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Hydro reservoir levels and power price dynamics. Empirical insight on the nonlinear influence of fuel and emission cost on Nord Pool day-ahead electricity prices

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Abstract

This paper examines the dependency of the hourly day-ahead electricity price on fundamentals in the Nord Pool power market. We examine whether power prices depend differently on supply and demand variables when hydro reservoir levels are low than when they are high as we expect that the competitive environment changes as a consequence. When reservoir levels are high, all hydro power producers want to sell to prevent invaluable spillovers, which leads to competitive pressure. With lower reservoir levels, hydro power agents are more preserved about their actions. We examine the change in dynamics using a supply and demand model and split the sample in observations from periods with extreme low and high reservoir levels. We show that the parameters of the supply curve model significantly differ over the two samples. In addition, we show that the influence of the marginal costs on the price formation is significantly larger at lower reservoir levels. The insights of this paper improve the understanding of power price dynamics in relation with fundamental

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1 Introduction

Currently, the Nord Pool, which consists of the Scandinavian countries; Norway, Sweden, Finland, Denmark and the Baltic States, is one of the world's largest, multinational, deregulated and advanced power market, with a yearly average electricity production of 420 TWh[4]. The three most important production technologies in the Nord Pool are hydro, thermal and nuclear power production, with hydro power, of which the "fuel", i.e. water, is stored into reservoirs, accounting for roughly half of the total power generation. The volume of these reservoirs varies considerably over time due to seasonal fluctuation of water inflow.

In a highly competitive market, like the Nord Pool, the short run marginal costs of the last required power plant to meet demand, i.e. the marginal technology, set the wholesale electricity price. This is called marginal price setting (Nielsen et al. (2011)). Generally, the marginal cost of hydro power is significantly lower than the marginal cost of thermal power. Hydro power requires no CO_2 certificates and the input for the hydroelectricity plants is basically for free. On the contrary, the marginal cost of a fossil-fuel power plant consists out of fuel cost and CO_2-emission costs.

In the Nordic power market the influence of these marginal costs on the wholesale electricity price seems to vary over time. This follows from hydro power producers having the choice to either generate electricity now or to wait. The value of this decision, i.e. the marginal cost of hydro power, depends on the expected loss from not being able to produce electricity in the future. When reservoir levels are (almost) full, the value of this option is low (or even zero). More electricity will be generated by hydro power stations, as not producing could lead to spillovers, which won't earn the producers anything. Hence, thermal power production technologies will be utilized to a lesser extent.
When reservoir levels are low, the value of this option is higher, i.e. higher marginal cost. Hydro producers will pick the moments when to produce more carefully and thermal production facilities will be needed more frequently to meet demand. Resultantly, thermal power production will be the marginal technology more often, which leads to a larger influence of the marginal cost of thermal power production on the electricity wholesale price for high reservoir levels, relatively to low reservoir levels.

The influence on the price formation from thermal power generation technologies, thus, seems to fluctuate over time as a natural result of varying reservoir levels. Or in other words, there seems to be

[4] Source: www.NordPoolspot.com.

a non-linear dependency of the wholesale electricity price on fuel and emission prices due to the varying availability of hydro supply in the Nordic power market.

In this paper, we examine whether the influence of fuel and emission cost on the hourly day-ahead electricity price, actually, is nonlinear. In order to capture these dependencies, which evolve around the supply side of the market, the demand and supply framework is used to structure a supply-curve. To account for price spikes, a prominent feature of electricity spot prices, a power function is proposed motivated by Huisman et al. (2014). Firstly, we investigate whether such a model actually succeeds in explaining the variation in the hourly day-ahead electricity price. Subsequently, the possible nonlinear relationship is examined via regressions on low and high reservoir level subsamples. Redl et al. (2009) also examine the fluctuations in hydro capacity, together with low and high thermal power generation, in forward prices at the Nord Pool. However, in the Nordic market over 80% of the trades are done at the day-ahead market. Also, nonlinear relations between the marginal costs and electricity prices are found in other day-ahead markets (e.g. Zachmann (2012)). But to our knowledge none articles exist examining these nonlinear interactions for the Nordic day-ahead electricity market. Our sample spans the period January 1st, 2011 to April 28th, 2013.

Knowledge about the form of the influence of fuel and emission prices on electricity prices in a market dominated by hydro power is important for multiple reasons. Firstly, understanding the influence of hydro supply on the price due to actions of hydro producers, is important in a competitive market for all power producers. Not only for hydro producers but also for thermal power producers, who need to compete with the lower marginal production cost of hydro power. Secondly, understanding the influence of the price determinants and changes in those dependencies over time is of vital importance for policymakers. An incomplete understanding of these relations could lead to an unintended outcome of the implied policy. And lastly, relations between the marginal cost and the wholesale electricity price could be used to evaluate the efficiency of the examined power markets. This paper advances the current literature by providing a first insight on how the electricity price dependencies on fuel and emission prices vary with hydro supply. These factors can contribute to the literature on fundamental electricity price models. Next to that, this paper contributes to papers on the influence of hydro power on electricity wholesale prices.

The results show that a supply curve structured with reservoir level, the CO_2 emission permit and the natural gas price explains 0.68 of the total variation in the hourly spot price. The model shows that hydro supply has a decreasing effect on the day-ahead electricity price and fuel prices and emission prices an increasing effect. The subsamples analysis shows that the parameters of the structured supply curve should be time-varying, from which we conclude that the parameters have a different influence on the electricity price for varying availability of hydro supply. This shows that agents have different competitive behavior for different reservoir levels, which changes the competitive setting in the power market. The results, also, show that the emission permit and natural gas price explain significantly more of the variation in the day-ahead electricity price when reservoir levels are low. Providing empirical evidence that thermal power production facilities are more often the marginal technology when reservoir levels are low. Both show the nonlinear relationship between the input prices and the day-ahead electricity price at the Nordic power market.

This paper is structured as follows. Paragraph 2 provides a theoretical framework and summarizes previous relevant articles. Paragraph 3 explains the relevant methodology. The data is described in paragraph 4. Subsequently, paragraph 5 provides the results and paragraph 6 discusses the limitations of the research. Lastly, paragraph 7 concludes.

2 Power prices in the Nord Pool market

This paragraph styles the theoretical framework for this paper.

2.1 The Nordic power market

In the beginning of the nineties the Scandinavian countries deregulated their domestic electricity markets with the goal to create more efficient power markets. This led, in 1996, to the establishment of a power exchange between Sweden and Norway named the Nord Pool ASA. Two years later Finland joined this power exchange and with the start of the 21st century the Scandinavian power market became fully unified after the integration of Denmark. Currently, the Nordic power market consists of the Scandinavian countries, the Baltic States and it is connected via submarine power cables or power grid lines with the Netherlands, Germany, Poland and Russia. This large web of connections makes the Nordic Power market, i.e. the Nord Pool, the most integrated and advanced power exchange in the world and accommodates in offering a secure supply of electricity. The Nord Pool Spot runs this broad energy exchange and offers both intraday and day-ahead markets.

Within each country different electricity production possibilities exist. Some countries have favorable weather conditions accommodating renewables, others do not and need to exploit different opportunities. Therefore, also within the Nordic market the produced electricity stems from a variety of power sources. Table 1 shows this variety in the production split of the Nord Pool in 2011[5]. Remarkable is that more than half of the total power supply in the Nordic market consists of hydropower. In Norway 95%, 121.4 TWh, of the power supply comes from hydro-based generators and in Sweden hydropower accounts for nearly half of the total electricity supply. The water used to generate this hydropower is stored in large reservoirs for which the required conditions are optimal in

[5] The Nordic production split for 2012 is included in Appendix 9.1 Table A1 and shows similar numbers as Table 1.

Norway. The second largest power source is nuclear power, which is situated only in Sweden and Finland. The third largest power supply is thermal power, which is located mainly in Finland, Denmark and the Baltic States. The remaining share of capacity in the Nord Pool consists of wind power and other renewables, respectively 4.4% and 6.4%[6]. Altogether, the Nordic power market has three main generation technologies; hydropower, nuclear power and thermal power.

Country / Energy source	Denmark	Finland	Norway	Sweden	Sum	Share of total generation (in %)
Hydropower	0.0	12.3	121.4	65.8	199.4	52.9
Nuclear power	0.0	22.3	0.0	58.0	80.3	21.3
Fossil fuels	21.8	24.2	4.8	5.4	56.1	14.9
Wind power	8.9	0.5	1.3	6.1	16.7	4.4
Other Renewables	2.4	10.5	0.0	11.2	24.1	6.4
Non-identifiable	0.0	0.7	0.0	0.0	0.7	0.2
Total production	33.1	70.4	127.4	146.4	377.4	100.0

Table 1: The production split of electricity in the Nordic area for 2011 in TWh for each country. The last column shows the shares per different generation technologies of the total electricity production in percentages. *Source: NordPool Spot – Production Split 2004 – 2012.*

2.1.1 Price formation and marginal cost

The main motive for the deregulation of the electricity markets was to increase the market competition, which had to result in a more cost efficient power market. Profit-seeking firms will try to improve their efficiency to minimize costs both in the short and long-run. Also, should the deregulation provide more security of supply and put downward pressure on the prices (Stoft 2002). An important part of a deregulated power market is a Power Exchange, with a day-ahead power market, i.e. spot market, for determining the market price using the rules of demand and supply, and a derivatives market for hedging purposes.

In the Nord Pool the day-ahead market for commercial players is the Elspot, which is run by Nord Pool Spot. On the Elspot, all participants, both buyers and sellers, have to place their bids and offers for each individual hour before 12 am the day *before* the actual delivery of electricity takes place[7]. Or stated differently, 12 to 36 hours before the physical transaction. All these individual bids are

[6] Table 1 shows the production split over a full year, namely 2011, but when observing the production per hour one obtains a similar result. For example, on the 19th of August 2013 between 6pm and 7pm, 39,100 MW of power was produced which consisted of 22,621 MW hydropower, 8,004 MW nuclear power, 6,593 MW thermal power, 1,335 MW wind power and 547 not specified power. This shows, again, that more than half of the produced electricity is hydropower. *Source:* http://www.statnett.no/en/Market-and-operations/Data-from-the-power-system/Nordic-power-balance/

[7] This is why it is also called a double-auction, as both buyers and suppliers have to place their bids.

accumulated to an aggregated demand and supply curve for each individual hour of the next day. The intersection of the hourly aggregated demand and aggregated supply curve is the hourly system price. This is the price that *every* buyer has to pay and *every* seller receives and is actually the winning bid with the highest price. The term for this type of price formation is uniform price setting, i.e. the same price for all the players or alternatively, a *marginal price auction system*, hereinafter referred to as "MPS" (Nielsen et al. 2011).

The market clearing price is, according to economic theory, in a market with perfect competition equal to the short-run marginal cost of production. In a MPS an equivalent relation is apparent between the market clearing price and the offers of the suppliers, which makes the short term marginal production costs and the bids of the suppliers (almost) equivalent to each other. The reason for this equality is simple, namely to win as much bids as possible. How? From a profit perspective this is quite reasonable. Bidding lower than the short-run marginal costs will, logically, not be sufficient enough to cover the (inevitable) short run production costs.

On the other side, a supplier must realize two things. Firstly, that it is the equilibrium price of the aggregated demand and supply curve that sets the market price. This price is actually the highest winning bid and is not the price bid by the supplier. And secondly, that the supplier benefits from every (positive) difference between the market price and his short run marginal cost. Meaning that if the supplier places a bid that is higher than his short run marginal costs, the supplier creates the possibility to lose the auction when the market price falls in between his short run marginal costs and his (larger) bid. In this setting, the supplier is thus in favor of placing a bid equal (or at least very close) to his short-run marginal cost. It is namely that offer, equal to the short run marginal cost, that not only gives the supplier the highest probability of winning the bidding, but next to that automatically lets the supplier earn a margin when a higher bid wins the auction (Cramton et. al. 2001). The MPS, therefore, forces the offers of the suppliers to the short-run marginal costs. This is similar to an efficient market, where the competition drives the market clearing price to the short-run marginal cost of production.

To summarize, the market clearing price in the electricity spot market is set, at each individual point in time, by the short run marginal cost of the last required power plant to meet demand. For the reason that it is the marginal cost of the last required power plant that is the most expensive winning suppliers' bid (Nielsen et al. 2011). If this does not apply the market is not efficient[8].

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[8] This is not entirely true. The electricity market clearing price can differ from the marginal cost under special circumstances. This is the case when the electricity demand is extremely high and the market utilizes all its available supply capacity. In this situation, due to scarcity, the market clearing price of electricity could be higher than the marginal cost of the last required generation technology to meet demand.

2.1.2 Marginal cost function of the Nord Pool

Table 1 shows that electricity in the Nord Pool is generated by a combination of different generation technologies. Different generation technologies, logically, have different marginal costs too. These costs even vary between power plants within the same generation technology. The marginal costs of a power plant consist mostly out of the variable costs for fuel, CO_2 emission allowances and operation and maintenance costs. In academic literature it is common to rank all generation units in a certain market at ascending order to its marginal cost, this is called a marginal cost function or supply stack (Weron et al. 2004, Sensfuss et al. 2008, Nielsen et al. 2011 and others) The real marginal cost curve can be approximated by a stepwise function. The model has this stepwise form, because the difference between the marginal cost within a group with similar generation technology is small, compared to the difference between the marginal costs of dissimilar generation technologies.

Since all suppliers place bids that are (almost) equal to their short term marginal cost, the marginal cost function approximates the short term supply curve of the power market. As explained above, the suppliers in the Nord Pool, despite the fact that some offer to sell against lower prices, will all receive the same price, which is the short run marginal cost of the last power plant required to meet demand i.e. the merit order principle (Sensfuss et al. 2008)). The equilibrium point is the intersection of the short term demand curve with the supply stack function.

Figure 1: Simplified and structured form of the short-run marginal cost function in the Nordic power market. The figure shows the stepwise marginal cost function, with every step being a different electricity generation technology.

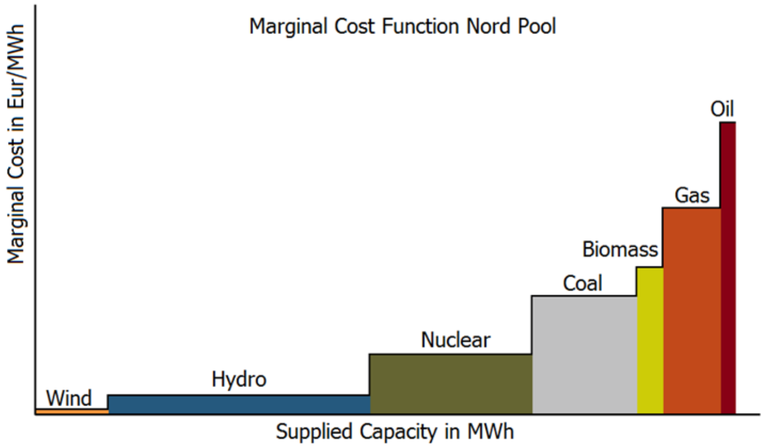

Figure 1 shows an approximation of the real marginal cost function for the Nord pool. The stepwise form, with every step being a different generation technology, is clearly visible. Last in line are the short-run marginal cost of thermal power supply; coal, gas and oil. In the Nord Pool, the thermal supply capacity is used to balance the fluctuations in hydropower caused by variations in water inflow. These generation technologies have relatively higher fuel cost and also have costs for CO_2 emission certificates. The fuel cost depends on the price of the corresponding fuel and on the efficiency of the power plant. The emission cost depends on the price of an emission allowance and the emission intensity of the power station (Redl et al. (2009)). The order of rank of these generation technologies depends on those factors, but in general are the marginal costs of a gas-fired power plant much higher than the marginal costs of a coal-fired power plant. Reversely, the start-up time of a coal fired power plant is longer than for a gas fired power plant. This makes the gas fired power plant more costly, but more flexible. For those reasons, gas-fired power plants only operate when demand is (very) high and coal-fired power plants provide a more constant load of supply. The generation technology that is the marginal technology that produces depends on the many factors that affect the demand and/or supply of electricity.

Nuclear power supply has very low short run marginal costs at around 10 €/MWh (Roques et al. (2006)). The reason for this is that the fuel cost and other variable cost are relatively low. A nuclear power plant is rather inflexible in its production and is most cost-effective when generating electricity on a constant level over time. Nuclear power, therefore, provides a constant base load power supply.

The marginal cost of wind power and hydropower are the lowest. The marginal cost of hydropower, wind power (and most other renewables) are close to zero[9]. This is quite reasonable, as there are no fuel or emission costs to run the sustainable power plants. Renewables produce electricity only if the input, e.g. wind or water, is available and are highly dependent on weather conditions. For that reason, renewables are also referred to as must-run generation. For example, the "fuel" for the hydroelectricity plants is water, which has no costs but is highly dependent on precipitation and melting snow. Resultantly, the available quantity of water to produce hydroelectricity varies considerably over time. Similar scenarios apply to wind or solar power. The only difference with hydropower is that the input, i.e. water, can be stored into reservoirs. This storability creates indirect costs, namely opportunity costs, as the decision needs to be made to either produce hydropower now or wait and generate electricity in the future against a possible better price. These opportunity costs, and thus the marginal cost, become smaller or become zero when the reservoirs are almost or entirely full and increase again when the hydro capacity decreases (Torró (2007)).

The different generation technologies, the MPS and the variation in the hydro capacity lie at the heart of this paper. The structure of the marginal cost function changes for different reservoir levels. To see this, two (extreme) situations are discussed. Hydro producers have the option to either generate hydropower or to wait. They decide, whether, the gain from producing hydro power now outweighs the expected loss from not being able to generate in the future when the prices are possibly higher. When reservoir levels are almost empty, the value of this option is high, i.e. high marginal costs, as producing now means even lower reservoir levels. Resultantly, to meet the demand more electricity is needed from other power producers, i.e. thermal producers which act as the swing-production state in the Nord Pool.

On the other side, when reservoir levels are almost full, the value of this option is almost zero, i.e. low marginal cost. Hydro producers will sell against lower prices in order to avoid spillovers, which won't earn the producers anything. Resultantly, less power is needed from other (thermal) power producers. As the production cost of the marginal technology set the price, the different components of those marginal costs will have an influence on the wholesale electricity price. The influence of the marginal cost of thermal power production, thus, seems to vary for different reservoir levels. Firstly, as one

[9] Some renewables even have negative marginal cost. This is, for example, the case when the generation of sustainable energy is subsidized per production unit (Nielsen et al. 2011).

would expect when reservoir levels are lower, more power needs to be generated by thermal power production units. Once reservoirs are almost full, more hydro supply is available and thermal production units will less frequently be the marginal technology. And secondly, due to the fact that the marginal cost, i.e. opportunity cost, of hydropower production varies for different reservoir levels. Based on this, a nonlinear relation seems apparent between the production fuel prices and CO_2 certificate prices, and the day-ahead wholesale electricity price. Lucia et al. (2008) hypothesize this nonlinear relation as the electricity wholesale price responding unequally to being in a situation of tight market conditions (almost full reservoirs) compared to being in a situation with low hydro supply (almost empty reservoirs). This paper examines if the influence of the production fuels prices and the emission prices actually is nonlinear for varying reservoir levels. The next section, discusses previous articles that covered a similar topic.

2.2 Literature on (Nord Pool) power prices and fundamentals

Firstly, some articles on cointegration are discussed as an introduction to the link between production fuels and electricity prices. Secondly, articles that more thoroughly examine the (nonlinear) relation between production fuels, emission allowances and electricity price series are discussed and relevant findings are highlighted.

2.2.1 Cointegration

A method often used to examine the existence of a possible link between commodity price series is cointegration and was first introduced by Engle and Granger (1987). Cointegration tries to capture common price movements and dynamics between different commodity price series. Emery et al. (2002) apply the cointegration technique between commodity and electricity price series. They analyze daily data of the NYMEX's electricity futures price of California-Oregon Border and Palo Verde and the price of natural gas future contracts over the sample period 03-29-1996 to 03-31-2000. They show that the futures price series are co-integrated and observe in both markets similar sensitivities for the two electricity futures price series to movements in the natural gas price series. Their explanation is that this is due to the fact that natural gas is in both markets the marginal technology for peak hour electricity production. Secondly, they show that only electricity prices respond to changes in the relationship, but gas prices not. This differs from their expectations, but the asymmetric response is explained by the fact that natural gas has multiple purposes and generating electricity is merely one of it, while for the power production natural gas is a very important resource.

Mjelde et al. (2009) study if dynamic relationships exist between different production fuels; uranium, natural gas, oil and coal, and US peak and wholesale off-peak day-ahead electricity prices for the

PJM[10] and Mid-C[11]. Their results show that the peak prices in both the PJM market and the Mid-C market respond similarly to shocks in the prices of natural gas. Next to that, they find that both peak and off-peak prices show equivalent movements to shocks in the production fuel price series. The strongest reactions are the result of shocks in the price series of the production fuel coal. The authors explain that this is due to the fact that a large share of the total electricity production is generated using coal.

Mohammadi (2009) investigates the long-run connections and the short-run dynamics between electricity prices and the prices of three fossil fuels, namely oil, coal and natural gas in the US. The data set contains yearly wholesale electricity prices and yearly fossil fuel prices in the United States over the period 1960 until 2007. A vector-error-correction model (VECM) is used to check for long and short-run causality among the electricity and fuel prices. The short-run dynamics are further analyzed with impulse response functions and variance decomposition. The results provide evidence of a statistical significant long-run relationship between wholesale electricity prices and the coal price, which is reasonable due to the importance of coal in the power production process, but do not show evidence for the long-run connection between electricity prices and the prices of gas and oil. The results, also, hint to an unidirectional influence from both natural gas prices and coal prices to the electricity price. As an explanation, the author points to the high capital costs in the power market and that fuel prices only encompass a minor part of the total costs.

2.2.2 Nonlinearity

The literature on the relation between electricity prices and commodity prices is substantial and over the recent years, as a result of more data availability and data at a higher frequency, it is vastly increasing. Kaminski (1997), when listing some facts of electricity prices, already mentions that a model for electricity prices needs to incorporate the changing correlation structure between electricity prices and possible electricity production fuel prices. A paper that develops a model to study the relationship of power supply and production fuels is Routledge et al. (2001). They develop an advanced general equilibrium model linking input fuel prices to output prices, which incorporates both the indirect storage possibilities of electricity via other commodities and the unidirectional conversion of commodities to electricity. The key outcome of their model is that symmetrical shocks in demand to the power market produce an asymmetrical electricity price distribution. For example, an increase in demand gives an positive skewed electricity price distribution. This effect is amplified if there are constraints on storage of electricity production fuels. Their explanation for the variation in

[10] PJM Interconnection coordinates the electricity prices in the Eastern US; Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia.
[11] Mid-C is part of the Northwest Power Pool, which includes the parts of Western Canada and Western U.S. of Washington, Oregon, California, Nevada, Utah Wyoming, Idaho, and Montana.

the correlation structure is that it follows naturally from the decision which fuel will act as the marginal production fuel for electricity. Routledge et al. (2001) use a hypothetical state of the world with natural gas and electricity, which serves as a numerical example to test the model.

Douglas et al. (2008) too observe that the constraint in the supply of the production fuel, in their case gas, only affects the distribution of the electricity price if that production fuel is the marginal generation technology.

Redl et al. (2009) analyze the relationship between futures and spot prices and, as an intermediate step, examine the important factors that influence the German EEX and Nord Pool forward prices. They note that, within a rational framework, the production costs of the marginal unit in a competitive market are important for the ultimate price realization and expect an significant influence of these costs. Firstly, they find a high and positive correlation between generation costs and electricity forward prices for both the German and Nordic market. Secondly, they test the relevance of different variables in a regression analysis in which the year-ahead base load prices of the German EEX and the Nord Pool are the dependent variables and the (short run) year ahead marginal production costs of coal and gas and the lagged spot prices serve as the independent variables. To account for non-linear relations the squared terms of the two generation costs are included in the regression. The results show that the forward prices in both markets depend on the year-ahead generation costs and provide evidence of a nonlinear influence of year-ahead gas production costs on Nordic forward prices. They argue that this is the result of the flexible storage capability of hydro in reservoirs. The nonlinear influence of production fuels on electricity prices is thus observable in Nordic forward prices. This article, however, focusses on the Nordic day-ahead power market, which accounts for around 80 percent of all power sales in the Nordic market.

Zachmann (2012) uses the facts that electricity is generated by different generation technologies with dissimilar marginal costs, and, that the electricity spot price in a deregulated market is determined by these marginal costs. The marginal costs consist of a linear combination of (1) the fuel cost, (2) the emission cost and (3) other variable cost and this linear combination has different forms per each generation technology. Power plants with relatively high marginal costs will only produce when the demand for electricity is high and/or the available supply capacity is low enough. In a competitive environment the electricity price is set by the last required marginal technology to meet demand. This marginal technology varies over time, the linear combination that determines the price thus varies too. Zachmann (2012) proposes a Markov regime switching (MRS) model to capture the non-linear dependency of the market prices on fuel and emission costs, which models the day-ahead electricity price as the production cost of the marginal technology. The different regimes are the different generation technologies and each regime has a different linear combination of fuel and carbon emission prices, which forms the day-ahead electricity price. This model is tested on the German and UK power market, both mature and liquid markets and most of all thermal power dominated. The MRS-model is, namely, unable to account for the opportunity cost of a hydropower plant. The model is estimated for the off-peak[12] and peak[13] week day prices and uses four regimes for the sample period of January, 1st 2004 to November, 30th 2010. The results show that the nonlinear MRS-model explains the variation in the day-ahead electricity prices with different linear combinations of the explanatory variables quite well and give a confirmation to the hypothesis that the electricity prices in the German and UK market have a non-linear relation with production fuels and emission costs.

Similarly, Huisman (2012) presumes a nonlinear relation between forward prices of electricity and the forward prices of fossil fuels, because it is possible to indirectly store electricity via forward contracts of the required commodities. A MRS-model is applied to the electricity forward prices in the German and Dutch market for the year 2011. Two regimes are proposed, both resembling the marginal production technology at that point in time. In one state the forward price of electricity is dependent on the marginal production cost of power via coal and in the other state on the marginal production cost of power via natural gas. In each regime the forward price is a different linear combination of the forward fuel prices and the required CO_2 certificates/allowances. The results show that the model is significantly successful in predicting the state, i.e. the marginal technology, and that the marginal costs have high explanatory power for the forward electricity prices. The off-peak prices in both markets are best explained by the coal regime, which shows that during off-peak hours coal mostly is the marginal technology. The peak prices, however, are better explained by natural gas forward prices.

The studies using cointegration show the link between the marginal production fuel and electricity prices. The other studies that we discussed the nonlinearity imbedded in this relationship. The model in this paper is different from the previous literature, as it models the supply side of the power market. A supply curve structured with hydro capacity, production fuels and emission permits, is proposed, which should provide insight in the relationship between electricity prices and input prices with varying reservoir levels. The methodology will be explained in the following paragraph.

3 Methodology

The focus of this paper is to provide insight in the relation between the day-ahead electricity price and important marginal costs. The first essential step is to model the supply side of the market, as the supply function is the part of the price setting mechanism that evolves around the input variables. We

[12] The price of 1 MW of electricity delivered between 21:00 and 07:00 from Monday to Friday.
[13] The price of 1 MW of electricity delivered between 08:00 and 20:00 from Monday to Friday.

use the demand and supply framework to structure the supply model, this is explained in section 3.1. Subsequently, we examine the structured supply model and define a framework to provide insight in the nature of the relationship between fuel and emission permit prices and electricity prices for varying hydro capacity. The model is based on Huisman et al. (2014) who apply the model to understand the influence of renewable (intermittent) energy supply on power prices.

3.1 (Linear) Demand and supply model

In the Nordic market the major part of the trades in electricity are done at the day-ahead market, the Elspot. At the Elspot the next days' hourly electricity price is determined by the basic principles of demand and supply. The buyers need to evaluate how much the demanded quantity of electricity for every hour the following day will be and what price they are willing to pay for it. The sellers make their own trade-off between benefits and costs and quantify how much they are willing to generate and against what price. This information is then entered in the form of orders into the system that operates the day-ahead market. All members, buyers and sellers, can place their orders for every hour separately, starting from twelve days up front until 12:00 CET the day before. From all these individual orders the trading system constructs the aggregated demand and supply curves for every single hour. This is done between 12:00 CET and 12:45 CET the day before. Figure 2 shows these aggregated demand and supply curves, where the aggregated demand curve is downward sloping and almost vertical as the demand for electricity is price inelastic in the short run (Borenstein 2002, Fridolfsson et al. 2009 and others). The aggregated supply curve is upward-sloping and has a hockey-stick (convex) shape, as small quantities are supplied by plants with low production costs but for larger quantities plants with higher production costs need to be utilized and because supply capacity is fixed in the short run. The intersection of the aggregated demand and supply curve is the market clearing price. To examine the relation between the day-ahead electricity price, fuel prices and emission allowances for varying reservoir levels, a functional form of the aggregated supply curve is needed. This paper constructs such a functional form using the demand and supply framework of the day-ahead electricity market.

Important dynamics of electricity prices are time-varying volatility, seasonality, mean-reverting behavior and sudden spikes. Those dynamics are the result of the (in general) impossibility of electricity storage and cause different demand and supply dynamics. It is valuable that a proper demand-supply model incorporates these characteristics. Different authors, among them Barlow (2002), Buzoianu et al. (2005), Skantze et al. (2000) and Cartea et al. (2008) use the demand and supply framework and succeed to incorporate these specific characteristics of electricity in such a dynamic demand and supply model. All impose functional forms for the demand and supply together with a stochastic process for demand and/or supply. Buzoianu et al. (2005) propose a time-varying exponential function for the supply curve, which depends on variation in gas prices, power plant outages and variation in power supply from production sources other than gas. The demand curve is a linear time dependent function with two seasonal components and an AR(1)-process. Similarly, Skantze et al. (2000) model electricity spot prices and propose an exponential form for the market clearing price. This exponential form includes stochastic forms of the demand and supply. Barlow (2002) suggests a non-linear Ornstein-Uhlenbeck as a mean-reverting process with a deterministic seasonal function for the demand curve and assumes a non-stochastic and time-independent supply curve. Cartea et al. (2008) is an extension of the work of Barlow (2002), because it suggests that supply also follows a stochastic process which is incorporated via a supply curve with an exponential form.

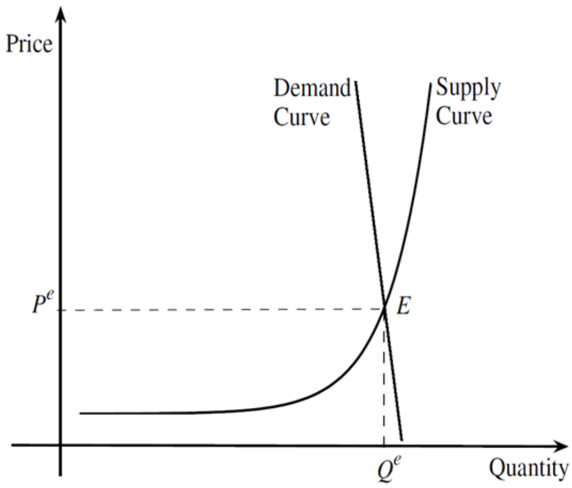

Figure 2: (Short-term) Aggregated demand and supply curve. The intersection E is the equilibrium point (P^e;Q^e), where P^e is the market clearing price and Q^e is the quantity at which the equilibrium is settled. The demand curve is almost vertical, because demand is fixed in the short run and the aggregated supply curve is increasing and convex, because the capacity is fixed in the short run.

3.1.1 Time dependence

The focus of this paper is to test whether there exists a nonlinear dependency of the electricity spot prices on the prices of generation fuel and CO_2 emission permits for varying hydro supply. Therefore, our interest lies in the structure of the supply curve and the eventual outcome of how the different components influence the price at different reservoir levels. Opposed to Barlow (2002), the structure of the supply curve in the Nordic electricity market is varying over time. That is, hydro supply varies over time due to fluctuations in water reservoir levels. The reservoir levels are mostly influenced by seasonal effects, as more precipitation or water from melting snow will increase the water levels in the reservoirs. These weather effects are forecastable and subsequently the levels of the reservoirs too. Following this reasoning, we opine that the structure of the supply curve will be different for different reservoir levels. This paper, therefore, suggests a supply curve that is *time-varying* and *dependent* on the available amount of hydro capacity. The time varying structure of the supply curve is also proposed by Buzoainu et al. (2005).

3.1.2 Functional form

Buzoianu et al. (2005) and Skantze et al. (2000) both model an exponential form of the supply curve, but this paper proposes a power function similar to the one in Barlow (2002). The preference for the power function stems from the fact that electricity prices exhibit sudden price spikes. Because of these price spikes the electricity price distribution exhibits excess kurtosis, or in other words the distribution has fatter tails. The power function handles these fat tails better than the exponential function that goes faster to infinity and is therefore too smoothed.

The model presented by Barlow (2002) includes a maximum price. This is quite reasonable as most power markets do have a maximum price level. The maximum price of the Nord Pool day-ahead market is set at € 2,000 per MWh. The reason to include this in the model is that traders keep this maximum price in mind when placing offers and it, hence, influences their actions. The Nord Pool Spot also has a minimum price level, this is set at € -200 per MWh[14]. But this minimum price is not included in the model.

Besides the price, another variable on which the supply curve depends is the quantity of electricity. It is reasonable to assume that the market's installed supply capacity is limited. Or stated otherwise, an electricity market cannot generate more than the maximum of its installed production facilities. Although, this installed capacity varies over time in both the short run, due to fluctuations in reservoir levels and power outages, and the long run, due to the new installation of capacity or the deactivation of existing facilities, we assume that the maximum installed capacity is constant and we set the maximum supply capacity at 100,000 MW[15].

We model the supply curve as a function of quantity. This is opposite to Barlow (2002) who models the supply curve as a function of price, i.e. the quantity results given a specific price. Barlow (2002), when including the maximum supply capacity, takes the inverse of the price function and then obtains a function of quantity. In this paper the electricity price is modeled directly as a function of quantity[16]. This provides results that are more convenient for interpretation. Summarizing, the proposed supply curve is a time-varying power function including a maximum price ($\bar{P}$) and a maximum installed

[14] Actually, the current minimum and maximum price are, respectively € -500 per MWh and €3,000 per MWh. But because the data used in this paper is over the period when the minimum and maximum price levels where €-200 per MWh and €2,000 per MWh respectively, those levels are chosen here.
[15] The 100,000 MW is an amount well above the observed quantities in the sample period.
[16] We assume that this does not seriously influence the results.

supply capacity ($\bar{S}$), which model the hourly day-ahead electricity price given a specific quantity (s_t). The power supply curve has the form:

$$P_t(s_t) = \bar{P} - a_t(\bar{S} - s_t)^{\alpha} \qquad (1)$$

In Formula (1) P_t is the price quoted on day *t* for hour *h* for the delivery of an amount of s_t MW of power during hour *h* in day *t+1*. The hour indicator *h* is left out for notational ease, but applies for all time subscripts. If the hour indicator is included things will become complex rather quickly. The subscript *t* in Formula (1) shows the time-varying structure of the supply curve, which, contrary to Barlow (2002) believes, is expected to be important. The a_t and α are the parameters of the equation. Restrictions on these parameters a_t and α should give the supply curve the upward sloping and convex structure as in Figure 2. The conditions for a function to be upward sloping and convex are that the first and second order derivatives both need to be larger than zero, or stated differently $P_t'(s_t) > 0$ and $P_t''(s_t) > 0$. The first and second order derivatives with respect to s_t of Formula (1) are:

$$P_t'(s_t) = \alpha a_t(\bar{S} - s_t)^{\alpha-1} \quad \text{and} \quad P_t''(s_t) = -(\alpha - 1)\alpha a_t(\bar{S} - s_t)^{\alpha-2} \qquad (2)$$

These expressions show that the conditions are satisfied if $a_t \geq 0$ and $0 \leq \alpha \leq 1$. Both a_t and α influence the upward sloping and convex structure of the supply curve, as both parameters are framed in both derivatives. However, we model the time-variation in the structure of the supply curve via a_t and choose α to be constant.

3.1.3 Independent variables

Now, an increasing and convex shaped model for the supply curve is constructed, the most important part is yet to come. The goal of the paper is to provide insight on the influence of fuel and emission prices on the electricity price for varying reservoir levels, so the model needs to include these fundamentals. As noted before, the time-variation in the structure of the supply curve will be modeled trough a_t. This time variation in the supply curve depends on the fundamentals of the different generation technologies. In 2011 the production split of the Nord Pool was roughly, 53% hydro power, 22% nuclear power, 16% thermal power and 9% other different sources. The thermal power production in the Nord Pool consists mainly of electricity generation from coal or gas-fired power plants. We assume that nuclear power generates a constant base load supply over time and together with a stable uranium price, we conclude not to include this in the model. The time variation in a_t is thus structured trough the fundamentals of the hydro and thermal power supply. The parameter a_t is then structured as:

$$a_t = a_0 + a_r r_t + a_c p_t^c + a_e p_t^e + a_g p_t^g \quad (3)$$

In Formula (3) r_t is the available hydro capacity for hour h on day $t+1$, as expected on day t. Whereas, $p_{c,t}$ and $p_{g,t}$ are the prices of, respectively, coal and gas available at time t for hour h, for the generation of electricity during hour h at day $t+1$. Lastly, $p_{e,t}$ represents the price of an emission allowance for hour h that is known at day t, which can be used to emit CO_2 at day $t+1$ during hour h.

The parameter a_t in equation (3) shows a linear dependency on the different fundamentals. Theoretic reasoning opines that a nonlinear relation seems apparent between the electricity price and the generation inputs. That is, for smaller amounts of available hydro capacity one expects a larger influence of fuel and emission prices on the electricity price and vice versa. The reason for modeling the relation linearly is two-fold. First, the linear relation can be used to test, whether there is an actual non-linear influence of the fuel and emission prices on the electricity price, as is done in this paper. Secondly, if one succeeds to construct a model that contains a non-linear relationship than one can compare the fit of this model to the fit of the model with a_t as a linear function.

3.1.4 General conditions

Next, the conditions for an upward sloping and convex supply curve are derived. The condition for the parameter a_t is that $a_t \geq 0$, i.e. a_t is strictly positive. To meet this condition we use the exponential transformation, which gives:

$$a_t = e^{a_0 + a_r r_t + a_c p_{c,t} + a_e p_{e,t} + a_g p_{g,t}} \quad (4)$$

For the parameter α, the condition is that 0≤α≤1. This is done by applying a logit transformation, which gives[17]:

$$\alpha = \frac{1}{1+e^{-a^*}} \quad (5)$$

When the equations (4) and (5) are substituted in equation (1) this yields:

$$P_t(s_t) = \bar{P} - e^{a_0 + a_r r_t + a_c p_{c,t} + a_e p_{e,t} + a_g p_{g,t}} (\bar{S} - s_t)^{\frac{1}{1+e^{-a^*}}} \quad (6)$$

Furthermore, we use the demand and supply framework in a similar way as Skantze et al. (2000), who note that in equilibrium the market clearing quantity is equal to the system load. Stated differently, the intersection of the two curves is the equilibrium point where the market clearing price is set, at that

[17] This gives precisely the requirements to meet the condition, namely $\lim_{\propto^* \to -\infty} \alpha \to 0$ and $\lim_{\propto^* \to \infty} \alpha \to 1$.

point the demanded quantity is equal to the supplied quantity, $s_t = d_t$, where one lets s_t (d_t) be the supplied (demanded) quantity at hour h in day $t+1$ as expected on day t. Substituting this in Formula (6), the result yields:

$$P_t(d_t) = \bar{P} - e^{a_0 + a_r r_t + a_c p_{c,t} + a_e p_{e,t} + a_g p_{g,t}} (\bar{S} - d_t)^{\frac{1}{1+e^{-a^*}}} \qquad (7)$$

3.1.5 Interpretation and estimation

Formula (7) includes all the fundamentals, namely hydro capacity, CO_2 certificate prices and generation fuel prices. The interpretation of the sign from one of the parameters a_r , a_c , a_e and a_g can be derived from the first order derivative with respect to one of these variables, for example:

$$\frac{dP_t}{dr_t} = -(a_r)\, e^{a_0 + a_r r_t + a_c p_{c,t} + a_e p_{e,t} + a_g p_{g,t}} (\bar{S} - d_t)^{\frac{1}{1+e^{-a^*}}} \qquad (8)$$

Formula (8) is the first order derivative with respect to r_t. This derivative shows that if the sign of a_r is, for example, positive than the first order derivative will be negative, which means that an increase in reservoir levels lowers the electricity price. Similar reasoning applies for the other parameters; a_c, a_e and a_g. We hypothesize that the estimate for the hydro capacity will be positive, which shows that an increase of the reservoir levels lowers the electricity price. And the estimates for the coal price, gas price and emission permit price are expected to be negative, which intends that an increase of those variables leads to an increase of the electricity price.

$$P_t(d_t) = \bar{P} - e^{a_0 + a_r r_t + a_c p_{c,t} + a_e p_{e,t} + a_g p_{g,t}} (\bar{S} - d_t)^{\frac{1}{1+e^{-a^*}}} + \epsilon_t \qquad (9)$$

Estimation of nested models from Formula (7) will determine if one is in favor of including these fundamentals in the model for explaining the variation in day ahead electricity prices. This section determines if a subset or all the explanatory variables have an important contribution to explaining the variation in the day-ahead electricity price. Determining the optimal structured supply curve is the hypothesis for this part. The estimation is done by nonlinear least squares (NLS) on Formula (9) and via a specific-to-general method[18]. The results are given in section 5.1. Formula (9) is used to test whether this relationship is actually nonlinear. The methodology that applies to this process is explained in the next section.

[18] The specific-to-general method is a bottom-up approach, that starts with estimating the smallest model, i.e. including only one term, and adds more variables while checking for the fit or the parameter t-value to evaluate whether the variable is included or not.

3.2 Low and High reservoir level subsample regression

In order to provide insight in the non-linear relationship between the day ahead electricity price, reservoir levels and the fuel and emission prices we test whether parameters are constant in different high and low reservoir level subsamples.

3.2.1 Subsample construction

At first, the sample is sorted on reservoir level. Next, the sample is split up in three parts; a high and low reservoir level subsample and a center subsample. The boundaries for the high and low subsamples are constructed by using the spread in the reservoir levels of the total dataset, which is the difference between the maximum and the minimum reservoir level. From this spread the 25% level is calculated. Subsequently, this quarter of the spread is then subtracted from (summed up) the maximum (minimum) reservoir level to determine the reservoir level 25% high (low) boundary, hereinafter referred to as $High_{25\%}$- and $Low_{25\%}$-sample[19].

The motivation for using the spread, instead of simply splitting up the samples in 25% - 50% - 25% samples based on number of observations, is because there is less dependence on the structure of the sample period. For example, if the reservoir levels were on average quite high during the chosen sample period, a 25% low sample based on the number of observations will with a larger probability include observations with relatively higher reservoir levels. Hence, the results will be more dependent on the chosen sample period. By using the spread we believe that this dataset dependency is diminished. Although still, the decision why to use the 25% level as a boundary level is arbitrary. Therefore, this analysis is also done with 15% as the boundary level, providing $High_{15\%}$- and $Low_{15\%}$-samples. In this way, we can also determine whether an possible observed nonlinear effect is evident only for the highest and lowest subsamples (15% subsamples), or whether it is more generally observed (25% subsamples). The construction of the $Low_{15\%}$- and $High_{15\%}$-samples happen in a similar manner[20].

3.2.1 Wald test

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[19] For example, the maximum and minimum reservoir levels in percentage are, respectively, 90 and 10 for the complete data set. This gives a spread of 80. The 25% high and low reservoir level boundaries are then 60% and 40%. That is, all data is selected that has a reservoir level of 60% or larger and this is the $High_{25\%}$-sample. And all data that has a reservoir level equal to or smaller than 40% is used as the $Low_{25\%}$-sample.

[20] Another method, instead of regressions on subsamples based on low and high reservoir levels, would have been to use dummy variables based on reservoir level in one complete model. The reason for the decision on the subsample regression is that the subsample regressions provides individual regression statistics, like for example the R^2 for each subsample. We believe that the use of subsample gives a more complete view in the relation between the variables and on the form of the possible nonlinearity.

The partition of the data set gives three subsamples of which only the lower and higher subsample are used. These two subsamples (possibly unequal in observations) are the $High_{x\%}$ and $Low_{x\%}$ - sample (where x is either 25 or 15) and are used to estimated Formula (9). The results will be compared and evaluated. And the equality of the fuel and emission price parameters will be tested for difference with a Wald-test. The Wald-test for structural differences between two subsamples with unequal subsample variances is a test to check if parameters are structurally different between two subsamples and is constructed in the following way;

$$\mathcal{W} = (\widehat{b_1} - \widehat{b_2})'(\widehat{V_1} + \widehat{V_2})^{-1}(\widehat{b_1} - \widehat{b_2}) \sim \chi^2(g) \tag{11}$$

Where $\widehat{b_1}$ is a vector with the relevant parameter estimates of the $Low_{x\%}$-sample for comparison and $\widehat{b_2}$ is the vector with relevant parameter estimates for the $High_{x\%}$-sample. The $\widehat{V_1}$ and $\widehat{V_2}$ are the covariance matrix of the estimated parameters for the low and high sample, respectively. The result, $\mathcal{W}$, follows a Chi-square distribution with the number of degrees of freedom equal to the number of parameter estimates in the vector b, this number is g. The null hypothesis of the Wald test is that the estimated parameters for the fuel and CO_2 permit price in the two subsamples are equal to each other. The alternative hypothesis is that this is not true. The Wald-statistic provides information about whether there is significant evidence of a structural difference in the parameters for the $High_{x\%}$ and $Low_{x\%}$ - samples. If this is the case, the parameters for different reservoir levels are different and the parameters in model E should actually be time-varying. We expect that the null-hypothesis is rejected, which would mean that a nonlinearity is present in the model via time-varying parameters.

4 Data

This paragraph consists of two parts. Firstly, it discusses the data used in this paper. Secondly, this paragraph summarizes the descriptive statistics of the data.

4.1 Data management

This paper focuses on the relationship between production fuel prices, reservoir levels and electricity prices at the Nordic market. To examine this relationship data is collected for the Nord Pool day-ahead electricity prices, consumption levels, reservoir levels, CO_2 emission prices and production fuel prices for the sample period January 1st, 2011 to April 28th, 2013.

The power exchange in the Nordic market is Nord Pool Spot, with the majority of the trades in power taking place at the Elspot. The pricing algorithm of the Elspot constructs the price for every hour individually, this is called the system price. This hourly system price does not take into account transmission constraints between bidding areas[21], therefore this price is also called the unconstrained market price. The day-ahead system price serves as a reference for the electricity price in the Nord Pool and will serve as the dependent variable in this paper. The electricity prices are on an hourly basis and are given in Euro/MWh. The data of the hourly system price is collected from the Nord Pool Spot database[22].

As an independent variable Formula (9) contains the demand at hour *h* in day *t+1*. The consumption prognosis of Nord Pool Spot will serve as a proxy for this explanatory variable. In a day-ahead market the price of time *t+1* is quoted at day *t* – i.e. the day before – at that time the consumption at time *t+1* is clearly unknown. The Nord Pool Spot determines a consumption prognosis for every single hour the following day, so when the price is quoted this consumption prognosis is already available. The data for the consumption prognosis is reported in MWh and is collected from the database on the website of Nord Pool Spot.

In Formula (9) r_t is the available capacity that can be used to produce hydropower. This paper employs the reservoir level as a proxy for the available hydro supply. Nord Pool Spot records the reservoir levels on a weekly basis and new recordings are published every Wednesday. The weekly reservoir levels are presented as a percentage of total available reservoir capacity in the Nordic market. The observations of the system price and the consumption prognosis are on an hourly time-scale, this means that in order to obtain comparable data, the weekly reservoir levels are firstly interpolated linearly to daily data. Secondly, we assume that the available hydro capacity is constant within a day. The data is collected from the database on the website of Nord Pool Spot.

Another independent variable is the coal price. This paper relies on the API 2 ARA CIF[23] coal price, which is the daily spot coal price. The API 2 index is the benchmark price for coal imported into Northwest Europe with delivery in Amsterdam, Rotterdam or Antwerp (ARA) and is therefore relevant for the coal price in the Nordic power market. The data is obtained from Datastream and consists of the closing prices recorded for each trading day. The day-ahead electricity price for hour *h* in day *t+1* is quoted at day *t*, at that point only the closing price of the day before (*t-1*) is available. The price of *t-1* is the last available information and is thus the known price for all hours when quoting the price. If the day before is a non-trading day, the last available closing price will apply. For

[21] Although transmission constraints do exist, their occurrence is exceptional and small in size. For this reason it is expected that deviations in the system price are usually minor and are further neglected in this paper.

[22] The day-ahead electricity prices can be collected at Bloomberg or at Nord Pool Spot. Bloomberg and Nord Pool Spot have different ways of structuring the day-ahead prices. Bloomberg reports the price at the day it is quoted, that is the price of hour h in day t+1 is reported for hour h in day t, as that is the day the price is quoted. At Nord Pool Spot the price of hour h in day t+1, which is quoted at day t, is reported on hour h day t+1. For this paper Nord Pool Spot's style of structuring the data is preferred above the style of Bloomberg.

[23] This is a trade term and refers to Cost, Insurance and Freight (CIF). It means that the prices are inclusive with the costs for insurance and transportation. (Incoterms® 2010)

example, when the day before is a Sunday, Friday's closing price will apply as the spot coal price on that particular Sunday. The coal spot price is given in United States Dollar per Metric Ton ($/Mt) and is converted into €/Mt with the exchange rate of that day[24].

The EEX EU Emission Allowances spot price will serve as the price for the right to emit carbon. We assume that the price for an EU emission allowance traded at the EEX also applies for the right to emit carbon in the Nordic electricity market. This price is reported at the end of each trading day and is given in Euro per European allowance. The delivery of the EUA is the next day, $t+1$. Similar as to the price of coal, at the time of quoting the day-ahead electricity price for hour h in day t, only the price of an EUA the last *trading* day before is known, $t-1$. No hourly contracts exist hence we assume that the price of an EUA is constant during the day.

The reference for the price of natural gas in the Nord Pool market is the day-ahead natural gas price of Gaspoint Nordic with the delivery the day after it is traded. Gaspoint Nordic is established through a collaboration of Energinet.dk and Gaspoint Nordic at the end of 2007 and is created to provide an open and competitive market place for trading in natural gas. Gaspoint Nordic provides day-ahead closing prices in €/MWh. The most important reason for using the Gaspoint Nordic day-ahead prices is the daily frequency of the data, i.e. it includes non-trading days[25]. Because Gaspoint Nordic is a day-ahead market, it could be possible that the price for day $t+1$ is available before the time that the electricity price for day $t+1$ is quoted at day t. This is a possibility, but as no information was found on the time of quoting the day-ahead natural gas price and to be sure that no information is used that is unknown, the natural gas price of day t is used in this paper. Again, it is assumed that the same price applies to all hours within the day.

To summarize, data is collected on day-ahead electricity prices, consumption prognosis, reservoir levels, emission permit, coal and natural gas prices and consists of a common sample of 20320 hourly observations.

4.2 Descriptive statistics

This part discusses the descriptive statistics of the main variables. Table 2 and Figure 3, 4 and 5 show the summary statistics. The first remark is the high kurtosis, 10.292, for the day-ahead electricity price. The high kurtosis reflects the fat tails of the day-ahead price distribution. This is in line with expectations, as a typical characteristic of electricity prices is sudden high or low price spikes. The high kurtosis also provides power in favor of the choice for using the power function. The

[24] The exchange rate is the WM/Reuters closing spot rate collected from DataStream.

[25] The correlation for the sample period between NCG (NetConnect Germany) day-ahead gas price and the Nord Pool day-ahead gas price is 0.95 and, eventually, both give comparable results.

highest observed price is 224.97 €/MWh. No negative prices are observed in this sample period. In Figure 3 one observes the sudden price spikes, with the largest peaks in the first two weeks of February 2012, as a result of a severe cold spell. And the lowest prices in September and October 2011 and July 2012, because of abundant hydro supply.

	Day-ahead Electricity Price (€/MWh)	Consumption Prognosis (MWh)	Reservoir Capacity (% of total capacity)	EU Emission Allowance (€/EUA)	API 2 ARA CIF Spot Coal Price (Eur/MT)	Nord Pool day-ahead Gas Price (€/MWh)
Mean	39.610	45786	60.645	9.392	77.901	24.988
Median	37.660	44972	65.042	7.880	76.160	24.310
Minimum	1.450	17387	16.463	2.680	60.950	16.92
Maximum	224.970	72088	90.259	16.840	100.58	78.64
St. Dev.	15.845	9681	23.049	3.799	9.421	3.828
Skewness	1.110	0.189	-0.338	0.572	0.0429	5.415
Kurtosis	10.292	2.357	1.727	2.146	1.604	58.798

Table 2: This table shows the descriptive statistics of the different variables for the sample period 01-01-2011 to 04-28-2013. The common sample contains a total of 20320 hourly observations for the Nordic power market.

Figure 4 clearly shows the seasonal variation in the electricity consumption. The consumption prognosis in the Nordic market is higher during the winter months, when more electricity is needed for heating the houses and is lower during the summer months. The reservoir levels also show a seasonal fluctuation in Figure 3. The reservoir levels decrease during the winter period and rise again during spring and summer as water from melting snow fills the reservoirs. The lowest reservoir level is observed in the first week of March 2011 at 16.46% of total capacity. The correlation matrix in Table 3 shows a negative correlation of -0.534 between reservoir levels and day-ahead electricity prices. This hints to a situation when there is an increase of the reservoir level, the day-ahead electricity price then decreases.

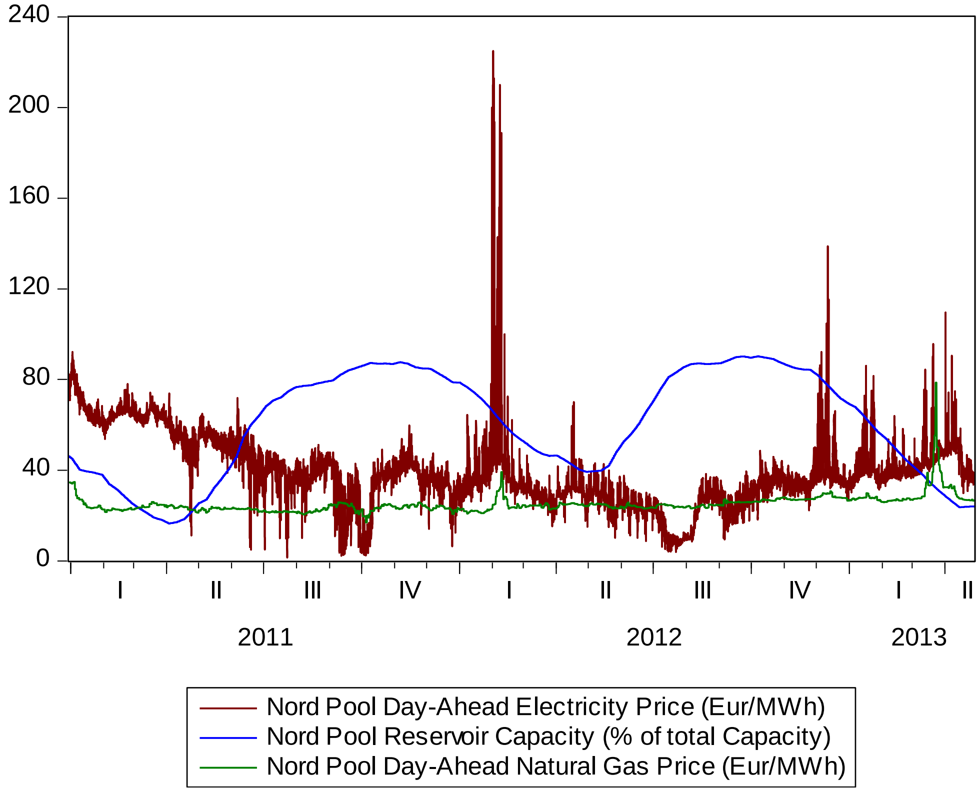

Figure 3: Shows the time-series for the variables; the day ahead hourly electricity price, the reservoir level and the day-ahead natural gas price, over the sample period 01-01-2011 to 04-28-2013. The time on the x-axis is plotted in yearly quarters

The price distributions of the emission allowance and coal both have a low kurtosis, which means that it has thinner tails and a rounder peak. The price distributions of these series have less extreme observations in the tails. This is also visible in Figure 5 which shows that both of the prices do not have large price spikes, i.e. large deviations from the general trend. Both lines are declining over the sample period. The correlation matrix in Table 3 shows that the price of an emission allowance and the price of coal have a large positive correlation, 0.821. This could potentially cause multicollinearity in the estimates of the parameters. If multicollinearity exists it may be preferable to delete one of these two variables. This will be clear once least squares is applied.

	Day-ahead Electricity Price	Consumption Prognosis	Reservoir Capacity	Emission Allowanc e	Coal Price	Gas Price
Day-ahead Electricity Price	1.000					
Consumption Prognosis	0.434	1.000				
Reservoir Capacity	-0.534	-0.168	1.000			
Emission Allowance	0.483	-0.281	-0.306	1.000		
Coal Price	0.353	-0.214	-0.0739	0.821	1.000	

Gas Price	0.141	0.377	-0.130	-0.413	-0.478	1.000

Table 3: The correlation matrix between different variables for the sample period 01-01-2011 to 04-28-2013.

Lastly, the day-ahead price distribution of the gas price in the sample period has a high kurtosis, which indicates fatter tails. These fatter tails are mainly due to very large positive price spikes, as the minimum is only two standard deviations from the mean and the maximum deviates about thirteen standard deviations. Figure 3 shows the gas price, with three (observable) large spikes. The first, a negative spike, at the end of the third quarter of 2011, is also observed in the day-ahead electricity price. Secondly, a positive spike, in the first two weeks of February 2012, when the market feared a possible natural gas supply disruption due to cold temperatures, together with the rise of the electricity wholesale price. And thirdly, also a positive spike, in March 2013 when again a cold spell surprised the market. The next paragraph discusses the results after estimating the models.

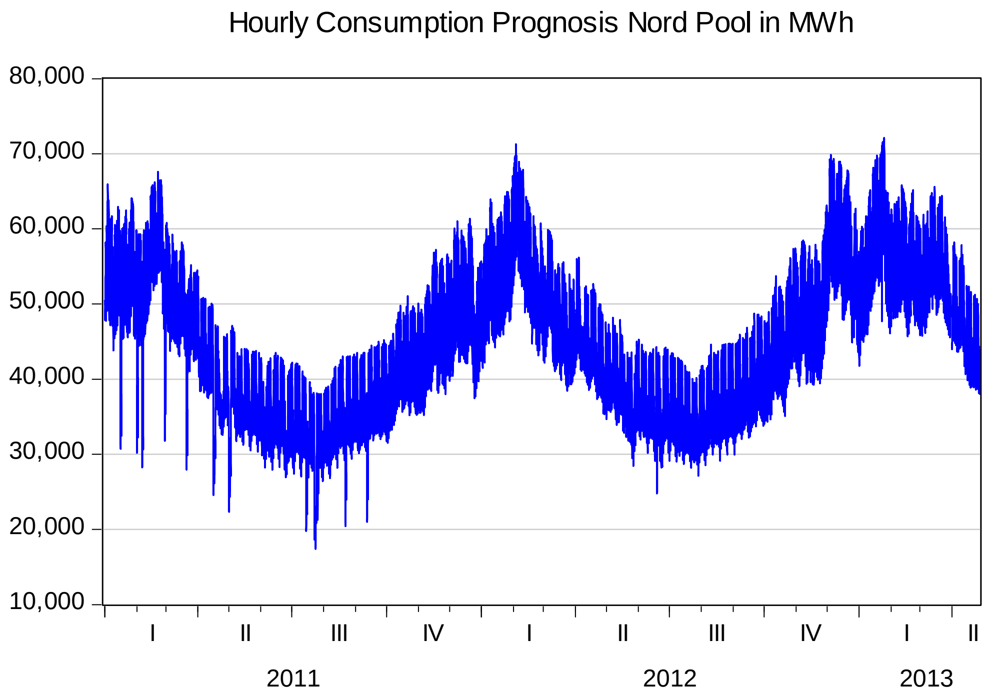

Figure 4: Hourly consumption prognosis in MW for the Nordic electricity market by Nord Pool Spot over the sample period 01-01-2011 to 04-28-2013. The time is plotted in yearly quarters on the x-axis.

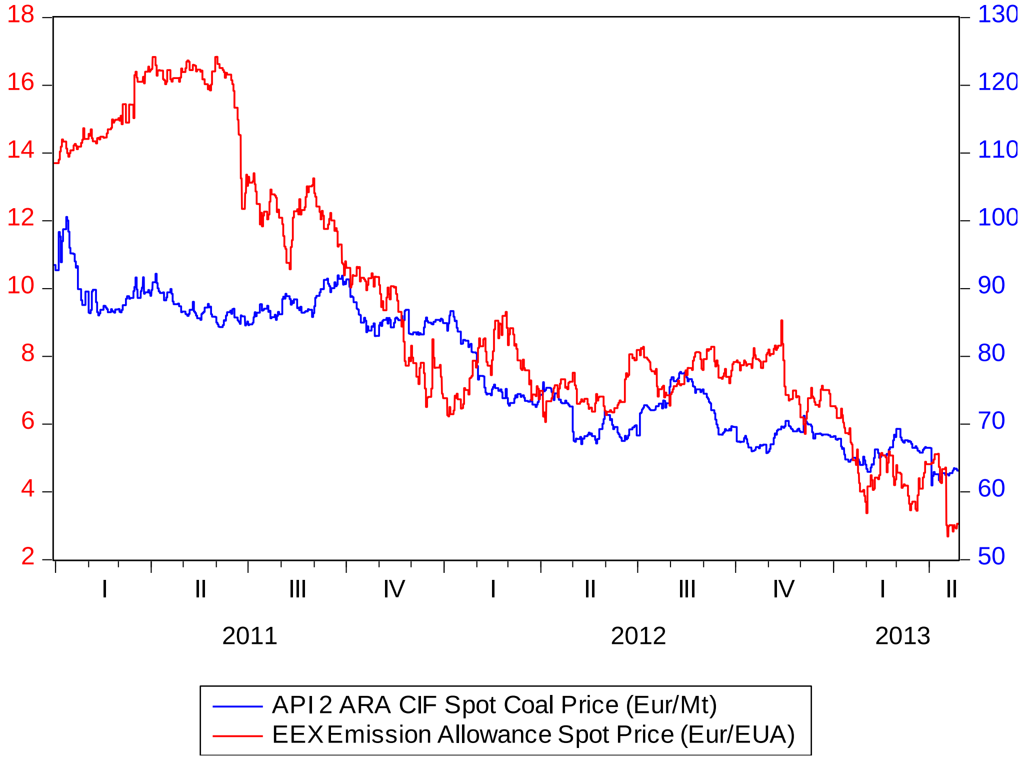

Figure 5: Shows the time-series for the variables; the emission permit price and the coal price, over the sample period 01-01-2011 to 04-28-2013. The axis on the left-hand side applies to the emission allowance price series (red) and the axis on the right-hand side to the API2 ARA CIF spot coal price (blue). The time on the x-axis is plotted in yearly quarters.

5 Results

This paragraph begins with structuring a supply curve by examining the relevant explanatory variables for the day-ahead electricity price in the Nord Pool. The structured supply model is then examined to get a hint of a nonlinear dependency of the day-ahead electricity price on relevant input variables. Then, a regression on a low and high reservoir level subsample is performed to check for parameter constancy

5.1 Structure of the supply model

This section discusses the results for different structures of the supply curve over the sample period January 1st, 2011 to April 28th, 2013 and concludes on a specific form of the supply curve. Different explanatory variables are examined in the least squares regressions and the fit of these regressions is compared. A bottom up approach is applied. This is helpful in the way that it will give information if one is in favor of incorporating fundamentals, which make the supply curve time dependent. The goal is to determine which supply curve is closest to reality, i.e. provides the best fit with interpretable parameter estimates, and henceforth will be used for investigating the nature of the relationship for varying reservoir levels. Table 4 shows the estimates of the parameters for different structures of the supply curve. The models in Table 4 are estimated while treating the dataset as a time series, although this is methodologically not entirely correct, it is presumed that this does on average give a sound view of the relation to the different regressors[26].

The models A to E in Table 4 are all nested models of model F (Formula (9)). Model A shows a supply curve that is independent of time, that is, the parameters a_r, a_c, a_e and a_g are restricted to be zero. All the parameters are significant in model A and the model explains 19.6% of the variation in hourly day-ahead electricity prices. The parameter estimate for a_0 is 7.374 and for α^* is -3.942, which gives an estimate for α of 0.0190 (after applying the logit transformation). Model B accounts for time varying hydro capacity by including the reservoir level in the supply curve. The $\overline{R^2}$ increases to 0.416 and the parameter estimates for a_0, a_r, α^* and α are respectively 7.399, 1.67e-04, -4.134 and 0.0158. The parameter estimates for a_0 and α, in comparison with model A, did not change much. However, the increased $\overline{R^2}$ of the model shows that including the hydro capacity improves the fit of the model substantially. This shows that including time-variation in the supply curve via hydro capacity is preferred over a constant supply curve (model A). The estimate for a_r is 1.67e-04. The sign of the estimate is in line with the hypothesis that an increase in hydro capacity, decreases the day-ahead electricity price in the Nordic power market.

	Model A	Model B	Model C	Model D	Model E	Model F
a_0	7.374	7.399	7.327	7.328	7.356	7.362
	(0.00295)	(0.00253)	(0.00203)	(0.00212)	(0.00362)	(0.00225)
a_r		1.67e-04	9.89e-05	9.86e-05	8.52e-05	8.89e-05
		(1.91e-06)	(1.57e-06)	(1.67e-06)	(1.62e-06)	(1.64e-06)
a_c				3.43e-06†		-5.03e-05
				(6.56e-06)		(6.53e-06)
a_e			-0.00117	-0.00118	-0.00132	-0.00121
			(9.81e-05)	(-1.77e-05)	(1.13e-05)	(1.72e-05)
a_g					-3.60e-04	-3.70e-04
					(2.07e-05)	(1.02e-05)
α^*	-3.942	-4.134	-3.721	-3.721	-3.789	-3.802
	(0.0145)	(0.0151)	(0.00829)	(0.00836)	(0.0148)	(0.00904)
α	0.0190	0.0158	0.0236	0.0236	0.0221	0.218
$\overline{\boldsymbol{R}^2}$	0.196	0.416	0.656	0.656	0.678	0.678

[26] Actually, the day-ahead electricity price is not a continuous time series, but can be seen as panel data, due to the structure of the price setting mechanism for all hours at the same time, 12:00 pm, the previous day.

Table 4: Shows the parameter estimates for nested models of $P_t(d_t) = \bar{p} - e^{a_0 + a_r r_t + a_c p_{c,t} + a_e p_{e,t} + a_g p_{g,t}} (\bar{s} - d_t)^{\frac{1}{1+e^{-\alpha^*}}} + \epsilon_t$ (in the table model F). All models can be constructed by putting restrictions on the different parameters. Model A is a constant supply curve, with the restrictions $a_r = a_c = a_e = a_g = 0$. Model B lets a constant and hydro capacity, with r_t (reservoir level in %) as a variable, structure the supply curve and with the restrictions on the parameters, $a_c = a_e = a_g = 0$. Model C includes a constant, the hydro capacity (r_t) and the CO_2 emission price ($p_{e,t}$) and has the parameter restrictions for the production fuels, namely $a_c = a_g = 0$. Model D includes variables of the emission price ($p_{e,t}$) and the coal price ($p_{c,t}$) and only has one parameter restriction $a_g = 0$. Model E has one parameter restriction $a_c = 0$. Model F is similar to Formula (9) and is the complete model without any restrictions. The table also gives the adjusted R^2 ($\overline{R^2}$) for every model and the α, which is obtained after applying the transformation $\alpha = \frac{1}{1+e^{-\alpha^*}}$. All regressions are performed using non-linear least squares (NLS) over the total sample period from 01-01-2011 until 04-28-2013, including a total number of 20320 hourly observations. Heteroskedasticity robust standard errors are shown in parentheses. The scientific notation: 1e-03 = 0.001 is applied. All estimates are significant at the 1% level, except for the one with the † that denotes an insignificant estimate.

The interest of the paper lies in the relation between the power prices and the different components of the production costs for varying reservoir levels. Therefore, model C relates the day-ahead power price to hydro capacity and the price to emit carbon. The coefficient for the emission price is negative and significant, which is in line with the hypothesis that an increase in the price of an emission permit, leads to an increase in the day-ahead electricity price. The constant and α* are significant and do not show a major difference compared to model A or B. However, the $\overline{R^2}$ increases quite extensively, to 0.656. This shows that the emission permit price is valuable in explaining the variation in the hourly day-ahead electricity price. Subsequently, model D structures the supply curve with the variables hydro capacity, the price to emit carbon and the coal price. The sample fit of model D is equal to that of model C, 0.656. The coefficient for the emission price is again negative and significant. However, the estimated coefficient for a_c is highly insignificant, a p-value of 0.601. This is probably the result of the high correlation between the coal and the CO_2 permit price. Again the other parameter estimates stay almost equal. From this we conclude that including both of the variables, emission price and coal price, leads to multicollinearity in the regression. This is the result of the high correlation between the two price series and leads to the decision to only include the carbon emission price in the supply curve, despite the fact that a large share of the electricity in the Nordic market is produced via coal power stations and imports via submarine cables will mainly stem from coal power plants[27].

Next, model E includes the hydro capacity, the CO_2 emission price and gas price. Again, the parameter estimates, for a_0, a_r, and α*, do not differ much from the previous models. Model E explains 67.8% of the variation in the Nord Pool day-ahead hourly electricity prices. The signs of the estimates are also in line with the hypotheses. The estimate for the parameter for the hydro capacity is positive, thus, once the hydro capacity increases this leads to a decrease in the day-ahead electricity price. The estimates for the emission price and the gas price are negative, which means that an

[27] Another possibility would have been to only include the coal price in the supply curve and restrict a_e to be 0. This, however, gives a smaller $\overline{R^2}$, namely 0.582. For this reason the price to emit carbon is incorporated and the coal price is discarded in the supply curve. The results of the regression where the carbon permit price is discarded and the coal price included are given in Appendix Table A2.

increase of one of these prices has a positive effect on the day-ahead electricity price. Although, the increase in fit of this model compared to model D is only minor, this model is preferred above model D. The reason for this is that we believe that the gas price serves as a good explanatory variable for periods where the demand is high, such that gas-fired power plants are needed. Therefore, the gas price is included in the model.

Lastly, Model F, or Formula 9 without restrictions, includes the hydro capacity, prices of the production fuels and the carbon permit prices. The fit of the model is 0.678, compared to model E, the coal price does not explain much extra of the variation in hourly day-ahead electricity prices. This together with the fact of multicollinearity, leads to the choice for model E to explain the variation in the Nordic day-ahead electricity prices. Model E shows that it is possible to model the hourly day-ahead electricity price via a structured supply curve with parameter estimates in line with the expectations formulated in the hypotheses. Namely, the empirical evidence shows that hydro supply decreases and the emission permit and natural gas price increase the electricity spot price. These are the first important findings of this paper. Although, model E presumes a linear relation between the production fuels, this model does explain a substantial part of the variation in hourly day-ahead electricity prices. The structured supply model will be valuable in the process to determine if the apparent non-linear relation actually exists and in what form. This is done by a low and high reservoir subsample regression. But, firstly the influence of the maximum supply capacity is examined.

5.1.1 Sensitivity analysis for the maximum supply capacity ($\bar{S}$)

No information was found on the maximum installed capacity in the Nordic market, but the maximum supply ($\bar{S}$) was set on 100,000 MW. We reason that this level is well above the observed maximum in the sample period, but the decision still is arbitrary. Hence, before proceeding, a sensitivity analysis for the maximum capacity ($\bar{S}$) is performed in order to determine if a different, but still reasonable, value for the maximum supplied capacity has a notable influence on the parameter estimates and the fit of Model E. The results are shown in figure 6, where Model E is estimated for an $\bar{S}$ varying from 80,000 MW to 140,000 MW and the different parameter estimates are plotted in graphs. The effect on the parameter estimates for reservoir level, emission permit price and natural gas is only minor and is regarded of no importance. The effect on the other parameter estimates, i.e. the constant, α and α*, is larger, but opposite to each other for the constant (a_0) and α. We presume that these two variables absorb the effect of not knowing the correct maximum supply capacity. The $\overline{R^2}$ shows a range of 0.680 to 0.674 for the varying maximum capacity. But 80,000 MW is just above the maximum observed quantity (see Table 2), hence, it is opined that the effect of the decision for the maximum supplied capacity is, for reasonable levels, negligible and the 100,000 MW is seen as a proper value.

Naturally, in a perfect world one would like to know the maximum installed capacity precisely, thus a more accurate estimation of this number still is valuable.

5.2 Low and High subsample regression

This section discusses the results of the regression on the low and high reservoir level subsamples. In order to make this method feasible the data management regarding the lagging of the variables is done before sorting the complete sample[28]. The summary statistics of the high and low samples, for both the 25% and the 15% levels, are included in the Appendix Table A3 and A4, respectively, and show that both the High-samples include almost three times the number of observations in the Low-samples.

5.2.1 $Low_{25\%}$ and $High_{25\%}$- subsample regression

Table 5 shows the results of estimating Model E for the $Low_{25\%}$- and $High_{25\%}$-samples. The estimate for a_e and a_g are more negative in the $High_{25\%}$-sample, namely -0.00169 and -5.28e-04, respectively, than in the $Low_{25\%}$-sample, -6.00e-04 and -2.61e-05. The Wald-test should provide insight in whether the

[28] To make sure that the data still matches the right structure outlined in paragraph 4, the lagging of the necessary variables is done before sorting on reservoir level. In this way the relation between the variables is still intact. If one would not do this, one would get a rather meaningless data set, which in turn leads to meaningless results.

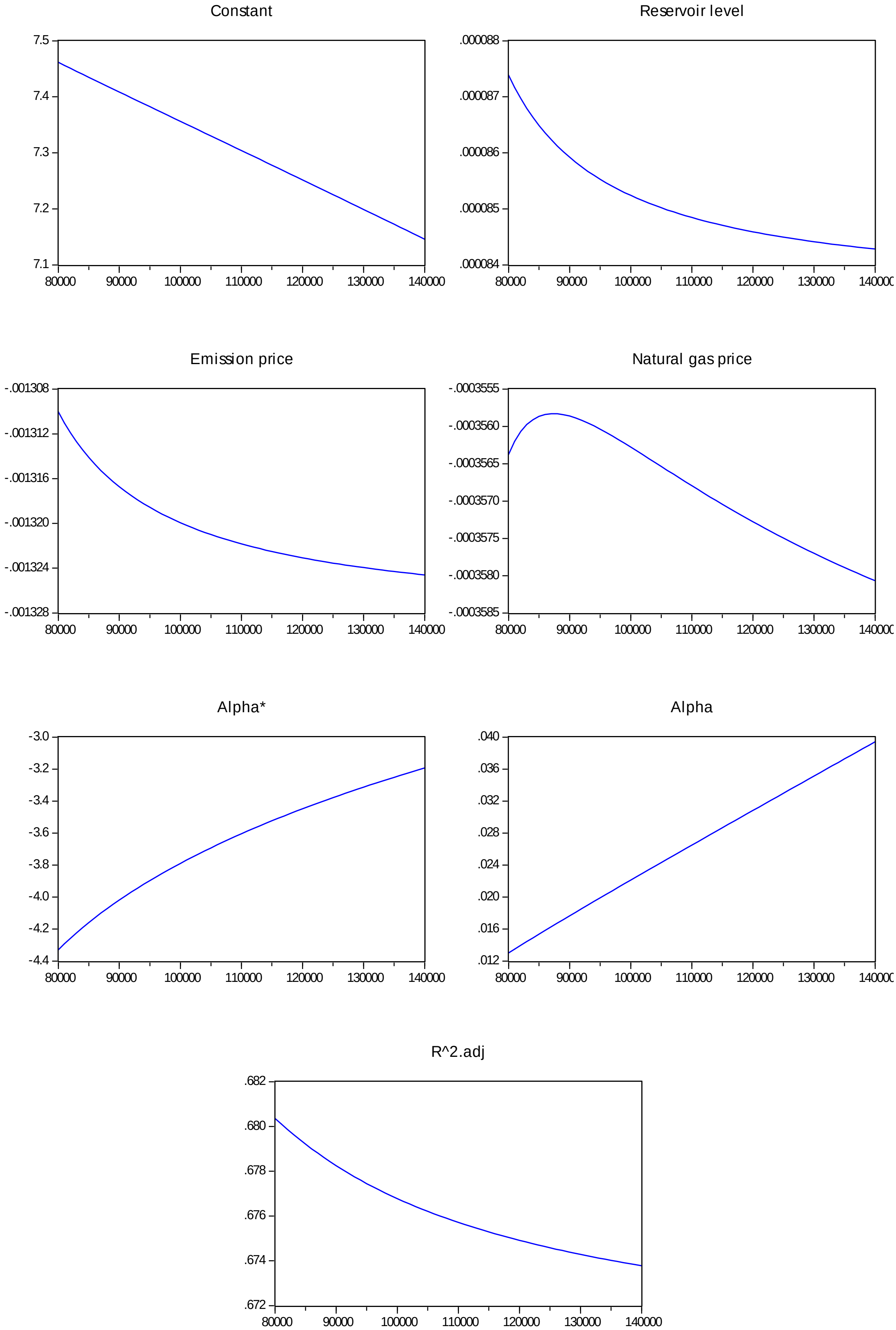

Figure 6: Shows the parameter estimates of the model $P_t(d_t) = \bar{p} - e^{a_0 + a_r r_t + a_e p_{e,t} + a_g p_{g,t}}(\bar{s} - d_t)^{\frac{1}{1+e^{-a^*}}} + \epsilon_t$ *with* $\alpha = \frac{1}{1+e^{-a^*}}$ *for different values of* $\bar{S}$ *(x-axis), ranging from 80,000 MW to 140,000 MW. The constant, reservoir level, emission price, natural gas price, alpha* and alpha show, respectively, the* a_0, a_r, a_e, a_g, α^* *and* α *estimates for different values of* $\bar{S}$.

estimated coefficients for the model differ significantly between the $\text{Low}_{25\%}$ and $\text{High}_{25\%}$-subsamples. The hypothesis for the Wald-test are as follows:

H_0: $a_{g,Low} = a_{g,High}$ & $a_{e,Low} = a_{e,High}$

H_a: H_0 is not true.

The number of parameters compared is the number of degrees of freedom. That means that the number of degrees of freedom (g) is 2. The Wald statistic is given in Table 6 and shows that there is a significant difference between the parameter estimates in the $\text{Low}_{25\%}$- and $\text{High}_{25\%}$-samples. This shows that the parameters of this model change significantly for different reservoir levels i.e. the parameters are time-varying. This is the first hint of some form of nonlinearity.

Table 5a: The least squares estimates for $\text{Low}_{25\%}$-sample

$\text{Low}_{25\%}$ -model	a_0	a_r	a_e	a_g	α^*	α	$\overline{R^2}$ [R^2]
Model E	7.381	4.97e-05	-6.00e-04	-2.61e-05*	-3.995	0.0181	0.710
	(0.00361)	(5.99e-05)	(1.07e-05)	(1.23e-05)	(0.0185)		[0.710]
Model B	7.401	2.42e-04			-4.166	0.0153	0.361
	(0.00490)	(1.19e-05)			(0.0297)		[0.361]

Table 5b: The least squares estimates for $\text{High}_{25\%}$-sample

$\text{High}_{25\%}$ -model	a_0	a_r	a_e	a_g	α^*	α	$\overline{R^2}$ [R^2]
Model E	7.307	1.13e-04	-0.00169	-5.28e-04	-3.584	0.0270	0.577
	(0.00357)	(9.78-05)	(2.68e-05)	(2.89e-05)	(0.0125)		[0.577]
Model B	7.349	2.04e-04			-3.892	0.0200	0.488
	(0.00405)	(9.98-05)			(0.0189)		[0.488]

Table 5: Table 5a and Table 5b give the parameter estimates for the model $P_t(d_t) = \bar{p} - e^{a_0 + a_r r_t + a_e p_{e,t} + a_g p_{g,t}}(\bar{s} - d_t)^{\frac{1}{1+e^{-\alpha^*}}} + \epsilon_t$ (model E) and for the model with the restrictions $a_c = a_g = 0$ (model B) for the $\text{Low}_{25\%}$-subsample and the $\text{High}_{25\%}$-subsample, respectively. Furthermore, the tables provide the $\overline{R^2}$ and the R^2 for every model, where the R^2 is reported between brackets. The α is obtained after applying the transformation $\alpha = \frac{1}{1+e^{-\alpha^*}}$. The $\text{Low}_{25\%}$-subsample contains 3552 hourly observations and the $\text{High}_{25\%}$-subsample 8688 hourly observations. Heteroskedasticity robust standard errors are shown in parentheses and the scientific notation: 1e-03 = 0.001 is applied. All estimates are significant at the 1% level, except for the one with the * (asterisk), that denotes 5% significance.

Test statistic	$\mathcal{W}$	d.o.f.	Probability
Chi-square	157.919	2	0.000

Table 6: Shows the Wald statistic for the differences in parameters between the two subsamples, $\text{Low}_{25\%}$ and $\text{High}_{25\%}$. The table reports the degrees of freedom (d.o.f.) and the Wald-statistic follows a χ^2(g) – distribution, where g stands for the number of degrees of freedom, i.e. the number of parameters compared.

One could reason that the effect of the natural gas and emission price on the day-ahead electricity price should be larger for low reservoir levels relative to high reservoir levels, as less hydro capacity is available and thermal power will be the marginal technology more often. Or stated differently, the estimates for the emission permit and natural gas price should be larger in magnitude, i.e. more negative, in the low subsample. But such a clear-cut interpretation is not shown in the results.

However, the R^2 of the models do show an important finding[29]. The R^2 for the $Low_{25\%}$-sample is substantially higher, relatively to the $High_{25\%}$-sample. The model explains 71.0% of the variation in hourly electricity prices in the $Low_{25\%}$-sample, opposite to 57.7% in the $High_{25\%}$-sample. The supply-model structured with the fundamentals reservoir level, emission price and the natural gas price, clearly, explains more of the variation in prices for the $Low_{25\%}$-sample, than for the $High_{25\%}$-sample, i.e. the supply-model fits the lower reservoir subsample better than the higher reservoir subsample. We believe that this significant difference in R^2 between low and high reservoir levels and the time varying parameters in the model, is the result of a change in competitive behavior of the hydro power producers in the Nordic power market. This change in competitive behavior of the hydro power producers, is caused by varying available hydro supply and leads to a change of the competitive setting in the entire Nordic electricity market.

For example, with high reservoir levels all hydro power producers have large available hydro supply. All agents want to sell hydropower, as not selling could lead to spillovers in the future, which won't earn the hydro producer anything. This increased drive to sell hydropower puts more pressure on the competition, i.e. the market tightens. Agents will be more willingly to sell and are probably less concerned about the actions of their competitors. Hydro suppliers, in this sense, have a smaller set of possibilities due to more pressure on the urge to sell as a result of abundant hydro capacity.

On the contrary, when reservoir levels are lower, hydro power producers have less available hydro supply. The decision when to sell will be made with more care, as selling now means even lower reservoir levels and possibly not being able to sell later. Therefore, the hydro power producer must be certain that he receives the best price when he actually makes a sale. Their competitive behavior will probably be more strategic; actions of their rivals will be observed more closely, they will pick their moments to sell power with more care and will be more restrained over their own actions. The set of possibilities of the hydro power producer, in this sense, is larger, possibly due to the high inelasticity of power demand.

[29] The R^2 is evaluated instead of the $\overline{R^2}$, because in this case the same model is compared on different datasets, instead of nested models on the same dataset.

The competitive behavior of the agents, thus, varies for different reservoir levels and therefore the competitive setting in the total Nordic power market. This leads to parameters, which have a different influence on the price for different reservoir levels, i.e. time varying parameters. Although the estimates for the emission permit price and the natural gas price do not show a smaller coefficient for the $Low_{25\%}$-subsample, the result that the competitive setting in the market changes, which leads to varying parameters in the model, shows some form of the nonlinear dependence of the electricity price on the natural gas and emission permit price.

The nonlinearity of the influence from the emission and natural gas price on the electricity price is clearly noticeable, if you compare the $\overline{R^2}$ of the model with and without the natural gas and emission permit price, i.e. model E and model B, in Table 5. The thermal power marginal cost variables, i.e. natural gas and carbon permit price, explain in model E, relatively to model B, in the $High_{25\%}$-subsample 0.08 more of the variation in day-ahead electricity prices. The increase in $\overline{R^2}$ for the $Low_{25\%}$-subsample after including the emission and natural gas price as variables in model E, relatively to model B, is 0.359. The increase in the fit of model E is tow times larger for the $Low_{25\%}$-subsample. This shows the change in dynamics of the influence, i.e. the nonlinearity, of the emission and natural gas price on the electricity price for different reservoir levels. With lower reservoir levels, the marginal cost of thermal power production explain four times more of the variation in day-ahead electricity prices relatively to higher reservoir levels. This is the result of thermal power production technologies being the marginal production technology more often. As, due to lower reservoir levels, hydro power producers will pick their moments to produce more wisely, and, hence, in order to meet demand more electricity is generated via thermal power production facilities.

5.2.2 $Low_{15\%}$ and $High_{15\%}$- subsample regression

The results for the $Low_{15\%}$- and $High_{15\%}$-samples are shown in Table 7 and 8 and illustrate similar results. The parameter estimates are more negative, i.e. larger in magnitude for the $High_{15\%}$ subsample. The Wald-statistic shows that there is a significant difference in the parameters between the two subsamples. The R^2 of the model is, again, notable larger for the $Low_{15\%}$-subsample, 0.765, compared to 0.596 for the $High_{15\%}$ subsample, showing the different competitive behavior of the hydro power producers. And, lastly, the increase of the $\overline{R^2}$ after including the natural gas price and emission permit price variables is larger for the Low-subsample, namely 34.1%, relatively to an increase in the High-subsample of 15%. Showing the increase in explanatory power in the day-ahead electricity prices for lower reservoir levels, when thermal power is the marginal technology more often.

5.2.3 Random behavior

Another fact that supports the change in competitive behavior of the hydro power producers, is shown in the summary statistics of the different subsamples in Appendix Table A3 and A4. For both samples, 25% and 15%, the minimum day-ahead electricity price in the Nordic market is lower in the High-samples. This, together with the larger negative skewness for both Low-samples and a larger kurtosis for the High-samples, i.e. fatter tails, provides evidence that more lower prices, or "negative" spikes, occur when the reservoir levels are higher. In our opinion this is in line with the proposed theory. When reservoir levels are high, more hydro supply is available. In order to prevent losses due to invaluable spillovers, agents are more willingly to accept, and will also sell against, lower prices. The hydro power producers, thus, show more random behavior when reservoir levels are (almost) full. Model E is not able to capture this random behavior. Resultantly, the fit of model E for the High-samples is lower.

Table 7a: The parameter estimates for $Low_{15\%}$-sample.

$Low_{15\%}$ -model	a_0	a_r	a_e	a_g	α^*	α	$\overline{R^2}$ (R^2)
Model E	7.362	6.17e-05	-8.20e-0.4	-5.80e-04	-3.805	0.0218	0.764
	(0.00594)	(1.63e-05)	(1.69e-05)	(3.66e-05)	(0.0240)		[0.765]
Model B	7.315	4.50e-04			-3.761	0.0227	0.423
	(0.00706)	(2.11-05)			(0.0283)		[0.424]

Table 7b: The parameter estimates for $High_{15\%}$-sample.

$High_{15\%}$ -model	a_0	a_r	a_e	a_g	α^*	α	$\overline{R^2}$ (R^2)
Model E	7.324	-1.40e-04	-0.00145	-0.00082	-3.546	0.0280	0.596
	(0.00389)	(1.75e-05)	(4.00e-05)	(3.50e-05)	(0.0132)		[0.596]
Model B	7.290	-4.06e-05			-3.571	0.0273	0.447
	(0.00397)	(2.52e-05)			(0.0157)		[0.447]

Table 7: Table A5a and A5b give the parameter estimates for the model $P_t(d_t) = \bar{p} - e^{a_0 + a_r r_t + a_e p_{e,t} + a_g p_{g,t}} (\bar{s} - d_t)^{\frac{1}{1+e^{-\alpha^*}}} + \epsilon_t$ (model E) and for the model with the restrictions $a_c = a_g = 0$ (model B) for the $Low_{15\%}$-subsample and $High_{15\%}$-subsample, respectively. Furthermore, the tables provide the $\overline{R^2}$ and the R^2 for every model, where the R^2 is reported between brackets. The α is obtained after applying the transformation $\alpha = \frac{1}{1+e^{-\alpha^*}}$. The $Low_{15\%}$-subsample contains 2375 hourly observations and the $High_{15\%}$-subsample 6360 hourly observations. Heteroskedasticity robust standard errors are shown in parentheses and the scientific notation: 1e-03 = 0.001 is applied. All estimates are significant at the 1% level, except for the one with the † that denotes an insignificant estimate.

Test statistic	$\mathcal{W}$	d.o.f.	Probability
Chi-square	212.51	2	0.000

Table 8: Shows the Wald statistic for the differences in parameters between the two subsamples, $Low_{15\%}$ and $High_{15\%}$. The table reports the degrees of freedom (d.o.f.) and the Wald-statistic follows a $\chi^2(g)$ – distribution, where g stands for the number of degrees of freedom, i.e. the number of parameters compared.

Summarizing, the Wald test on the parameter estimates for the emission permit price and the natural gas price in the Low- and High-samples shows that the parameters in the structured supply curve are time varying. The the parameters have a different influence on the price with low or high hydro supply. An explanation for this is the change in competitive behavior of hydro power producers due to varying reservoir levels, which result in a dissimilar competitive setting in the market for low and high reservoir levels. That is, low reservoir levels the hydro producers have a larger set of possibilities to produce or not, high reservoir levels more competitive pressure and more random behavior. The large difference in the increase of the fit between the Low- and High-samples, after including the emission permit and natural gas price, shows a larger explanatory power of the thermal power variables for lower reservoir levels. This is the result of thermal power production being the marginal technology more often when reservoir levels are low. The time varying parameters in the model and the difference in the fit of the model for high and low reservoir levels, show the nonlinearity in Model E.

The high and low subsample regressions show that the parameters and the fit of the model is significantly different for lower and higher reservoir levels. In our opinion, this shows that agents of hydro power stations behave differently for dissimilar reservoir levels. With high reservoir levels, all hydro power producers will have large hydro supply and all will be more eager to sell in order to prevent unbeneficial reservoir spillovers. The set of possibilities from the agents seems to be smaller for higher reservoir levels, leading to more random behavior. With low reservoir levels the agents act more preserved, more closely monitoring the actions of other market participants. This creates a different competitive setting in the market for different reservoir levels. Therefore, the parameters of the model have a different influence on the price for different reservoir levels.

Secondly, the fit of the model also shows the nonlinear influence of the thermal power marginal costs on the electricity price. Including the emission permit price and the natural gas price in the low-sample, increases the fit substantially, in comparison to a minor increase in the High-samples. Apparently, thermal power production is more often the marginal technology when reservoir levels are low, since the emission permit price and the natural gas price are of more importance in the price formation when reservoir levels are low. This is probably due to the higher opportunity costs of hydropower with low hydro supply.

6 Conclusion

The goal of this paper is to provide empirical insight into to the relation of the fuel and emission prices on the day-ahead hourly electricity price for varying reservoir levels. Therefore, this paper firstly models the (short-term) supply-side of the market by using the demand and supply framework. This results in the first important finding of this paper, a time-varying supply curve that is structured with reservoir level (in percentages of total capacity), the natural gas price and the CO_2 emission permit price. The coal price is not included in the model, due to the high correlation with the emission price. The supply curve explains 0.68 of the total variation in hourly day-ahead electricity prices, which is quite substantial. This confirms the believe of Routledge et al. (2001), that the dynamics of the demand and supply framework can be used to structure a supply curve with fuel and emission prices. And builds on models from, e.g. Barlow (2002), to come to a successful model for the Nordic power market. The signs of the parameter estimates are in line with our hypotheses. An increase of hydro supply, or more precisely reservoir level, has a decreasing effect on the day-ahead electricity price and an increase of the emission permit price and the natural gas price an increasing effect.

This structured supply model resembles the supply side of the market and the interest of this paper lies in the effects of the production fuel and emission permit price variables on the day-ahead electricity price for different reservoir levels in the Nordic electricity market. The parameter constancy is examined by regressions performed on different low and high reservoir level. The Wald-tests show that the parameters of the power supply curve model differ significantly for dissimilar reservoir levels. We believe that this shows a change in competitive behavior of market agents at different reservoir levels, which changes the competitive environment in the market. During periods of high reservoir levels the hydro producers want to avoid spillovers. Resultantly, they want to sell hydro power, as all hydro agents have abundant hydro supply and want to sell this at the same time, the competition on the market increases, i.e. tight market conditions. As a result of this competitive pressure, the hydro suppliers will care less about the actions of their competitors, but be more concerned about selling their hydro power to avoid invaluable losses and therefore accept lower prices. The hydro agents will show more random behavior. This part is strengthened by the fact that more lower prices (or negative price spikes) occur during periods with higher reservoir levels.

This is different when reservoir levels are low. None of the hydropower producers have the urge to sell, i.e. the pressure to sell is lower. This makes that the agents will show different (more strategic) behavior, e.g. pick the moments when to trade more carefully and monitoring the market and the actions of the competitors more closely, as selling hydro power now could mean not being able to sell tomorrow. The competitive behavior of the hydro producers, thus, changes and, resultantly, the competitive environment in the market changes with different reservoir levels. Leading to different parameters and a different influence of those parameters on the price formation. Lucia et al. (2008) hypothesize this inequality in the price formation, this paper, now, provides empirical evidence for it.

This change in the competitive setting between the agents, with more random behavior at higher reservoir levels, is also visible in the difference of the R^2 in the subsample regressions. The R^2 is significantly higher for the Low-samples, relatively to the High-samples. Showing on the one hand, the increase in random behavior at higher reservoir levels which the model is less able to cope with. And on the other hand, that the structured supply curve with the emission permit price and the natural gas price explains more of the variation in day-ahead electricity price during periods with lower reservoir levels. This difference in explanatory power is even better observable when the $\overline{R^2}$ of a model with and without the emission permit and natural gas price variable for the Low- and High-samples are compared. From this we conclude that more thermal power is produced when reservoir levels are low, which leads to thermal power being the marginal technology more often. Hence, the emission permit and natural gas price have larger explanatory power for the day-ahead electricity price at lower reservoir levels. This provides empirical evidence for our hypothesis of a nonlinear influence of the marginal cost of thermal power on the electricity wholesale price.

With this result, we contribute to the literature on the influence of renewables on the power market and to papers on electricity spot price determinants, while shining light on the dynamic relation between fuel prices, emission permit prices and electricity wholesale prices in the Nordic power market. The aim is, eventually, to come up with a general framework that uses the supply and demand dynamics to define the electricity price. Providing empirical evidence of this nonlinear dependency and the dynamic competitive setting in the Nord Pool is a first, minor step. Resultantly, the next step for fundamental modelling of the price formation process is to include the results of this paper in a dynamic model. Naturally, more research is desired and extensions to the model, some possibilities already discussed in paragraph 6, are valuable.

8 References

[1] **Barlow**, M.T., 2002, "A Diffusion Model for Electricity Prices", *Mathematical Finance,* Volume 12, Issue 4, pp. 287-298.

[2] **Borenstein**, S., 2002, "The trouble with electricity markets: understanding California's restructuring disaster", *Journal of Economic Perspectives,* Volume 16, Issue 1, pp. 191-211.

[3] **Buzoianu**, M., Brockwell, A.E. and Seppi, D.J., 2005, "A Dynamic Supply-Demand Model for Electricity Prices", *Carnegie Mellon University working paper,* pp. 1-18.

[4] **Cartea**, A. and Villaplana, P., 2007, "Spot Price Modeling and the Valuation of Electricity Forward Contracts: the Role of Demand and Capacity", *Journal of Banking and Finance,* Volume 32, Issue 12, December 2008, pp. 2502 – 2519.

[5] **Chiang**, T.C., 1988, "The Forward Rate as a Predictor of the Future Spot Rate – a Stochastic Coefficient Approach"*, Journal of Money, Credit and Banking*, Volume 20, Issue 2, May 1988, pp. 212 – 232.

[6] **Cramton**, P.C., Kahn, A.E., Porter, R.H. and Tabors, R.D., 2001, "Uniform Pricing or Pay-as-bid Pricing: A Dilemma for California and Beyond", *The Electricity Journal,* Volume 14, Issue 6, pp. 70-79.

[7] **Douglas**, S. and Popova, J., 2008, "Storage and the Electricity Forward Premium", *Energy Economics 30*, Issue 4, July 2008, pp. 1712 – 1727.

[8] **Emery**, G.W. and Liu, Q., 2002, "An Analysis of the Relationship between Electricity and Natural-gas Futures Prices", *The Journal of Futures Markets,* Volume 22, Issue 2, pp. 95 – 122.

[9] **Engle**, R.E. and Granger, C.W.J., 1987, "Co-integration and Error Correction: Representation, Estimation and Testing", *Econometrica*, 55, pp. 251-276.

[10] **Fridolfsson**, S.O. and Tangeras, T.P., 2009, "Market power in the Nordic electricity wholesale market: A survey of the empirical evidence", *Energy Policy,* Volume 37, Issue 9, pp. 3681 – 3692.

[11] **Huisman**, R., Huurman, C. and Mahieu, R., 2007, "Hourly Electricity Prices in Day-ahead Markets", *Energy Economics,* Volume 29, pp. 240 – 249.

[12] **Huisman**, R, 2012, "The Influence of Underlying Fossil Fuels on Forward Electricity Prices", pp. 1 – 17.

[13] **Huisman**, R., V. Stradnic and S. Westgaard, 2014, "Renewable Energy and Electricity Prices: Indirect Empirical Evidence from Hydro Power", working paper.

[14] **Kaminski**, V, 1997, "The Challenge of Pricing and Risk Managing Electricity Derivatives: in the US Power market", *Risk Publications*, pp. 149 – 171.

[15] **Lucia**, J.J. and Torró, H., 2008, "Short-term Electricity Futures Prices: Evidence on the Time-varying Risk Premium", *Working Paper,* pp. 1 – 36.

[16] **Mjelde**, J.W. and Bessler, D.A., 2009, "Market Integration among Electricity Markets and their Major Fuel Source Markets", *Energy Economics*¸ Volume 31, Issue 3, May 2009, pp. 482 – 491.

[17] **Mohammadi**, H., 2009, "Electricity prices and fuel costs: Long-run relations and short-run dynamics", *Energy Economics,* Volume 31, Issue 3, pp. 503-509.

[18] **Nielsen**, S., Sorknæs, P. and Østergaard, P.A., 2011, "Electricity market auction settings in a future Danish electricity system with a high penetration of renewable energy sources – A comparison of marginal pricing and pay-as-bid", *Energy,* Volume 36, Issue 7, pp. 4434-4444.

[19] **Nordpool Spot**, 2012, "Production Split 2004 – 2012", Oslo: NordPool, pp. 1-10.

[20] **Ramberg**, J, 2011, "ICC Guide to Incoterms® 2010", *ICC Publication No. 720.*

[21] **Redl**, C, Haas, R, Huber, C and Böhm, B, 2009, "Price Formation in Electricity Forward Markets and the Relevance of Systematic Forecast Errors", *Energy Economics*, Volume 31, Issue 3, pp. 356-364.

[22] **Roques**, F.A., Nuttall, W.J., Newbery, D.M., de Neufville, R. and Connors, S., 2006, "Nuclear Power: A Hedge Against Uncertain Gas and Carbon Prices", *The Energy Journal,* Volume 27, Issue 4, pp. 1-24.

[23] **Routledge**, B.R., Spatt, C.S. and Seppi, D.J., 2001, "The "Spark Spread:" An Equilibrium Model of Cross-Commodity Price Relationships in Electricity", *Tepper School of Business*, Paper 413.

[24] **Sensfuβ**, F., Ragwitz, M. and Genoese, M., 2008, “The Merit-order Effect: A Detailed Analysis of the Price Effect of Renewable Electricity Generation on Spot Market Prices in Germany”, *Energy Policy,* Volume 36, Issue 8, pp. 3086 – 3094.

[25] **Skantze**, P., Gubina, A. and Ilic, M., 2000, “Bid-based Stochastic Model for Electricity Prices: the Impact of Fundamental Drivers on Market Dynamics”, *Report 00-04 Energy Laboratory,* MIT.

[26] **Stoft**, S., 2002, “Power system economics: designing markets for electricity”, *Wiley-IEEE Press*.

[27] **Torro**, H. 2007, “Forecasting Weekly Electricity Prices at Nord Pool”, *Fondazione Eni Enrico Mattei working paper,* Sept. 2007, pp 1 – 36.

[28] **Weron**, R., Simonsen, I. and Wilman, P., 2004, “Modeling Highly Volatile and Seasonal Markets: Evidence from the Nord Pool Electricity Market”, *Applications of Econophysics,* pp. 1-10.

[29] **Zachmann**, G., 2013, “A Stochastic Fuel Switching Model for Electricity Prices”, *Energy Economics,* Volume 35, pp. 5-13.

[30] **Zivot**, E. and Wang, J., 2002, “Modeling Financial Time Series with S-PLUS”, *Springer-Verlag*, New York.

9 Appendix

This paragraph provides the tables, figures and derivations that are not of primary importance for the reader, but are still valuable for the report. Firstly, the appendix for the literature review is provided. Secondly, the additional tables for the results are reported.

9.1 Appendix Literature Review

9.1.1 The production split for the Nord Pool in 2012

Country	Denmark	Finland	Norway	Sweden	Sum	Share of total

Energy source						generation (in %)
Hydropower	0,0	16,7	142,9	77,7	237,3	57,0
Nuclear power	0,0	22,1	0,0	61,2	83,3	20,0
Fossil fuels	16,4	17,1	3,4	4,6	41,5	10,0
Wind power	10,3	0,5	1,6	7,1	19,5	4,7
Other renewable	12,5	10,4	0,0	10,8	33,8	8,1
Non-identifiable	0,0	0,9	0,0	0,0	0,9	0,2
Total production	39,2	67,7	147,8	161,6	416,3	100,0

Table A1: The generation of electricity in the Nordic area for 2012 per generation technology in TWh for each country. The last column shows the shares per different generation technologies of the total electricity production in percentages. *Source: NordPool Spot – Production Split 2004 – 2012.*

9.2 Appendix Results

9.2.1 Supply model structured with coal price

Table A2: Parameter estimates for the model $P_t(d_t) = \bar{P} - e^{a_0+a_r r_t+a_c p_{c,t}}(\bar{S} - d_t)^{\frac{1}{1+e^{-\alpha^*}}} + \epsilon_t$

	a_0	a_r	a_c	α^*	α	$\overline{R^2}$
Model C*	7.384	1.51e-04	-3.60e-04	-3.900	0.0198	0.582
	(0.00215)	(1.62e-06)	(4.01e-06)	(0.0104)		

Table A2: Shows the parameter estimates a nested model of $P_t(d_t) = \bar{P} - e^{a_0+a_r r_t+a_c p_{c,t}+a_e p_{e,t}+a_g p_{g,t}}(\bar{S} - d_t)^{\frac{1}{1+e^{-\alpha^*}}} + \epsilon_t$. This is the model obtained by putting the restrictions on $a_e = a_g = 0$. Model C* lets a constant, hydro capacity structure the supply curve with r_t (reservoir level in %) as a variable and the coal price ($p_{c,t}$) structure the supply curve. The table also gives the adjusted R^2 ($\overline{R^2}$) and the α, which is obtained after applying the transformation $\alpha = \frac{1}{1+e^{-\alpha^*}}$. The regression is performed using non-linear least squares (NLS) over the total sample period from 01-01-2011 until 04-28-2013, including a total number of 20320 hourly observations. Heteroskedasticity robust standard errors are shown in parentheses and the scientific notation: 1e-03 = 0.001 is applied.

9.2.2 Descriptive statistics for the $Low_{25\%}$ and $High_{25\%}$ subsamples

Table A3a: Descriptive statistics $Low_{25\%}$-subsample.

	Day-ahead Electricity Price (€/MWh)	Consumption Prognosis (MWh)	Reservoir Capacity (% of total capacity)	EU Emission Allowance (€/EUA)	Nord Pool day-ahead Gas Price (€/MWh)
Mean	55.96	46966	24.93	12.40	26.44

Median	57.22	46927	24.37	15.1	23.76
Minimum	11.19	18608	16.46	2.68	21.24
Maximum	109.55	67335	34.98	16.83	78.64
St. Dev.	9.442	8240	5.291	5.390	7.246
Skewness	-0.513	0.0578	0.116	-0.899	3.814
Kurtosis	3.547	2.527	1.954	1.906	22.51

Table A3b: Descriptive statistics $High_{25\%}$-subsample.

	Day-ahead Electricity Price (€/MWh)	Consumption Prognosis (MWh)	Reservoir Capacity (% of total capacity)	EU Emission Allowance (€/EUA)	Nord Pool day-ahead Gas Price (€/MWh)
Mean	31.87	43477	83.20	8.78	24.38
Median	34.19	42426	84.77	7.92	24.30
Minimum	1.45	21563	71.91	5.71	16.92
Maximum	138.76	70067	90.26	13.25	30.64
St. Dev.	11.78	8782	4.96	2.01	2.25
Skewness	-0.084	0.520	-0.55	0.74	0.16
Kurtosis	5.50	2.727	2.15	2.18	2.80

Table A3: This table shows the descriptive statistics of the different variables for the $Low_{25\%}$-subsample and the $High_{25\%}$-subsample, respectively, Table A3a and Table A3b. The common sample contains a total of 3553 hourly observations for the Nordic power market in the $Low_{25\%}$-subsample and a total of 8688 hourly observations for the Nordic power market in the $High_{25\%}$-subsample.

9.2.3 Descriptive statistics for the $Low_{15\%}$ and $High_{15\%}$ subsamples

Table A4a: Descriptive statistics $Low_{15\%}$-subsample.

	Day-ahead Electricity Price (€/MWh)	Consumption Prognosis (MWh)	Reservoir Capacity (% of total capacity)	EU Emission Allowance (€/EUA)	Nord Pool day-ahead Gas Price (€/MWh)
Mean	56.18	45567	21.90	13.08	24.76
Median	58.20	45711	22.74	16.10	23.97
Minimum	11.19	21942	16.46	2.68	21.24
Maximum	90.54	67335	27.36	16.83	33.59
St. Dev.	9.56	6927	3.36	5.30	2.58
Skewness	-0.83	0.12	-0.16	-1.20	1.55

Kurtosis	3.65	2.82	1.64	2.51	5.46

Table A4b: Descriptive statistics $High_{15\%}$-subsample.

	Day-ahead Electricity Price (€/MWh)	Consumption Prognosis (MWh)	Reservoir Capacity (% of total capacity)	EU Emission Allowance (€/EUA)	Nord Pool day-ahead Gas Price (€/MWh)
Mean	30.32	43473	85.74	8.54	24.85
Median	33.31	42811	86.49	7.88	24.65
Minimum	2.16	27756	79.11	5.71	16.92
Maximum	92.15	70067	90.26	13.25	29.81
St. Dev.	11.70	7777	2.83	1.66	1.90
Skewness	-0.44	0.49	-0.51	0.89	-0.38
Kurtosis	3.85	2.96	2.62	2.77	4.00

Table A4: This table shows the descriptive statistics of the different variables for the $Low_{15\%}$-subsample and the $High_{15\%}$-subsample, respectively, Table A4a and Table A4b. The common sample contains a total of 2375 hourly observations for the Nordic power market in the $Low_{15\%}$-subsample and a total of 6360 hourly observations for the Nordic power market in the $High_{15\%}$-subsample.