	0.079	**0.068**	**0.085**	**0.130**	**0.108**	**0.108**	**0.089**
Demand	**0.488**	**0.243**	**0.204**	**0.217**	**0.178**	**0.236**	**0.291**	**0.264**	**0.345**
Reservoir	0.101	0.081	0.041	**-0.036**	**-0.051**	**-0.113**	**-0.175**	**-0.256**	**-0.401**
Wind	**-0.015**	**-0.016**	**-0.015**	**-0.015**	**-0.014**	**-0.013**	**-0.011**	**-0.010**	-0.009
Gas	-0.116	-0.037	**-0.027**	-0.002	0.003	0.010	0.007	0.000	-0.024
Oil	**0.355**	0.032	**0.039**	**0.015**	0.010	-0.006	-0.027	**-0.071**	**-0.183**
Coal	-0.220	-0.055	-0.025	-0.001	0.011	**0.066**	**0.127**	**0.215**	**0.395**
EUA	0.005	-0.003	-0.001	0.002	0.002	**0.005**	**0.009**	**0.007**	0.000
Elcertificate	-0.038	-0.005	-0.007	0.007	0.005	**0.012**	**0.015**	0.018	0.025
Volatility	**-0.171**	**-0.091**	**-0.063**	**-0.024**	**0.005**	**0.025**	**0.043**	**0.053**	**0.062**
R^2	0.657	0.711	0.720	0.731	0.732	0.716	0.682	0.642	0.602

Table 5: The table presents quantile regression coefficients and R-squared for period 11. Bold coefficients are significant at either 1%, 5% or 10% level.

	1%	5%	10%	25%	50%	75%	90%	95%	99%
Yesterd.price	**0.768**	**0.756**	**0.702**	**0.685**	**0.589**	**0.512**	**0.462**	**0.435**	**0.435**
Last w. price	**0.290**	**0.270**	**0.292**	**0.272**	**0.334**	**0.338**	**0.308**	**0.261**	**0.313**
Demand	**0.491**	**0.302**	**0.290**	**0.284**	**0.314**	**0.418**	**0.479**	**0.488**	**0.691**
Reservoir	-0.027	-0.032	**-0.061**	**-0.050**	**-0.050**	**-0.081**	**-0.108**	**-0.103**	-0.081
Wind	-0.008	**-0.014**	**-0.014**	**-0.013**	**-0.015**	**-0.018**	**-0.018**	**-0.017**	**-0.024**
Gas	0.060	0.007	-0.004	0.003	-0.003	0.007	-0.005	**-0.042**	**-0.141**
Oil	**-0.085**	-0.016	-0.001	0.008	**0.019**	**0.021**	**0.035**	**0.076**	**0.180**
Coal	-0.130	-0.002	0.011	0.017	**0.030**	**0.032**	**0.078**	**0.115**	0.032
EUA	0.000	0.003	0.003	**0.003**	**0.003**	**0.007**	**0.010**	**0.015**	**0.024**
Elcertificate	0.023	0.025	0.016	0.013	-0.004	**0.009**	**0.017**	**0.022**	**0.045**
Volatility	**-0.132**	**-0.092**	**-0.064**	**-0.036**	**-0.008**	**0.018**	**0.057**	**0.083**	**0.134**
R^2	0.746	0.740	0.740	0.740	0.737	0.717	0.687	0.669	0.664

For period 04, the R-squared related to extreme quantiles, i.e. the 1%, 95% and 99% quantiles, are the lowest. For period 11, the lowest R-squared is the one associated with the 99% quantile. Generally, extreme quantile coefficients are estimated with the majority of the observations lying above the regression line (for low quantiles) or below the regression line (for high quantiles). If a change in one observation do not change the sign of the residual, the change will not alter the fitted regression line (Hao and Naiman, 2007, p. 41). However, the probability of a sign switch increases the fewer observations there are either above or below the line. Thus, extreme quantiles are more sensitive to outliers and hence is less robust than middle quantiles. Moreover, extreme price peaks are often caused by severe random shocks. Such events might be plant outages, transmission failures or extreme weather conditions. Shocks to the electricity price are beyond what fundamental factors are able to explain, which justify the generally lower R-squared in extreme quantiles. Extremely high prices might also indicate that producers are practicing some market power by offering prices higher than short-run marginal costs or by holding back available generation capacity in order to increase revenues. However, there is no empirical evidence of systematic exploitation of market power at Nord Pool (Fridolfsson and Tangerås, 2009).

7.1 Adaptive Behavior: Yesterday's Price and Price Last Week

7.1.1 Yesterday's price

Yesterday's price represents the price range in which the electricity price is within during a period. Figure 7 shows the development of yesterday's price's coefficient across quantiles. The elasticity of lagged price is positive and significant at 1% level for all quantiles in both periods, in accordance with expectations. The coefficient is below 1, except for the 1%, 5% and 10% quantile in the off-peak period which have a coefficient slightly above 1. Thus, the electricity price generally seems to be mean reverting. The system price tends to turn back to yesterday's level for the same hour, which is in line with the discussion in Karakatsani and Bunn (2008) and Bunn et al. (2016). Results are consistent with the autocorrelation and partial autocorrelation functions presented in Table A.3 to A.6 in Appendix A, showing positive correlation for price levels and negative correlation for returns.

Figure 7: The graphs show the development of the yesterday's price coefficient for the 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% and 99% quantile in period 04 and period 11.

Two factors indicate that agent learning is more important in times with low prices, which means that high price is caused mainly by other factors than adaptive behavior. Firstly, the influence of yesterday's price is generally higher for the off-peak period than the peak period, indicating that agent learning is stronger in periods with lower load levels. Secondly, decreasing elasticities with higher quantiles imply that a price change yesterday has larger influence on today's price if the price is initially low. Overall, however, the learning effect based on yesterday's price is large.

7.1.2 Last week's price

The elasticity of last week's price is positive and significant at 1% or 5% level across all quantiles except for the 5% and 10% quantile in period 04. This means that the electricity price tends to revert to last week's level for the same hour. Again, this gives evidence of mean reversion and is in line with expectations together with results in Karakatsani and Bunn (2008).

As shown in Figure 8, the coefficient is higher in period 11 than in period 04 for all quantiles, indicating that the weekly learning effect is stronger in the peak period. For period 04, the elasticity is highest for the lower quantiles and the trend is generally decreasing. Learning effect is strong when the price is relatively low, while other factors dominate the price formation at higher price levels. On the other hand, the influence is rather constant across quantiles for period 11, meaning that the learning from last week is in the same magnitude regardless of the initial price level.

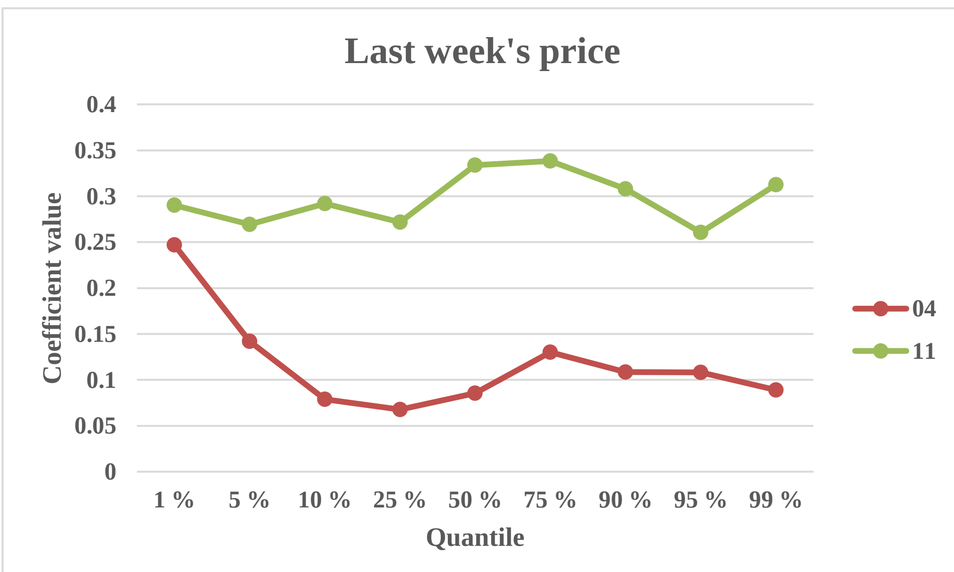

Figure 8: The graphs show the development of the last week's price coefficient for the 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% and 99% quantile in period 04 and period 11.

7.2 Demand

Demand is measured relative to its median value in order to soak up effects on price when demand differs from the normal. Coefficients must hence be interpreted as sensitivities towards demand beyond central values. The development of coefficients is shown in Figure 9.

The sensitivity to demand is strongly positive and generally significant at 1% level, which is according to expectations. Sensitivity is increasing from the 50% quantile, meaning that demand has a stronger influence when prices are already high. These results point out the relationship between supply and demand discussed earlier. A positive shift in the inelastic demand curve when the electricity price already is high increases the price non-linearly due to the steeply increasing and convex merit order curve. This is due to the placing of production technologies on the merit order curve, where production plants with lowest marginal costs enter to the very left of the curve and the production plants with highest marginal costs entering last. An increase in demand will have a stronger impact on price the further to the right on the merit order curve the demand curve initially is intersecting, as all plants with low marginal costs are already fully utilized and more expensive plants must be turned on. Sensitivity is especially noticeable for the highest quantiles in period 11, reflecting high demand and price levels in the peak period. Similar results are found by Bunn et al. (2016).

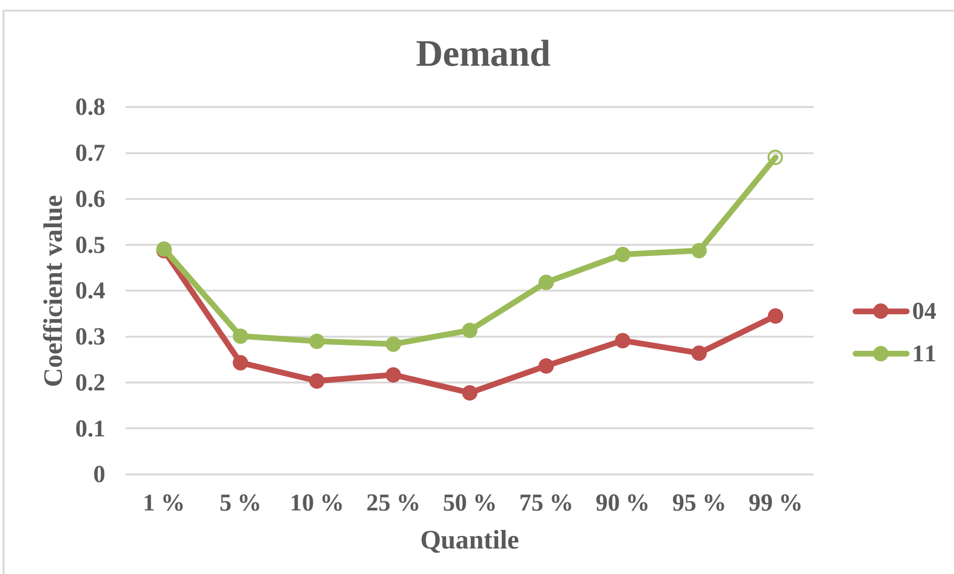

Figure 9: The graphs show the development of the demand coefficient for the 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% and 99% quantile in period 04 and period 11.

Elasticities are, however, generally constant from the 5% quantile to the 25% quantile. Furthermore, for all quantiles, the coefficient is higher in period 11, indicating that demand, not surprisingly, has bigger influence on price in the peak period. One possible explanation is that when demand is initially low, plants with low marginal costs have available production capacity and will be able to cover an increase in demand. Hence, prices will not be very much affected by a demand shift. This is illustrated by the left part of the merit order curve, which is relatively horizontal.

7.3 Water Reservoir Levels

Reservoir levels are measured relative to its median value in order to soak up effects on price when reservoir levels differ from the normal. Coefficients must hence be interpreted as sensitivities towards hydro capacity beyond central values.

The coefficient of water reservoir level is generally negative and significant at the 1% level, as expected. This is in line with results found by Huisman et al. (2013) and Huisman et al. (2014). An increase in the reservoir level seems to decrease the electricity price. Looking back at the merit order curve, higher reservoir level is equivalent to an increase in low marginal costs supply. It would thus not be necessary to turn on expensive generation plants if a positive shift in demand occurs. Exceptions are the 1%, 5% and 10% quantiles of period 04, which exhibits positive sensitivity and insignificant coefficients, together with the insignificant coefficients in the 1%, 5% and 99% quantile of period 11. This might indicate that hydro capacity is not important in explaining the price formation in these quantiles.

As shown in Figure 10, sensitivity is relatively constant for period 11, whereas period 04 shows a growing negative sensitivity with higher quantiles. Moreover, the coefficient is much larger in absolute values for period 04 than period 11 in the upper quantiles. One possible explanation is that hydro capacity is already fully utilized in the peak period independently of the price interval, making other factors more important in explaining the price formation. For period 04, the growing negative coefficient might point out that hydro producers increase production when prices are relatively high to make use of, for the time being, high value of hydropower, as more inflow is likely leading hydropower to being the marginal technology, causing decreasing prices (Burger et al., 2014, p. 338). Hence, prices react negatively to increased reservoir levels. Due to large coefficients, hydro capacity seems to be a very important fundamental factor in explaining prices, especially in the off-peak period.

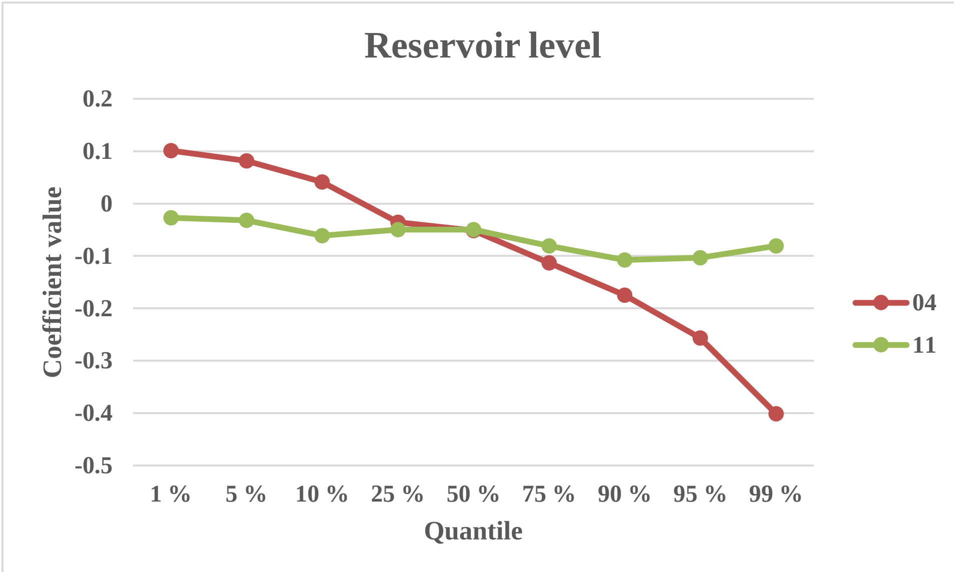

Figure 10: The graphs show the development of the reservoir level coefficient for the 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% and 99% quantile in period 04 and period 11.

7.4 Wind Power

The influence of wind power is generally negative and significant at the 1% level across all quantiles, in accordance with expectations. As with reservoir levels, higher wind power production increases the low marginal costs supply since wind power enters to the left of the merit order curve. Similar results are obtained by e.g. Gelabert et al. (2011), Huisman et al. (2013) and Paraschiv et al. (2014). However, Figure 11 shows that elasticities are small, reflecting the fact that wind still contributes to only a small share of the total electricity generation at Nord Pool.

The negative effect is slightly decreasing for period 04, whereas it is increasing for period 11. In contrast to hydropower, wind cannot be stored and hence wind power plants are must-run facilities. As a consequence, electricity generation fluctuates with the availability of wind. When demand is low, inflow of wind power to the grid decreases prices since it substitutes generation from base load plants which already are relatively cheap to run. In order to avoid costs related to shutting down and starting up, suppliers of electricity from base load plants accept low prices due to wind power penetration (Paraschiv et al., 2014, p. 4). Hence, wind power contributes to further decreasing the electricity price when it is already low, as reflected especially in the lower quantiles of period 04, but generally across all quantiles of the off-peak period. Sensitivity in the highest quantiles of period 11 implies that wind power has a stabilizing effect on positive price peaks. When all base load plants are fully utilized and expensive fossil-fuel plants run to meet demand, low marginal costs wind power replaces some of the high marginal costs peak plant generation. As a result, wind power has a relatively large negative effect in the highest quantiles in period 11, compared to the effect in other quantiles.

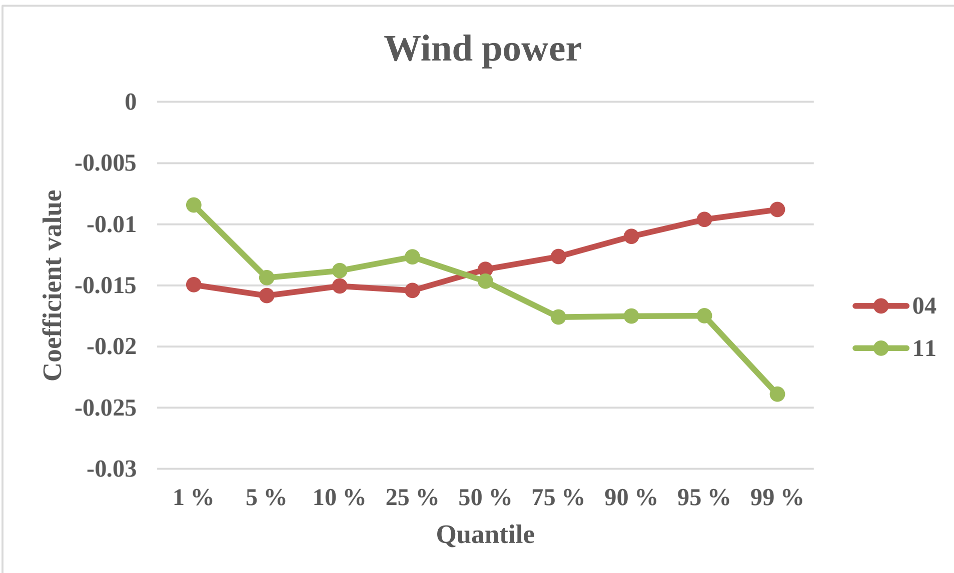

Figure 11: The graphs show the development of the wind power coefficient for the 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% and 99% quantile in period 04 and period 11.

7.5 Fossil Fuel Prices: Gas, Oil and Coal Prices

Overall, results show that prices of coal and oil influence the electricity price positively in the upper quantiles. The effect of coal dominates compared to gas and oil, but oil is important for the price formation in the extreme quantiles in period 11. It seems, however, that gas is not contributing to explaining the price formation in neither of the periods of interest. Effects of fossil fuels are smaller than those found by Bunn et al. (2016) and Paraschiv et al. (2014), reflecting the fact that the Nordic market is less dependent on fossil fuels in electricity generation than for instance the British and the German market. Moreover, they obtain positive and significant effect of gas.

7.5.1 Gas

Figure 12 shows the development of the gas coefficient. The elasticity of gas is generally small and insignificant. Additionally, sensitivity is mainly negative. These results are not in accordance with expectations. Since gas-fueled plants have high flexibility and are used as an additional generation source in periods of high demand, one would expect positive coefficients in the highest quantiles, especially in the peak period.

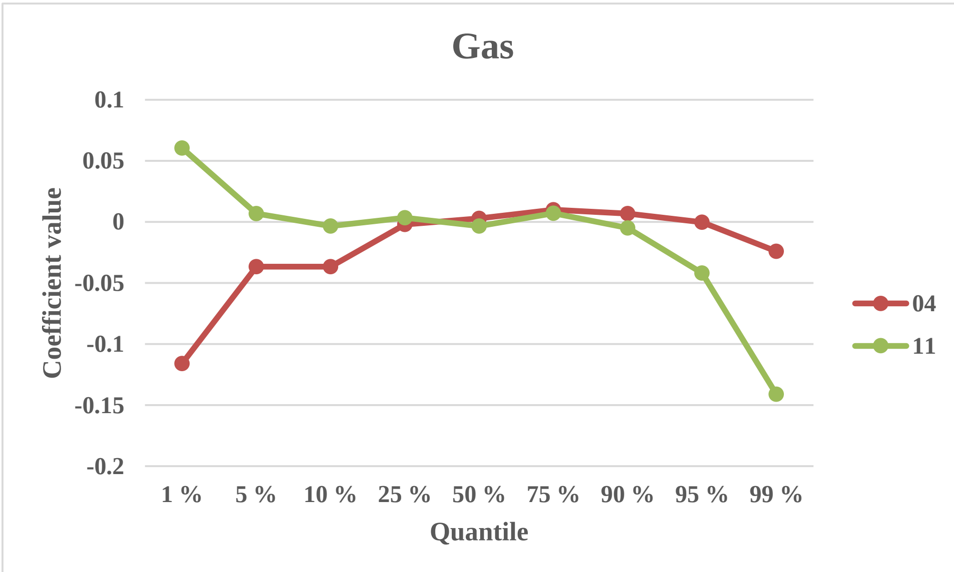

Figure 12: The graphs show the development of the gas coefficient for the 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% and 99% quantile in period 04 and period 11.

One possible explanation for insignificant coefficients is that gas overall is of little importance for the price formation at Nord Pool. The large share of electricity coming from hydropower makes this market less dependent on fossil-fueled plants. As gas-fired plants mostly are used to cover peaks in demand, its share of the total electricity generation in for instance Germany, a close exchange partner of the Nordic market, is rather small (Paraschiv et al., 2014, p. 4). On the other hand, gas is the main fuel used in the Russian market, which is another important exchange partner. In the view of this, negative coefficients remain difficult to explain in spite of the generation mix at Nord Pool. Another reason might be the high correlation between fossil fuel prices as discussed in Section 5.3. Nevertheless, regressions without either coal or oil as a fundamental factor still exhibit the same coefficient pattern of gas, meaning that multicollinearity does not give the full explanation for this behavior.

7.5.2 Oil

The coefficient of oil develops differently in the off-peak and peak period, as shown in Figure 13. For period 04, there is no pattern regarding significance across quantiles. Sensitivity is positive in the lower quantiles and negative in the upper quantiles, which is not in line with expectations. Except for the 1% quantile, coefficients are small. These results indicate that oil is likely not a prominent factor for the price formation in the off-peak period.

For period 11, coefficients are generally negative, decreasing and insignificant in the lower quantiles. From the 25% quantile, sensitivity is slightly positive, but still insignificant. From the 50% quantile, the effect is positive, increasing and significant with higher quantiles. This is in accordance with expectations. Insignificant effects in the lower quantiles implies that oil does not take part in the price formation when prices are relatively low. This makes sense as oil-fueled plants are mainly used in addition to other generation technologies when needed to meet demand. Extreme price peaks are usually caused by unexpected events such as plant outages or unusual weather conditions, which in turn lead to a supply shortage. Hence, other factors rather than regular market mechanisms are likely to determine prices in the highest quantiles. Positive and significant effects in the upper quantiles might indicate that oil-fueled plants are used as reserve capacity due to their high flexibility when unexpected events arise.

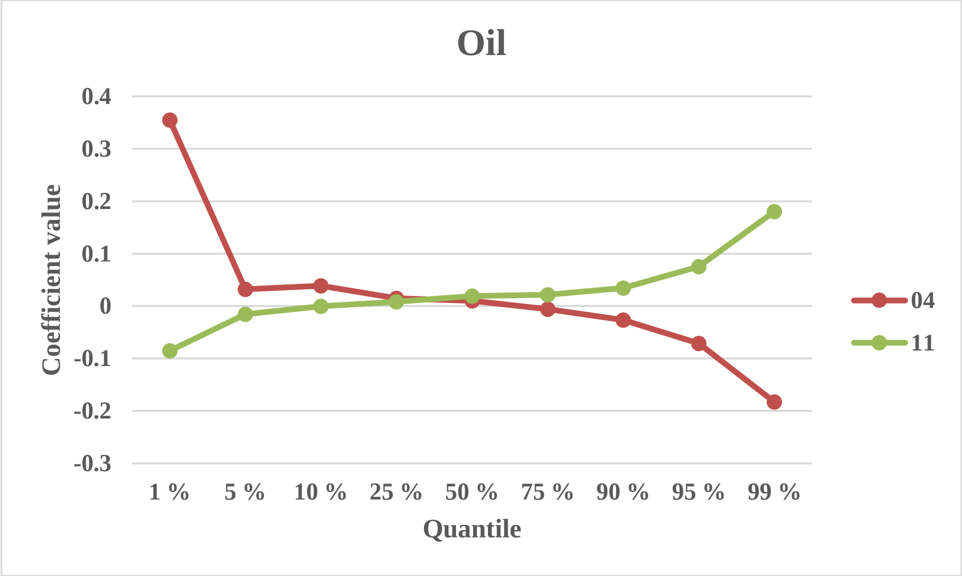

Figure 13: The graphs show the development of the oil coefficient for the 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% and 99% quantile in period 04 and period 11.

7.5.3 Coal

Figure 14 shows the development of the coal coefficient. The elasticity of coal is insignificant in the lower quantiles together with the 99% quantile of period 11, but significant generally at the 1% level in the remaining quantiles. The sign changes from negative to positive in the 50% quantile for period 04 and the 25% quantile for period 11. Based on these results, coal seems not to influence the price formation in the lower quantiles. On the other hand, sensitivity in the remaining quantiles is as expected.

The positive elasticity increases non-linearly for the off-peak period. A plausible explanation is that coal is the most relevant fuel in many European countries, for instance Germany and Poland, which are exchange partners of the Nordic countries. The upper quantiles are hence affected by the coal price due to imports. This effect strengthens with higher quantiles because the market is more dependent on import as demand increases. The same trend is observed for the 75%, 90% and 95% quantiles for period 11, although effects are smaller. For the 99% quantile, however, sensitivity decreases and is insignificant. This is probably due to the fact that extreme prices in the peak period are caused by severe unanticipated shocks, as discussed earlier. Hence, oil makes an important task as reserve capacity whereas coal does not. All in all, coal seems to have a bigger impact on the electricity price in period 04 than in period 11.

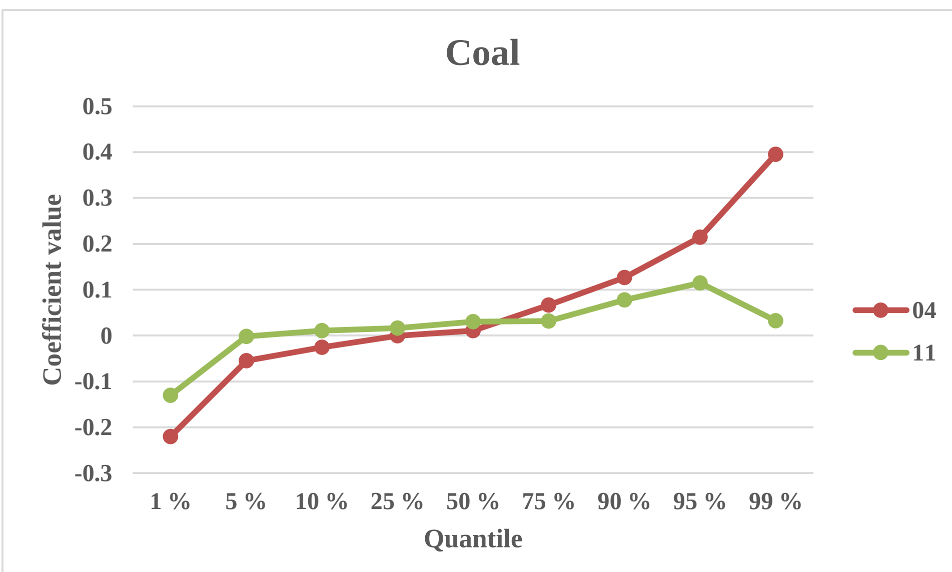

Figure 14: The graphs show the development of the coal coefficient for the 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% and 99% quantile in period 04 and period 11.

7.6 CO_2 Emissions Allowance Price

The influence of the EUA price is generally positive and significant at the 1% level in the upper quantiles and insignificant otherwise. The effect is small regardless of quantile, shown in Figure 15, reflecting the fact that fossil fuels are less important to the Nordic market compared to other European markets. Positive influence of the EUA price is also found in Bunn et al. (2016) and Paraschiv et al. (2014).

Positive yet small coefficients are as expected due to the link between the EUA price and fossil fuel prices. However, the coefficient increases across quantiles for period 11, but decreases in the upper quantiles of period 04. Moreover, effect is insignificant in the 99% quantile of period 04. As coal-fired plants emit most CO_2 it seems natural to expect that the coefficient of EUA follows the same path as the coefficient of coal. Following the results in section 7.5.2 and 7.5.3, the coefficient of EUA would have increased with the upper quantiles in period 04, whereas the effect had been smaller for period 11, but still increasing. However, this is not the case. Most likely, the coefficient in the upper quantiles of period 04 is unreliable since it decreases in significance and becomes insignificant in the highest quantile.

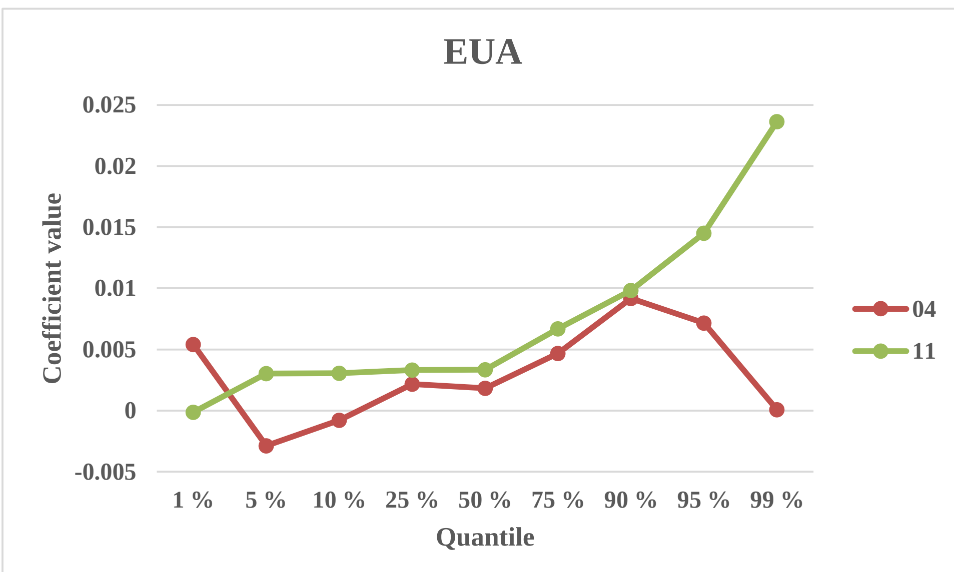

Figure 15: The graphs show the development of the EUA coefficient for the 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% and 99% quantile in period 04 and period 11.

7.7 Electricity Certificate Price

The effect of el-certificate price is generally small and insignificant for period 04 except for the 75% and 90% quantile. For period 11, the coefficient is positive, yet small in magnitude and generally significant at 5% level in the upper quantiles. This is shown in Figure 16. Thus, in contrary to expectations, an increase in the certificate price is not compensated by a decrease in the system price.

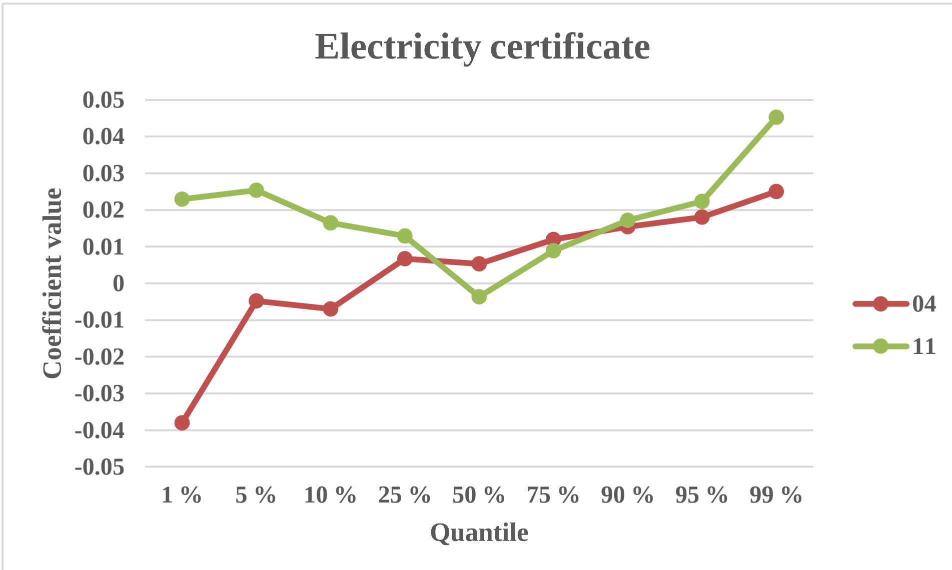

Figure 16: The graphs show the development of the electricity certificate coefficient for the 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% and 99% quantile in period 04 and period 11.

In the upper quantiles of the peak period together with the 75% and 90% quantile in the off-peak period, an increase in the el-certificate price increases the system price. Electricity suppliers are obligated to buy el-certificates. Additionally, they pay the spot price for electricity in which they resell to end-users. Both the cost of el-certificates and the cost of buying electricity are in turn charged consumers. Hence, in the above-mentioned quantiles, it seems like the certificate system is financed by end-users through two different channels. When the electricity price is initially high, end-users pay for the system through increased electricity price in addition to the el-certificate price itself, which work as an add-on to the electricity bill. This implies that owners of non-environmental friendly plants to some extent enjoy the benefits of the certificate system via increased system price at the cost of end-users.

For the lower quantiles of period 11 and the remaining quantiles of period 04, however, el-certificates do not have any impact on the electricity price due to the insignificance of coefficients. Thus, when prices are relatively low, end-users finance the certificate system only by paying for the el-certificates.

7.8 Price Volatility

The coefficient of volatility is significant at 1% level across all quantiles, except for the 50% quantile in period 04 which is significant at the 5% level. Sensitivity is negative in the lower quantiles and positive in the upper quantiles. The shift to positive sign occurs in the 50% quantile for period 04 and in the 75% quantile for period 11. The negative effect decreases before the sign shifts, thereafter the positive effect increases with higher quantiles. Thus, volatility has larger influence on price in the tails than in the center of the distribution. Results are partly according to expectations, which stated negative impact of volatility in period 04 and positive impact in period 11, as well as increasing sensitivity with extreme quantiles.

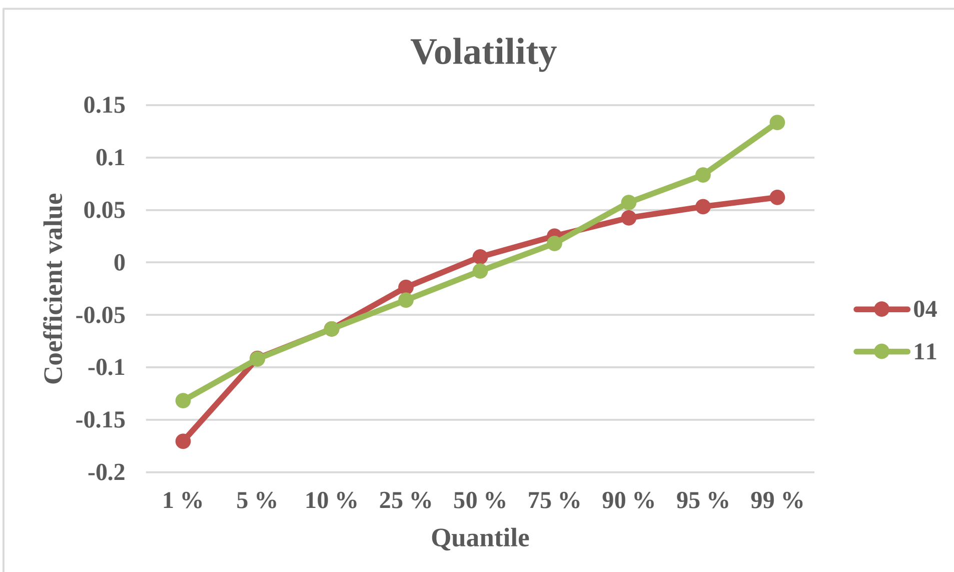

Figure 17: The graphs show the development of the volatility coefficient for the 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% and 99% quantile in period 04 and period 11.

Volatility seems to reinforce already extreme prices by driving low prices even lower and high prices even higher. This is in accordance with results found by Bunn et al. (2016). As previously explained, other factors than market fundamentals might play an essential role for the price formation in the tails of the distribution. This means that an increase in volatility enlarges the sensitivity towards severe events causing negative and positive price peaks, beyond the effect in which can be explained by fundamentals. As shown in Figure 17, the impact of volatility is especially noticeable in the 99% quantile of period 11, which represents the most extreme positive peaks, and in the 1% quantile of period 04, which represents the most extreme negative peaks.

7.9 Dummy Variables

Results for the CO_2 emissions allowance price dummy, the weekend dummy and the month dummies are presented in Appendix E. They are of importance for the model for reasons discussed in Section 4.6.1 and 4.9, respectively. The significance and sign of the coefficients vary across quantiles, but they overall seem to improve the results of the fundamental factors.

Coefficients of the dummy variables should, however , not be interpreted as isolated effects since they are of no interest in themselves. Rather, they should be regarded as a tool for improving the model by controlling for influence on price in which the explanatory variables are not able to explain.

8 Application of the Models: Value-at-Risk Calculations

We have seen that the Nord Pool system price is highly volatile with occasional price spikes. For agents involved in exchange activities, market risk management and assessment is therefore a key issue. Market risk involves uncertainty regarding future income and cost due to changes in electricity prices. Value-at-Risk (hereafter called VaR) is a market risk quantification method commonly used by agents to determine optimal trading limits. Well estimated tail probabilities are crucial in VaR applications, which has resulted in a broad literature in search for accurate quantile forecasting methods.

In this section, a semi-parametric approach to 1-day-ahead VaR models is proposed by use of the quantile regression model presented in Equation (1), in order to examine the framework's out-of-sample performance. VaR can be interpreted as the maximal loss a financial position can generate during a given time period for a pre-determined probability (Tsay, 2005, p. 288). From a statistical point of view, VaR models are defined as conditional quantile functions. Quantile regression models can, hence, be directly translated into VaR models, which is yet another advantage of this methodology.

The confidence level is chosen to be 95%, meaning that the 5% significance level VaR is of interest. By modeling the 5% quantile in the left tail and the 95% quantile in the right tail of the price distribution, the 5% 1-day-ahead VaR for both long positions (the 5% quantile) and short positions (the 95% quantile) in the Nordic electricity market are computed. For long positions, risk is associated with price drops, whereas short positions are concerned with price increases. The 1-day time interval is chosen because market risk events usually happens within short time intervals. Thus, with 95% confidence, the loss of the financial position over one day will be less than or equal to VaR. More precisely,

$$\Pr\left(\ln(price_{t+1}) < x_{q=0.05} = VaR_{t+1}^{long} \,|F_t\right) = 5\% \qquad (8)$$
$$\Pr\left(\ln(price_{t+1}) > x_{q=0.95} = VaR_{t+1}^{short} \,|F_t\right) = 5\%$$

where x_q is the real number associated with the corresponding quantile of the distribution of ln of price and F_t is the information set available at time t. Note that the VaR defined in (8) is not given in absolute numbers, meaning VaR_{t+1}^{long} is a negative number and VaR_{t+1}^{short} is a positive number. In total, four different VaR models are computed: 5% VaR for both long and short positions for the ln of price in period 04 and 5% VaR for both long and short positions for the ln of price in period 11.

The performance of quantile regression VaR is compared to the corresponding performance of the RiskMetrics method, which is a widely used parametric approach by market practitioners. Both models can be regarded as simple models compared to more complicated approaches to estimating VaR such as CAViaR, and will on the grounds of this be suitable for comparison. Note that the quantile regression approach is based on the ln of price series, whereas RiskMetrics is based on the log return series.

8.1 Estimation

8.1.1 Quantile regression out-of-sample VaR forecasts

VaR with quantile regression is given by

$$\begin{aligned} VaR^q_{t+1} = Q^q(\ln P_{i,t+1}) = \alpha^q_i + \beta^q_{i,1}\ln P_{i,t} + \beta^q_{i,2}\ln P_{i,t-6} + \beta^q_{i,3}\ln Demand_{i,t+1} \\ + \beta^q_{i,4}\ln \mathrm{Re}\,servoir_t + \beta^q_{i,5}\ln Wind_{i,t+1} + \beta^q_{i,6}\ln Gas_t + \beta^q_{i,7}\ln Oil_t \\ + \beta^q_{i,8}\ln Coal_t + \beta^q_{i,9}\ln EUA_t + \beta^q_{i,10}\ln Elcert_t + \beta^q_{i,11}\ln Vol_{i,t+1} \\ + \beta^q_{i,12} Dbreak_{t+1} + \beta^q_{i,13} DWeekend_{t+1} + \beta^q_{i,14} DFeb_{t+1} + \ldots + \beta^q_{i,24} DDec_{t+1} \end{aligned} \tag{9}$$

where q=5%, 95% and i=4,11.

Coefficient estimates are computed using a rolling window approach, with fixed window size of 2000 observations. The first 5% quantile and 95% quantile model are estimated using the first 2000 observations in the data set. Then, the 5% and 95% quantile for observation 2001 are forecasted. Thereafter, the models are re-estimated with use of observation 2 to 2001 in order to forecast the 5% and 95% quantile for observation 2002. This procedure is repeated 1286 times in total, giving 1286 observations to verify the VaR performance.

8.1.2 RiskMetrics out-of-sample VaR forecasts

A brief description of the theoretical framework and estimation procedure will be given. For details, see JP Morgan's RiskMetrics Technical Document by Longerstaey and Spencer (1996).

RiskMetrics assumes that the daily log return of price, $r_{t,}$ follows a normal distribution. Let $r_t = \ln(P_t / P_{t-1})$. Then,

$$r_t = e_t \tag{10}$$

$$e_t = v_t \sigma_t, v_t \sim N(0,1) \tag{11}$$

$$\sigma_t^2 = \lambda \sigma_{t-1}^2 + (1-\lambda) r_{t-1}^2 . \tag{12}$$

σ_t^2 is the conditional variance of r_t. Further, λ is referred to as the decay factor, which is typically set to 0.94.

The 1-day conditional volatility forecast is then given by

$$\sigma_{t+1|t} = \sqrt{0.94\sigma_t^2 + 0.06 r_t^2} . \tag{13}$$

Here, the first observation is set equal to the observed standard deviation of the residuals, as suggested by Engle (2001).[10]

Having calculated (13), the 1-day-ahead 5% VaR for long positions is computed according to

$$VaR_{t+1} = \Phi^{-1}(0.05) \times \sigma_{t+1} . \tag{14}$$

Equivalently, the 1-day-ahead 5% VaR for short positions is given by

$$VaR_{t+1} = \Phi^{-1}(0.95) \times \sigma_{t+1} . \tag{15}$$

$\Phi^{-1}(q) = Q^q$ is the inverse of the standard normal cumulative distribution function for q=5% and 95%, respectively. This procedure is repeated 1286 times, giving 1286 observations to verify the VaR performance.

[10] It follows from (10) that the standard deviation of the observed residuals equals the standard deviation of the log return series.

8.2 Model Validation: Backtesting

The out-of-sample forecast performance of the models are validated with two different tests, often called "backtests", since it is important to assess the accuracy of VaR models. Backtesting a VaR model means to check whether the VaR predictions are close to the corresponding realized daily prices or returns. A sufficiently long test period of 1286 days (over 3 years) ensures that the tests are powerful.

Both tests considered are based on an indicator function I_{t+1} with the following properties:

$$I_{t+1} = \begin{cases} 1\, if \;\; violation\, occurs \\ 0\, if \;\; no\, violation\, occurs. \end{cases} \tag{16}$$

Violation occurs for long positions if the realized price/return is lower than the VaR estimate, whereas violation for short positions occurs if the realized price/return is higher than the VaR estimate. An accurate VaR model should have a percentage of exceedances equal to the pre-specified significance level, which in this case is 5%. That is, of the out-of-sample observations, 95% of the true prices and returns of the forecast interval should be lower in absolute value than the predicted VaR of interest.

8.2.1 The Kupiec (1995) test

The first test considered is the unconditional coverage test proposed by Kupiec (1995). Under the null hypothesis, the indicator function has a constant probability of violation equal to the chosen significance level. The likelihood ratio statistic is under the null hypothesis given by

$$-2\ln(LR_{uc}) = -2\ln\left[\frac{\pi_{\exp}^{n_1}(1-\pi_{\exp})^{n_0}}{\pi_{obs}^{n_1}(1-\pi_{obs})^{n_0}}\right] \sim \chi_1^2\,. \tag{17}$$

n_0 is the number of non-violations, n_1 is the number of violations, $\pi_{\exp}$ is the expected proportion of exceedances and π_{obs} is the observed proportion of exceedances.[11]

8.2.2 The Christoffersen (1998) test

The second test considered is the conditional coverage test proposed by Christoffersen (1998), which is a joint test for correct coverage and whether the exceedances tend to cluster. The test is

[11] $n_0 + n_1 = n$, where n is the out-of-sample size.

concerned with one particular clustering pattern in which an exceedance is immediately followed by another. Under the null hypothesis of a correct probability of violations and no clustering of violations, the test statistic is given by

$$-2\ln(LR_{cc}) = -2\ln\left[\frac{\pi_{\exp}^{n_1}(1-\pi_{\exp})^{n_0}}{\pi_{01}^{n_{01}}(1-\pi_{01})^{n_{00}}\pi_{11}^{n_{11}}(1-\pi_{11})^{n_{10}}}\right] \sim \chi_2^2 . \qquad (18)$$

n_{ij} is the number of observations with value i followed by an observation with value j, where $i, j = 0,1$ and the value is given by the indicator function. Further, $\pi_{01} = n_{01}/(n_{00}+n_{01})$ and $\pi_{11} = n_{11}/(n_{10}+n_{11})$.

Ideally, for both the Kupiec and Christoffersen test, one should not be able to reject the null hypothesis.

8.3 Results

Table 6 presents the observed percentage of violations, the test statistic for the Kupiec test and the test statistic for the Christoffersen test for the different VaR models. Bold test statistics mean the test is rejected at the 5% significance level.

Three of four quantile regression models pass the Kupiec test, meaning they have the correct percentage of violations. The VaR for short positions are especially accurate, only slightly underestimating the number of exceedances. The test statistic is rejected for the period 04 long positions VaR. Looking at the observed percentage of violations, this model is the furthest away from the pre-specified 5% significance level. In comparison, two of four RiskMetrics models provide the correct percentage of violations whereas the remaining models are flawed. Moreover, on average, the percentage of exceedances is 4.59% for the quantile regression approach and 5.58% for the RiskMetrics approach, meaning the former is closer to the target percentage of violations. Thus, the quantile regression framework performs better than RiskMetrics in terms of providing the correct unconditional coverage. One possible explanation might be that exogenous risk factors included in the former model is of importance for accurate tail predictions.

Table 6: The table presents the observed percentage of violations, the test statistic for the Kupiec test and the test statistic for the Christoffersen test for different VaR models. The 5% critical value for the Kupiec test is 3.841. The 5% critical value for the Christoffersen test is 5.991. Bold values mean that the test is rejected at the 5% significance level.

Period	Model	5% VaR position	Observed percentage of violations	Kupiec	Christoffersen
04	Qreg	Long	3.421 %	**7.551**	**10.683**
04	Qreg	Short	4.432 %	0.906	**61.622**
04	RiskMetrics	Long	6.532 %	**5.819**	**7.125**
04	RiskMetrics	Short	4.588 %	0.472	0.789
11	Qreg	Long	5.988 %	2.490	**8.045**
11	Qreg	Short	4.510 %	0.671	**49.010**
11	RiskMetrics	Long	4.432 %	0.906	3.105
11	RiskMetrics	Short	6.765 %	**7.633**	**14.607**

Turning to the Christoffersen test, none of the quantile regression models give satisfying results. They thus seem to suffer from clustering of exceedances. Looking at the size of the test statistics, this problem is more severe for the short positions. In comparison, the two RiskMetrics models which provide a satisfying unconditional coverage also pass the conditional coverage test, meaning that exceedances occur randomly. The poor conditional coverage of the quantile regression might be a consequence of the model-free historical volatility term included, which probably is unable to soak up volatility clustering, leading to one violation followed by another. Results would arguably improve if a more complicated volatility formulation, for instance a GARCH(1,1) term, were implemented instead. Bunn et al. (2016), suggest that clustering might be caused by the fact that predicted quantiles are not directly dependent on the last residual term. Contrary, RiskMetrics is actually an IGARCH(1,1) model, in which the volatility term contributes to a large part of the model's process. This might explain why the latter approach performs better than the quantile regression approach when concerned with conditional coverage.

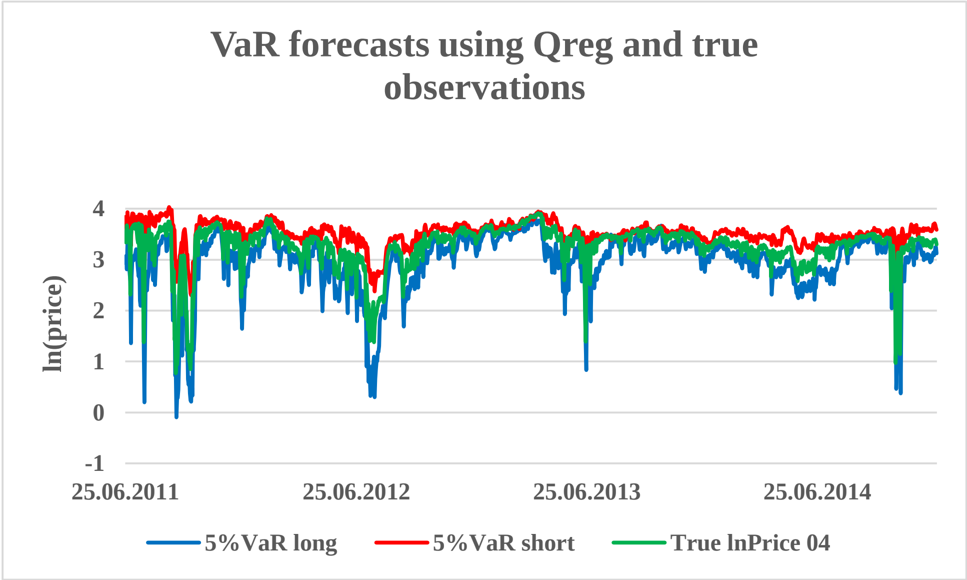

Figure 18: The figure shows the 5% VaR model using quantile regression methodology for long and short positions together with the true ln of price series for period 04. The out-of-sample period spans from 25 June 2011 to 31 December 2014.

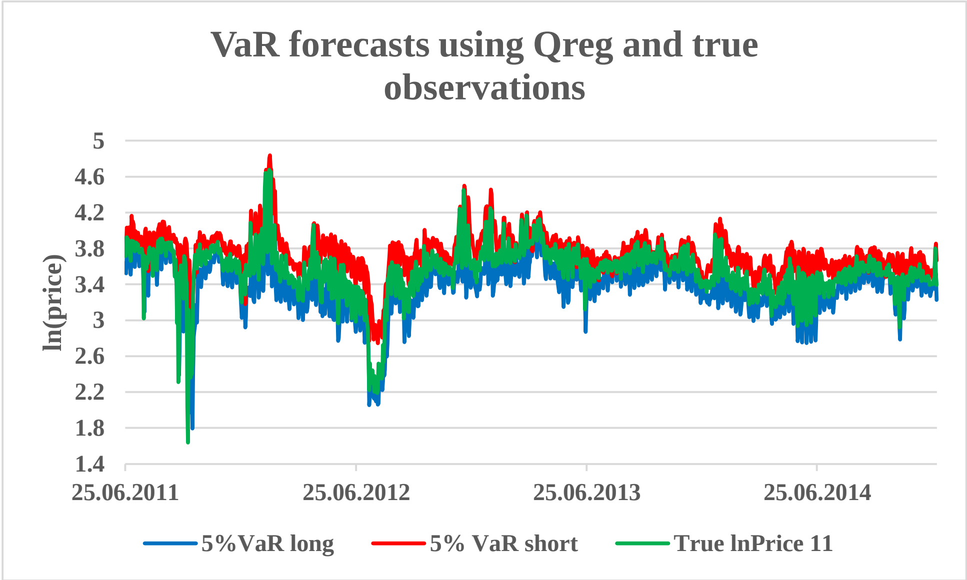

Figure 19: The figure shows the 5% VaR model using quantile regression methodology for long and short positions together with the true ln of price series for period 11. The out-of-sample period spans from 25 June 2011 to 31 December 2014.

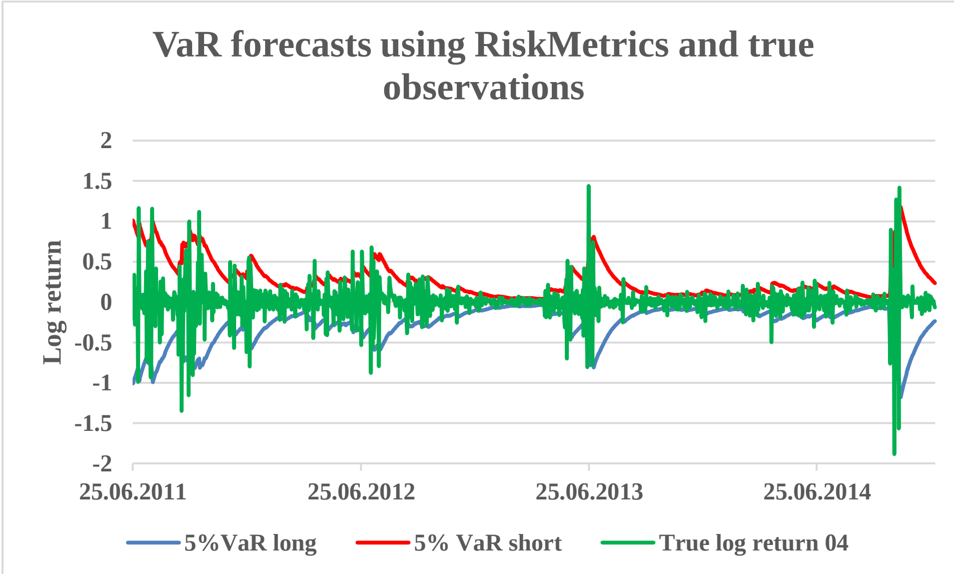

Figure 20: The figure shows the 5% VaR model using RiskMetrics for long and short positions together with the true log return series for period 04. The out-of-sample period spans from 25 June 2011 to 31 December 2014.

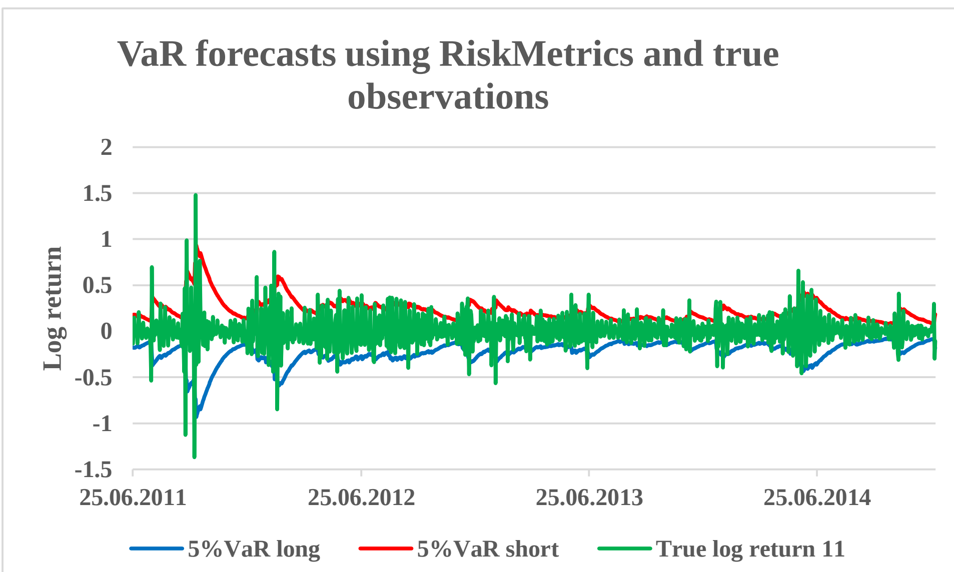

Figure 21: The figure shows the 5% VaR model using RiskMetrics for long and short positions together with the true log return series for period 11. The out-of-sample period spans from 25 June 2011 to 31 December 2014.

Figure 18 to Figure 21 depict the VaR forecasts together with true values. Tail predictions using the quantile regression approach are flexible compared to RiskMetrics, revealing that the simple formulation of RiskMetrics is too crude. In RiskMetrics, VaR is proportional to the inverse of the standard normal cumulative distribution function, leading to the same variation in risk regardless of the sign of returns. This is shown by the symmetric long and short VaR lines for the same period around the mean. On the other hand, with quantile regression changes in risk are associated with fluctuations in all of the exogenous variables included in the model. Although RiskMetrics performs better than the quantile regression approach in terms of conditional coverage, the latter framework adapts more quickly to changing market circumstances, highlighting the usefulness of this methodology in modeling electricity prices and forecasting tail risk in practice.

9 Conclusions

With this thesis, I have proposed a model for the Nord Pool system price using linear quantile regression. By estimating nine quantiles for each period of interest covering the whole price distribution, a complete examination of explanatory variables' impact on the electricity price for different levels is made possible. This study hence contributes to a deeper understanding of how fundamental factors influence different quantiles of the distribution of the Nord Pool system price, which is the thesis' main goal.

Briefly summarized, results show strong positive influence of agent learning, especially in the lower quantiles, suggesting mean reversion in the price behavior. High and positive elasticity of demand generally increases with quantiles and is stronger in the peak period. Sensitivity towards reservoir level is negative with larger magnitude in the off-peak period, in which the impact increases with quantiles. Wind power, although small in magnitude, shows a negative influence across quantiles. Effects of fossil fuel prices vary considerably between quantiles and periods. Coal has positive influence in the upper quantiles of period 04 whereas oil show positive impact in the upper quantiles of period 11, reflecting the fact that they are used differently in production depending on the demand situation. Contrary, the effect of gas seems to be absent in the Nordic market. Overall, effects of fossil fuels are smaller compared to studies of other markets, emphasizing the uniqueness of the Nord Pool area due to its high share of hydropower in electricity generation. The CO_2 emissions allowance price generally has positive yet small elasticities in the upper quantiles, which, in connection with results of fossil fuel prices, is plausible. Findings show small positive effect of the el-certificate price in the upper quantiles of period 11. Volatility has negative impact in lower quantiles and positive impact in upper quantiles, implying that price uncertainty reinforce already extreme prices. Generally, the findings reveal that most fundamentals influence the Nordic system price in quite intuitive ways when taking into consideration the characteristics of the Nordic market. Furthermore, results are in line with previous studies of Nord Pool. This leads to the conclusion that the proposed framework gives valuable insight in the price formation process, and is in this respect a satisfying model.

Overall, findings imply that autoregressive effects and demand are the most important determinants of the Nord Pool system price movements. Further, results suggest that the influence of fundamental factors vary non-linearly across quantiles, both in size and significance. These findings are valuable to agents concerned with price fluctuations. With knowledge of the main price drivers in different price intervals, they are able to manage and assess risk more accurately. Moreover, impact of factors vary considerably between the off-peak and the peak period, demonstrating intra-day variations in price behavior. This insight benefits market participants affected by activity only in particular trading periods. With advantage, agents can hence adapt and implement the proposed framework as it suits them in order to adjust and improve short-term operations and risk management strategies.

Next, for the sake of demonstrating the range of use of the proposed model, I performed 1-day-ahead VaR calculations for both long and short trading positions in an out-of-sample setting. Findings imply that the quantile regression framework provides the correct percentage of exceedances, as three of four models pass the unconditional coverage test. Additionally, forecasts seem to adapt quickly to price changes. However, none of the models pass the conditional coverage tests, implying that the framework suffers from clustering of exceedances. In sum, considering the quite accurate percentage of violations and the easy-to-implement formulation due to the fact that VaR is defined as conditional quantile functions, quantile regression models are a beneficial approach to forecasting VaR.

Unfortunately, I did not have access to data for demand forecasts and wind power forecasts. Although prognosis today is well-known to be accurate, making use of actual data as approximations arguably accepted, the use of actual data is still a drawback with the thesis worth mentioning. In order to plan consumption and production and, hence, determining bids and offers, agents must take into account demand and wind power prognosis. It goes without saying that actual numbers for the following day remains unknown before the power exchange closes for the concerned delivery day. Therefore, future research is recommended to collect forecast data for demand and wind power.

Several extensions of the analysis can be considered. Future research can examine all 24 intra-day trading periods with use of the quantile regression framework presented, in order to increase the understanding of the market dynamics in each period. Moreover, data for reservoir level and wind power can be collected from all countries in the Nordic market rather from only the main production country, with a view to fully encapsulate each factor’s influence on the system price. Also, more explanatory variables can be included to increase the model’s goodness of fit. The available production capacity of nuclear power plants has already been stated as a relevant factor. If solar power generation technology expands in the Nordic area in the future, it would be natural to include solar power as an explanatory variable as well.

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11 Appendix

A Descriptive Statistics

1. Descriptive statistics for the level-series and ln-series of the electricity price

Table A.1: The table presents the mean, median, minimum observation, maximum observation, standard deviation, skewness and kurtosis for the level-series and ln-series of electricity prices in period 04 and period 11.

Variable	Mean	Median	Min	Max	Std dev	Skewness	Kurtosis
P04	33.834	32.505	0.490	81.630	13.695	0.463	3.478
lnP04	3.418	3.481	-0.713	4.402	0.511	-1.755	8.869
P11	42.693	40.295	5.140	208.160	14.702	1.563	12.604
lnP11	3.697	3.696	1.637	5.338	0.346	-0.557	5.318

2. Distribution of the electricity price: Illustrations

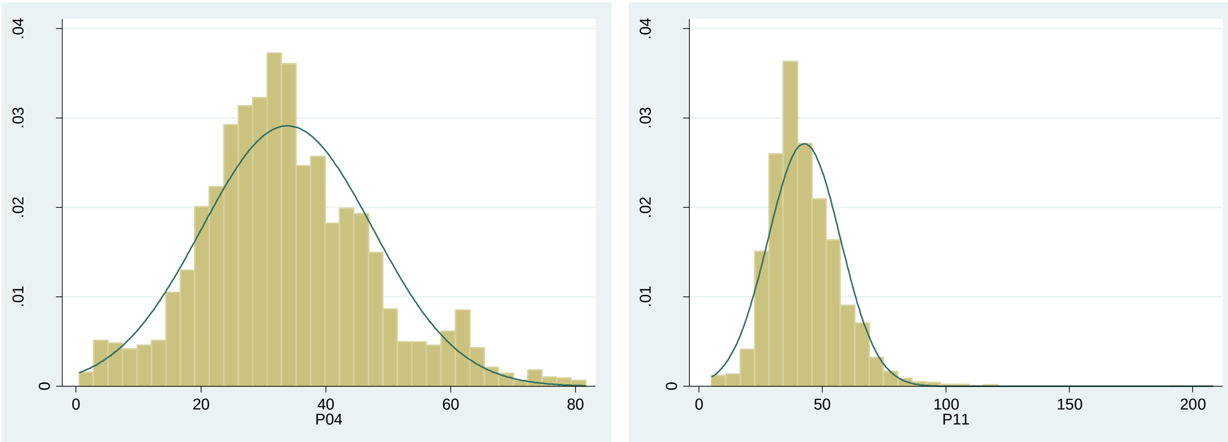


Figure A.1: The figure shows the distribution of the period 04 (left illustration) and period 11 (right illustration) price level series compared to a normal distribution illustrated by the blue line. The horizontal axis measures the price level while the vertical axis measures the density. A normal distribution has no skewness and a kurtosis coefficient of 3. The electricity prices have positive skewness, shown by a long right tail, and excess kurtosis, shown by the peak around the mean.

3. The Jarque-Bera test for normality

*Table A.2: The Jarque-Bera test for normality in the price level series. H_0: Skewness and excess kurtosis are jointly zero. Under H_0, the JB statistic follows a chi-squared distribution. Critical value for 1% significance level and 2 degrees of freedom is 9.210. The asterisks *** mean rejection of H_0 at 1% significance level.*

Period	04	11
Test statistic	1508.158***	141491.823***

4. Autocorrelation, partial autocorrelation and Ljung-Box test of linear dependence

Table A.3: The table presents the autocorrelation (AC) coefficient, partial autocorrelation (PAC) coefficient and Q-statistics of the period 04 price level series. The Ljung-Box test of linear dependence has H_0: the autocorrelation coefficients are jointly 0. Under H_0, the Q statistic follows a chi-squared distribution. Critical value at 1% significance level with 20 degrees of freedom is 37.566.

LAG	AC	PAC	Q	Prob>Q	-1 0 1 [Autocorrelation]	-1 0 1 [Partial Autocor]
1	0.9572	0.9573	3013.6	0.0000		
2	0.9361	0.2365	5896.5	0.0000		
3	0.9226	0.1532	8697.9	0.0000		
4	0.9106	0.0845	11428	0.0000		
5	0.8994	0.0547	14092	0.0000		
6	0.8880	0.0252	16689	0.0000		
7	0.8790	0.0452	19235	0.0000		
8	0.8600	-0.1053	21672	0.0000		
9	0.8467	0.0087	24036	0.0000		
10	0.8353	0.0138	26337	0.0000		
11	0.8223	-0.0128	28568	0.0000		
12	0.8120	0.0279	30744	0.0000		
13	0.8059	0.0729	32888	0.0000		
14	0.7998	0.0431	35000	0.0000		
15	0.7878	-0.0305	37050	0.0000		
16	0.7739	-0.0555	39029	0.0000		
17	0.7645	0.0131	40961	0.0000		
18	0.7567	0.0264	42854	0.0000		
19	0.7512	0.0420	44720	0.0000		
20	0.7482	0.0548	46572	0.0000		

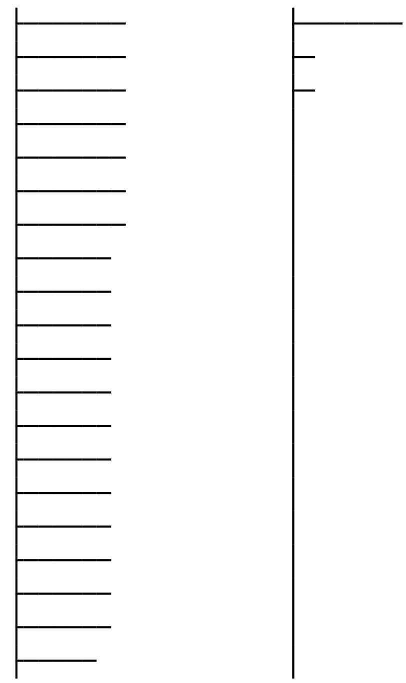


Table A.4: The table presents the autocorrelation (AC) coefficient, partial autocorrelation (PAC) coefficient and Q-statistics of the period 11 price level series. The Ljung-Box test of linear dependence has H_0: the autocorrelation coefficients are jointly 0. Under H_0, the Q statistic follows a chi-squared distribution. Critical value at 1% significance level with 20 degrees of freedom is 37.566.

LAG	AC	PAC	Q	Prob>Q	-1 0 1 [Autocorrelation]	-1 0 1 [Partial Autocor]
1	0.8795	0.8797	2543.9	0.0000		
2	0.8097	0.1599	4701.1	0.0000		
3	0.8012	0.2821	6813.8	0.0000		
4	0.7909	0.1296	8873.2	0.0000		
5	0.7713	0.0794	10832	0.0000		
6	0.7906	0.2423	12891	0.0000		
7	0.8224	0.2378	15120	0.0000		
8	0.7699	-0.1819	17074	0.0000		
9	0.7264	-0.0496	18813	0.0000		
10	0.7186	-0.0065	20517	0.0000		
11	0.7076	-0.0150	22168	0.0000		
12	0.6965	0.0399	23769	0.0000		
13	0.7134	0.0857	25449	0.0000		
14	0.7446	0.1438	27279	0.0000		
15	0.6995	-0.1234	28896	0.0000		
16	0.6674	0.0094	30368	0.0000		
17	0.6681	0.0268	31843	0.0000		
18	0.6644	0.0182	33302	0.0000		
19	0.6506	-0.0083	34702	0.0000		
20	0.6686	0.0696	36181	0.0000		

Table A.5: The table presents the autocorrelation (AC) coefficient, partial autocorrelation (PAC) coefficient and Q-statistics of the period 04 1.difference of price level series. The Ljung-Box test of linear dependence has H_0: the autocorrelation coefficients are jointly 0. Under H_0, the Q statistic follows a chi-squared distribution. Critical value at 1% significance level with 20 degrees of freedom is 37.566.

LAG	AC	PAC	Q	Prob>Q	-1 0 1 [Autocorrelation]	-1 0 1 [Partial Autocor]
1	-0.2528	-0.2528	210.19	0.0000		
2	-0.0897	-0.1641	236.69	0.0000		
3	-0.0169	-0.0931	237.63	0.0000		
4	-0.0102	-0.0622	237.97	0.0000		
5	0.0036	-0.0321	238.01	0.0000		
6	-0.0287	-0.0515	240.73	0.0000		
7	0.1168	0.0986	285.73	0.0000		
8	-0.0674	-0.0160	300.7	0.0000		
9	-0.0222	-0.0209	302.33	0.0000		
10	0.0200	0.0056	303.65	0.0000		
11	-0.0326	-0.0349	307.16	0.0000		
12	-0.0493	-0.0791	315.17	0.0000		
13	0.0005	-0.0486	315.18	0.0000		
14	0.0696	0.0251	331.18	0.0000		
15	0.0210	0.0496	332.63	0.0000		
16	-0.0522	-0.0192	341.64	0.0000		
17	-0.0178	-0.0322	342.69	0.0000		
18	-0.0278	-0.0473	345.25	0.0000		
19	-0.0283	-0.0596	347.89	0.0000		
20	0.0249	-0.0231	349.93	0.0000		

Table A.6: The table presents the autocorrelation (AC) coefficient, partial autocorrelation (PAC) coefficient and Q-statistics of the period 11 1.difference of price level series. The Ljung-Box test of linear dependence has H_0: the autocorrelation coefficients are jointly 0. Under H_0, the Q statistic follows a chi-squared distribution. Critical value at 1% significance level with 20 degrees of freedom is 37.566.

LAG	AC	PAC	Q	Prob>Q	-1 0 1 [Autocorrelation]	-1 0 1 [Partial Autocor]
1	-0.2096	-0.2096	144.47	0.0000		
2	-0.2533	-0.3113	355.67	0.0000		
3	0.0062	-0.1495	355.8	0.0000		
4	0.0381	-0.0955	360.58	0.0000		
5	-0.1613	-0.2534	446.3	0.0000		
6	-0.0522	-0.2443	455.3	0.0000		
7	0.3511	0.1763	861.49	0.0000		
8	-0.0376	0.0426	866.15	0.0000		
9	-0.1491	-0.0034	939.52	0.0000		
10	0.0137	0.0063	940.14	0.0000		
11	0.0002	-0.0483	940.14	0.0000		
12	-0.1163	-0.0929	984.79	0.0000		
13	-0.0591	-0.1493	996.34	0.0000		
14	0.3167	0.1176	1327.6	0.0000		
15	-0.0539	-0.0159	1337.2	0.0000		
16	-0.1350	-0.0323	1397.4	0.0000		
17	0.0206	-0.0211	1398.8	0.0000		
18	0.0433	0.0073	1405	0.0000		
19	-0.1347	-0.0742	1465.1	0.0000		
20	-0.0915	-0.1527	1492.8	0.0000		

5. Correlation between electricity price lags

Table A.7: The table presents the pairwise correlation of lags for period 04 price level series and 1.difference of price level series. Li indicates the lag, i=1, 7, 14.

	L1P04	L7P04	L14P04
L1P04	1.000		
L7P04	0.888	1.000	
L14P04	0.806	0.879	1.000

	L1DifP04	L7DifP04	L14DifP04
L1DifP04	1.000		
L7DifP04	-0.029	1.000	
L14DifP04	0.001	0.117	1.000

Table A.8: The table presents the pairwise correlation of lags for period 11 price level series and 1.difference of price level series. Li indicates the lag, i=1, 7, 14.

	L1P11	L7P11	L14P11
L1P11	1.000		
L7P11	0.791	1.000	
L14P11	0.714	0.823	1.000

	L1DifP11	L7DifP11	L14DifP11
L1DifP11	1.000		
L7DifP11	-0.052	1.000	
L14DifP11	-0.059	0.352	1.000

6. The Augmented Dickey-Fuller test for stationarity

*Table A.9: The table presents the Augmented Dickey-Fuller test for stationarity in the electricity price level series. H_0: There is a unit root. Under H_0, the Dickey-Fuller statistic follows a MacKinnon distribution. Critical value for 1% significance level is -3.430. The asterisks *** mean rejection at 1% significance level.*

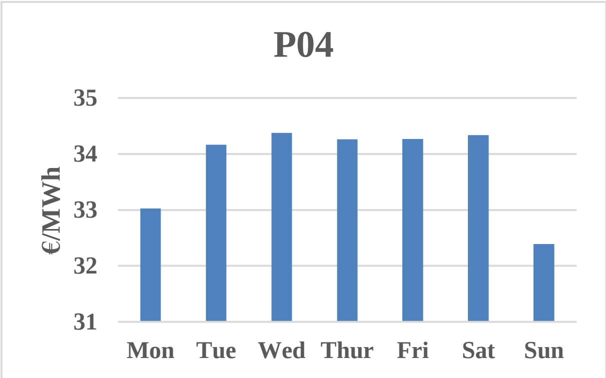
Period	04	11
Test statistic	-4,937***	-5,034***

7. Empirical quantiles

Table A.10: The table presents the empirical 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% and 99% quantiles of the level-series and ln-series of the electricity price.

Variable	1%	5%	10%	25%	50%	75%	90%	95%	99%
P04	3.98	12.75	17.9	25.03	32.505	41.74	51.3	60.71	72.52
P11	12.45	23.64	26.92	33.18	40.295	50.8	61.17	67.89	86.37
lnP04	1.381	2.546	2.885	3.220	3.481	3.732	3.938	4.106	4.284
lnP11	2.522	3.163	3.293	3.502	3.696	3.928	4.114	4.218	4.459

8. Seasonal patterns in the electricity price



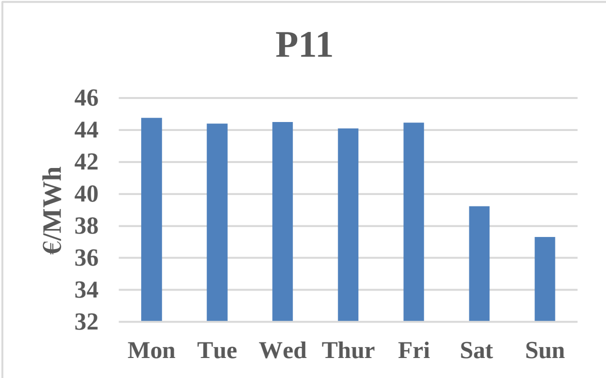


Figure A.2: The figure shows variations in the average electricity price across weekdays in period 04 and 11, respectively. Data spans from 2 January 2006 to 31 December 2014.

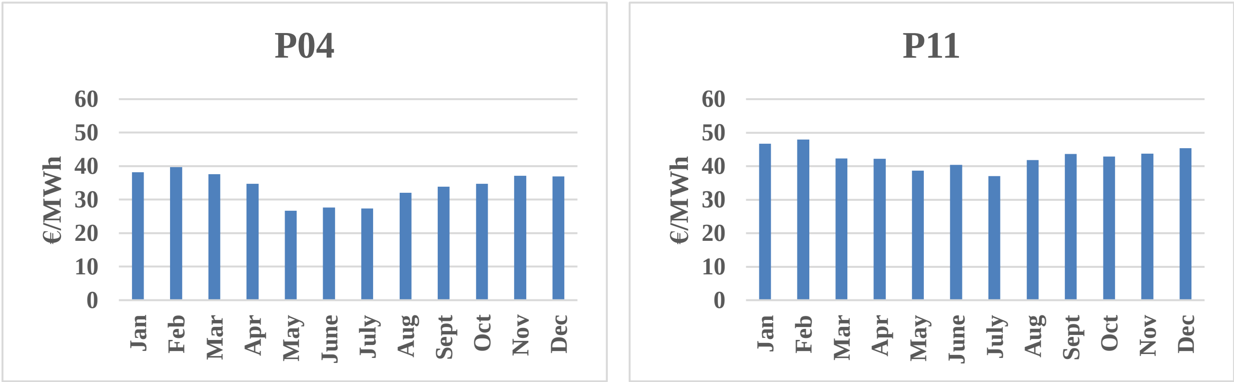


Figure A.3: The figure shows variations in the average electricity price across months in period 04 and 11, respectively. Data spans from 2 January 2006 to 31 December 2014.

B Descriptive Statistics of Fundamental Factors

Table B.1: The table presents the mean, median, minimum observation, maximum observation, standard deviation, skewness and kurtosis of the fundamental factors.

Variable	Mean	Median	Min	Max	Std dev	Skewness	Kurtosis
Demand04	37537.310	36800.500	11812.000	56831.000	7086.575	0.371	2.187
Demand11	47637.430	46649.000	14555.000	68604.000	8351.183	0.241	2.368
Reservoir	50996.160	53016.000	14831.000	77014.000	15828.740	-0.326	2.059
Wind04	921.598	663.600	1.300	4270.800	828.856	1.180	3.803
Wind11	1017.466	745.100	0.800	4385.500	900.073	0.994	3.257
Gas	62.325	66.380	24.762	123.112	18.278	-0.286	2.595
Oil	66.628	66.186	26.614	96.850	15.993	-0.224	1.870
Coal	44.480	43.656	28.643	90.921	10.363	1.304	5.699
CO2	10.760	10.265	0.010	29.800	7.067	0.524	2.719
El-certificate	24.051	23.011	0.106	43.013	5.155	0.608	4.179
Volatility04	2.511	1.729	0.121	18.524	2.440	2.599	11.480
Volatility11	4.267	3.149	0.422	61.947	4.530	6.326	63.787

9. Correlation between the electricity price and fundamental factors

Table B.2: The table presents the correlation between the electricity price level in period 04 and period 11 with their respective fundamental factors.

	P04	P11
Demand04	0.381	-
Demand11	-	0.350
Reservoir	-0.295	-0.238
Wind04	-0.105	-
Wind11	-	-0.155
Gas	0.190	0.180
Oil	-0.075	-0.038
Coal	0.255	0.341
CO2	0.401	0.465
El-certificate	0.200	0.249
Volatility04	-0.182	-
Volatility11	-	0.339

10. Correlation between fundamental factors

Table B.3: The table presents the pairwise correlation of fundamental factors in the model for period 04.

	Demand04	Reservoir	Wind04	Gas	Oil	Coal	CO2
Demand04	1.000						
Reservoir	-0.296	1.000					
Wind04	0.199	0.033	1.000				
Gas	0.173	0.195	0.166	1.000			
Oil	-0.132	0.076	0.170	0.532	1.000		
Coal	-0.052	0.030	-0.028	0.551	0.442	1.000	
CO2	-0.003	-0.181	-0.189	0.164	-0.131	0.575	1.000
El-certificate	0.072	-0.017	-0.076	-0.056	-0.156	0.342	0.378
Volatility04	-0.311	0.044	-0.021	0.019	0.093	0.204	0.137

	El-certificate	Volatility04
El-certificate	1.000	
Volatility04	0.007	1.000

Table B.4: The table presents the pairwise correlation for fundamental factors in the model for period 11.

	Demand11	Reservoir	Wind11	Gas	Oil	Coal	CO2
Demand11	1.000						
Reservoir	-0.202	1.000					
Wind11	0.150	0.023	1.000				
Gas	0.174	0.195	0.131	1.000			
Oil	-0.134	0.076	0.160	0.532	1.000		
Coal	-0.049	0.030	-0.031	0.551	0.442	1.000	
CO2	-0.016	-0.181	-0.175	0.164	-0.131	0.575	1.000
El-certificate	0.069	-0.017	-0.071	-0.056	-0.156	0.342	0.378
Volatility11	0.263	-0.078	-0.020	0.042	0.061	0.129	0.145

	El-certificate	Volatility11
El-certificate	1.000	
Volatility11	0.089	1.000

11. Distribution of demand and water reservoir level

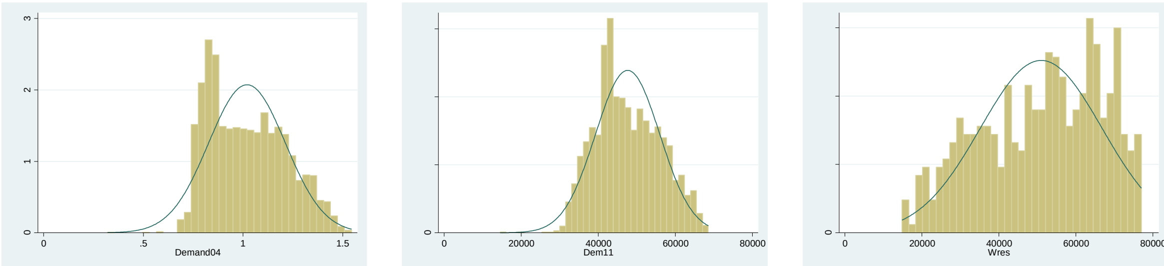


Figure B.1: The figure shows the distribution of demand in period 04, demand in period 11 and water reservoir level, respectively, compared to the normal distribution illustrated by the blue line. The horizontal axis measures demand in MWh and water reservoir level in GWh, respectively, while the vertical axis measures the density. The normal distribution has no skewness and a kurtosis coefficient of 3.

12. The Jarque-Bera test for normality: Demand and water reservoir level

*Table B.5: The table presents the Jarque-Bera test for normality performed on the demand and water reservoir level series. H_0: Skewness and excess kurtosis are jointly zero. Under H_0, the JB statistic follows a chi-squared distribution. Critical value for 1% significance level and 2 degrees of freedom is 9.210. The asterisks *** mean rejection of H_0 at 1% significance level.*

Variable	Demand 04 in MWh	Demand 11 in MWh	Water reservoir level in GWh
Skewness	0.370	0.241	-0.326
Kurtosis	2.187	2.369	2.059
Test statistic	1675.852***	873.359***	1818.120***

C Peak- and Off-Peak Period

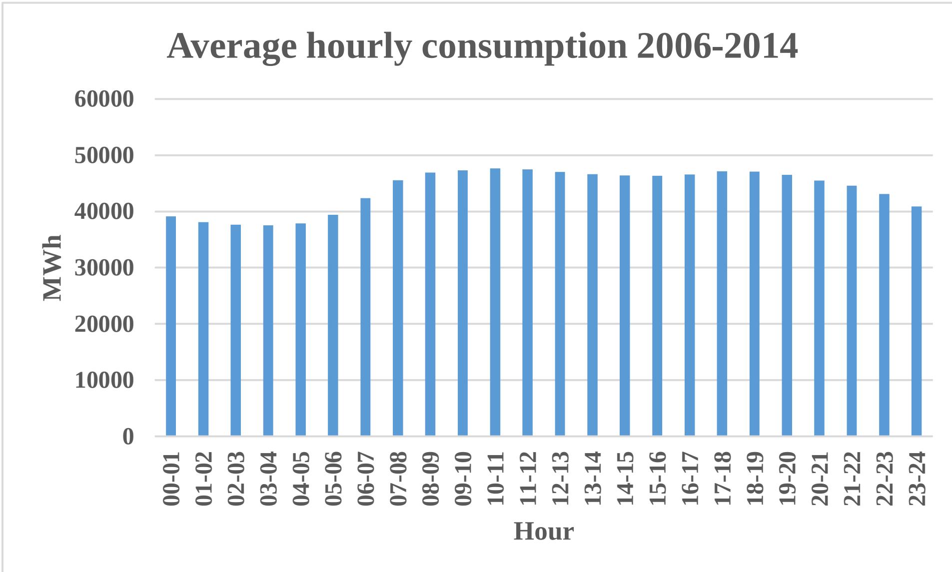


Figure C.1: The figure shows average hourly demand. Period 11 (10:00-11:00) and period 04 (03:00-04:00) are the peak-and off-peak periods, meaning they have the highest and lowest average hourly demand in the dataset, respectively.

D CO$_2$ Emissions Allowance Price Dummy Variable

13. OLS regression

The Chow test splits the data series into two sub-periods and then tests for parameter stability. OLS regressions are the point of departure for the Chow test.

The following OLS regressions are run:

$$\begin{aligned} \ln CO2_t &= \alpha_0 + \alpha_1 \ln gas_t + \alpha_2 \ln oil_t + \alpha_3 \ln coal_t + \alpha_4 Di + \alpha_5 Di \ln gas_t \\ &\quad + \alpha_6 Di \ln oil_t + \alpha_7 Di \ln coal_t + u_t \end{aligned} \qquad (D.1)$$

where i=1,2 and t=(1 January 2006, 30 December 2014) for model 1 and t=(26 April 2006, 30 December 2014) for model 2, respectively.[1]

14. Test 1: A structural break on 26 April 2006

The data spans from 1 January 2006 to 30 December 2014. The sub-periods are T_1= 1 January 2006 to 25 April 2006 and T_2=26 April 2006 to 30 December 2014, respectively. The dummy variable D_1 equals 1 for t in T_1 and 0 otherwise.

*Table D.1: The table shows OLS regression results with time span from 1 January 2006 to 30 December 2014. The asterisks *** mean the coefficient is significant at 1% level.*

Variable	Coefficient
Gas	-0.735***
Oil	-0.779***
Coal	4.255***
D1	5.527
Gas*D1	0.475
Oil*D1	1.648
Coal*D1	-3.363
Constant	-7.973***
R^2	0.278

[1] The CO$_2$ emissions allowance price is also referred to as the EUA price.

15. Test 2: A structural break on 1 February 2008

The data spans from 26 April 2006 to 30 December 2014. The sub-periods are T_1= 26 April 2006 to 31 January 2008 and T_2= 1 February 2008 to 30 December 2014, respectively. The dummy variable D_2 equals 1 for t in T_1 and 0 otherwise.

*Table D.2: The table shows OLS regression results with time span from 26 April 2006 to 30 December 2014. The asterisks *** mean the coefficient is significant at 1% level.*

Variable	Coefficient
Gas	-1.087***
Oil	-0.684***
Coal	2.496***
D2	19.702***
Gas*D2	2.707***
Oil*D2	-16.491***
Coal*D2	9.380***
Constant	0.097
R^2	0.679

16. The Chow test for structural break

*Table D.3: The Chow test for structural break. H_0: There is no structural break in the data series, i.e. $\alpha_4 = \alpha_5 = \alpha_6 = \alpha_7 = 0$. Under H_0, the Chow statistic follows an F-distribution. Critical value for 1% significance level is 3.32 for both tests. The asterisks *** mean rejection of H_0 at 1% significance level.*

Test	Test 1	Test 2
Numerator degrees of freedom	4	4
Denominator degrees of freedom	3278	3163
Test statistic	27.01***	1045.52***

17. White's test for heteroscedasticity

*Table D.4: White's test for heteroscedasticity. H_0: The error terms are homoscedastic. Under H_0, the test statistic follows a chi-squared distribution. Critical value for 1% significance level and 19 degrees of freedom is 36.191 for both tests. The asterisks *** mean rejection of H_0 at 1% significance level.*

Model	Model 1	Model 2
Test statistic	704.65***	2249.22***

E Quantile Regression Results

18. Period 04

*Table E.1: The table presents quantile regression results for the 1%, 5%, 10%, 25% and 50% quantile in period 04. The asterisks *, ** and *** mean the coefficient is significant at either 10%, 5% or 1% level, respectively.*

	1%	5%	10%	25%	50%
Yesterday's price	1.004***	1.004***	1.005***	0.922***	0.848***
Last week's price	0.247**	0.142	0.079	0.068**	0.085***
Demand	0.488**	0.243**	0.204***	0.217***	0.178***
Reservoir	0.101	0.081	0.041	-0.036***	-0.051***
Wind	-0.015**	-0.016***	-0.015***	-0.015***	-0.014***
Gas	-0.116	-0.037	-0.027**	-0.002	0.003
Oil	0.355***	0.032	0.039**	0.015*	0.010
Coal	-0.220	-0.055	-0.025	-0.001	0.011
EUA	0.005	-0.003	-0.001	0.002	0.002
El-certificate	-0.038	-0.005	-0.007	0.007	0.005
Volatility	-0.171***	-0.091***	-0.063***	-0.024***	0.005**
DBreak	0.082	-0.014	-0.011	-0.001	0.000
DWeekend	-0.049	-0.027*	-0.014**	-0.015***	-0.006**
DFeb	-0.100**	0.004	-0.004	-0.019***	-0.021***
DMar	-0.070	0.032	0.018*	-0.017**	-0.029***
DApr	-0.001	0.042	0.030	-0.006	-0.019**
DMay	-0.834**	-0.014	-0.011	0.014	0.010
DJune	-0.138	0.016	0.026	0.057***	0.046***
DJuly	-0.426	-0.208	0.014	0.067***	0.064***
DAug	0.007	0.093	0.072**	0.097***	0.088***
DSept	0.103	0.048	0.050**	0.071***	0.067***
DOct	-0.045	0.031	0.024	0.055***	0.053***
DNov	-0.033	0.023	0.027*	0.040***	0.033***
DDec	-0.136**	-0.021	-0.001	0.013*	0.014***
Constant	-1.175	-0.320	-0.234**	-0.008	0.180***
R^2	0.657	0.711	0.720	0.731	0.732

*Table E.2: The table presents quantile regression results for the 75%, 90%, 95% and 99% quantile in period 04. The asterisks *, ** and *** mean the coefficient is significant at either 10%, 5% or 1% level, respectively.*

	75%	90%	95%	99%
Yesterday's price	0.703***	0.611***	0.511***	0.362***
Last week's price	0.130***	0.108***	0.108***	0.089***
Demand	0.236***	0.291***	0.264***	0.345**
Reservoir	-0.113***	-0.175***	-0.256***	-0.401***
Wind	-0.013***	-0.011***	-0.010***	-0.009
Gas	0.010	0.007	0.000	-0.024
Oil	-0.006	-0.027	-0.071**	-0.183***
Coal	0.066***	0.127***	0.215***	0.395***
EUA	0.005***	0.009***	0.007*	0.000
El-certificate	0.012***	0.015**	0.018	0.025
Volatility	0.025***	0.043***	0.053***	0.062***
DBreak	0.024***	0.069***	0.095***	0.108***
DWeekend	-0.007**	-0.003	-0.001	0.012
DFeb	-0.033***	-0.033***	-0.034**	-0.043
DMar	-0.056***	-0.065***	-0.084***	-0.130***
DApr	-0.040***	-0.060***	-0.093***	-0.155***
DMay	0.012	0.009	-0.044	-0.045
DJune	0.083***	0.105***	0.103*	0.208
DJuly	0.096***	0.123***	0.107	0.234**
DAug	0.126***	0.145***	0.164***	0.233***
DSept	0.109***	0.151***	0.159***	0.210***
DOct	0.087***	0.126***	0.139***	0.149***
DNov	0.057***	0.074***	0.089***	0.110***
DDec	0.023***	0.041***	0.050***	0.035*
Constant	0.342***	0.601***	0.853***	1.373***
R^2	0.716	0.682	0.642	0.602

19. Period 11

*Table E.3: The table presents quantile regression results for the 1%, 5%, 10%, 25% and 50% quantile in period 11. The asterisks *, ** and *** mean the coefficient is significant at either 10%, 5% or 1% level, respectively.*

	1%	5%	10%	25%	50%
Yesterday's price	0.768***	0.756***	0.702***	0.685***	0.589***
Last week's price	0.290***	0.270***	0.292***	0.272***	0.334***
Demand	0.491***	0.302***	0.290***	0.284***	0.314***
Reservoir	-0.027	-0.032	-0.061**	-0.050***	-0.050***
Wind	-0.008	-0.014***	-0.014***	-0.013***	-0.015***
Gas	0.060	0.007	-0.004	0.003	-0.003
Oil	-0.085*	-0.016	-0.001	0.008	0.019***
Coal	-0.130	-0.002	0.011	0.017	0.030***
EUA	0.000	0.003	0.003	0.003**	0.003***
El-certificate	0.023	0.025	0.016	0.013	-0.004
Volatility	-0.132***	-0.092***	-0.064***	-0.036***	-0.008***
DBreak	-0.037	-0.005	0.001	0.004	0.005
DWeekend	-0.066	-0.024**	-0.019**	-0.017***	-0.008
DFeb	0.003	-0.003	-0.022	-0.020**	-0.021***
DMar	0.051	0.017	-0.007	-0.016*	-0.019**
DApr	0.162*	0.066*	0.023	0.014	0.016
DMay	0.124	0.031	0.037	0.049***	0.064***
DJune	0.309***	0.162***	0.133***	0.102***	0.097***
DJuly	0.228**	0.118***	0.115***	0.108***	0.110***
DAug	0.285***	0.189***	0.162***	0.139***	0.131***
DSept	0.221	0.129***	0.119***	0.101***	0.102***
DOct	0.132	0.096***	0.100***	0.080***	0.079***
DNov	0.124*	0.089***	0.075***	0.057***	0.051***
DDec	0.040	0.045**	0.035***	0.025**	0.011
Constant	0.153	-0.154	-0.065	0.018	0.151***
R^2	0.746	0.740	0.740	0.740	0.737

*Table E.4: The table presents quantile regression results for the 75%, 90%, 95% and 99% quantile in period 11. The asterisks *, ** and *** mean the coefficient is significant at either 10%, 5% or 1% level, respectively.*

	75%	90%	95%	99%
Yesterday's price	0.512***	0.462***	0.435***	0.435***
Last week's price	0.338***	0.308***	0.261***	0.313***
Demand	0.418***	0.479***	0.488***	0.691***
Reservoir	-0.081***	-0.108***	-0.103***	-0.081
Wind	-0.018***	-0.018***	-0.017***	-0.024***
Gas	0.007	-0.005	-0.042*	-0.141**
Oil	0.021*	0.035**	0.076***	0.180***
Coal	0.032**	0.078***	0.115***	0.032
EUA	0.007***	0.010***	0.015***	0.024***
El-certificate	0.009**	0.017**	0.022	0.045**
Volatility	0.018***	0.057***	0.083***	0.134***
DBreak	0.018**	0.045***	0.068***	0.073**
DWeekend	0.000	0.001	0.006	0.060**
DFeb	-0.040***	-0.059**	-0.099***	-0.145
DMar	-0.045***	-0.083***	-0.120***	-0.245***
DApr	-0.005	-0.048	-0.095**	-0.168
DMay	0.072***	0.048	-0.008	-0.098
DJune	0.108***	0.088**	0.013	-0.036
DJuly	0.138***	0.151***	0.104**	0.011
DAug	0.159***	0.154***	0.087**	-0.016
DSept	0.124***	0.120***	0.074*	-0.002
DOct	0.084***	0.081***	0.027	-0.050
DNov	0.047***	0.031	-0.026	-0.134*
DDec	0.012	-0.014	-0.064**	-0.158**
Constant	0.347***	0.454***	0.605***	0.757***
R^2	0.717	0.687	0.669	0.664