UNIVERSITY OF VAASA

SCHOOL OF ACCOUNTING AND FINANCE

Samuli Visa

THE RELATIONSHIP BETWEEN NORD POOL SPOT PRICE DISTRIBUTION AND RISK PREMIUMS IN ELECTRICITY FUTURES MARKETS

Master's Thesis in
Accounting and Finance

Master's Degree Programme in Finance

VAASA 2019

TABLE OF CONTENTS page

LIST OF FIGURES AND TABLES

FIGURES

TABLES

UNIVERSITY OF VAASA
School of Accounting and Finance
Author: Samuli Visa
Topic of the Thesis: The Relationship Between Nord Pool Spot Price Distribution and Risk Premiums in Electricity Futures Markets
Name of the Supervisor: Timo Rothovius
Degree: Master of Science in Economics and Business Administration
Department: Department of Accounting and Finance
Master's Programme: Master's Degree Programme in Finance
Year of Entering the University: 2010
Year of Completing the Thesis: 2019 **Pages: 128**

ABSTRACT

This Master's thesis studies spot- and futures pricing in the Nordic electricity markets. Electricity markets provide an interesting and challenging framework for financial research. Studies of electricity derivatives pricing are usually based on the Risk Premium literature, but this thesis also discusses whether electricity futures pricing could be modeled from the perspective of the Theory of Storage.

The data set consists of daily spot electricity prices, monthly futures on spot electricity, and 13 explanatory variables. The explanatory variables include Nordic water level factors, Nordic weather temperature factors, several fuel price proxies, and market risk / sentiment variables. The sample period begins 1.1.2005 and ends 31.12.2015.

Electricity prices are highly volatile and often extreme. Extreme prices are known as price spikes in the literature. To study the tail behavior of prices and price spikes, the thesis studies the entire spot price distribution using quantile regression methodology. The thesis continues by studying the risk premiums of electricity futures using reduced form model originally introduced to the literature by Bessembinder & Lemmon (2002) and Longstaff & Wang (2004). Finally, the thesis combines the findings of previous two hypotheses in order to develop an optimally performing model of the Nordic futures pricing.

The thesis provides contribution to the existing literature by identifying significant factors across the spot price distribution and by studying how those factors affect risk premiums in the derivative markets. The thesis also contributes to the discussion regarding the concept of Indirect Storability in electricity futures pricing. Moreover, the thesis provides contribution by developing a population weighted average temperature index for the Nordic countries. The daily index is obtained from 58 different weather observation stations throughout the Nordic countries. Temperatures are weighted by the population living in the proximity of the weather observation station to better understand how local weather conditions affect the demand for electricity.

KEYWORDS: Electricity Market, Nord Pool, Risk Premium, Quantile Regression

1. INTRODUCTION

Electricity markets provide many interesting venues for financial research. One of the most distinctive features of electricity markets originates from the physical characteristics of electricity. Essentially, all the other commodities are physical. Physical commodities can be stored and the storage costs and rationale for storing the commodity may vary. However, electricity has no physical form and it is in fact current of energy that can be used to power equipment. Electricity should be considered as a constant flow of energy and there is no economically reasonable way to store it in a large scale. For example, oil markets trade in barrels of oil, gold trades in troy ounces, and corn trades in bushels; whereas electricity trades in megawatt hours (MWh). MWh is a unit of energy and one MWh equals a constant flow of 1 MW over the period of one hour. The nonstorable nature of electricity has strong effects on both electricity spot prices and derivative prices. (CME Group homepage)

In historical sense, electricity markets have only recently started to open for competition and this makes them an interesting research topic. Before the liberalization of the markets, it made sense to have electricity companies and producers as government owned utilities. Electricity is an absolute necessity for any modern society and the markets have many monopolistic features. For example, there cannot be competition in electricity grids. Electricity generation and transmission is also highly capital-intensive business and economies of scale have pronounced effect on the markets. Furthermore, before the liberalization entering the markets was hard or even impossible because of legislation.

In the Western countries, the deregulation process started with great promise during the 1990s. However, the liberalization process proved to be no easy matter and there were several setbacks in pursuit of free markets. One of the best-known textbook examples of the realized risks of deregulation, in any industry, is the Enron Crisis that occurred in 2001. Enron was able to obtain stellar profits by cornering the markets and by engaging highly unethical trading activities in the recently opened California energy markets. Unethical trading, lack of legislation, and risk management led to the bankruptcy of the one of the largest companies in the US. The state of California also suffered from unprecedented electricity blackouts because of the crisis. (Puller 2007; Stoft 2002; Geman 2005:251-282; Deakin & Konzelmann 2004)

Nonstorability of electricity causes major challenges to the suppliers in the electricity markets. In addition, there are some demand characteristics that greatly affect the price discovery process of electricity. Most importantly, the price inelasticity of the demand for electricity causes the price discovery to greatly differ from the standard microeconomics textbook case. Consumers are initially price takers in the markets and do not actively change their consumption behavior in respect to changes in market prices. This results in a unique situation where the market price is practically determined by the supply function of electricity. The suppliers of electricity have obligation to provide the volume demanded by the markets at all times. If they were to fail in meeting this obligation, the result would be large and expensive power outages. The cost structure of different generation methods varies significantly. When the volume demanded by the markets exceeds the capacity of the cheapest available generation method, the producers start to use more expensive generation methods and fuels to meet the additional demand. In theory, the market price of electricity is determined by the marginal cost of the most expensive generation method, also known as the marginal fuel, used to meet the market demand. This unique market microstructure makes electricity prices highly volatile and prone to suffer from periods of extremely high prices, known as price spikes in the literature.

Nord Pool was the first established joint country power exchange and it was founded in 1996. In 1998, Finland joined the exchange previously formed by Norway and Sweden. All the Nordic countries have been part of the exchange since 2000 when Denmark joined the exchange. Nowadays, also the Baltic countries and UK are included in the market. Nord Pool is considered to be highly efficient and well-functioning power market in the global comparison. It has some unique characteristics which makes it particularly interesting for researchers. One of its key characteristics is that it is a highly hydro dominant market. Norwegian and Swedish hydropower reserves have proven themselves as highly efficient and cost-effective buffers against demand peaks and price spikes in the markets. (Nord Pool AS homepage, Geman 2005: 251-282)

All the publicly traded derivative contracts for Nord Pool electricity are traded in Nasdaq Commodities Europe. Futures contracts, forward contracts, options and swing option contracts on electricity deliveries are some examples of financial contracts that can be traded in electricity markets. The main use of derivative contracts is to meet the hedging purposes of the market participants. By taking a long position in electricity forward or futures contract electricity companies can stabilize the price they are paying for electricity at a certain period in the future. This provides predictability for otherwise highly volatile markets and derivative contracts are thus valuable tools of risk management. (Nasdaq OMX Commodities homepage)

Commodity derivatives pricing is most commonly approached using the assumptions of the 'Theory of Storage' by Kaldor (1939), Working (1948), Brennan (1958), and Telser (1958). However, the key assumption of this theory is that the commodities can be stored for future consumption or trading. Because of the nonstorable nature of electricity, the Theory of Storage cannot (straightforwardly) be used to model derivatives pricing in electricity markets.

Risk management literature and the concept of hedging pressure is in the center of electricity derivatives pricing literature. Electricity market participants are assumed to have demand for hedging their positions using derivative contracts for reducing their operational risks. The counterparties of these hedges however usually require some kind of premium for bearing the risks, and this creates supply and demand conditions for derivative contracts. Models that apply hedging pressure for pricing electricity derivatives contracts are called equilibrium-pricing models. Ever since the pioneering papers of Bessembinder and Lemmon (2002) and Longstaff and Wang (2004), the equilibrium models have been the norm in the literature. However, some recent papers argue that nonstorability of electricity might not be a definitive condition of the markets. Authors including Douglas and Popova (2008), Van Treslong and Huisman (2010), and Huisman and Killic (2012) argue that electricity can actually be stored indirectly in the form of fuels and that this has an effect on the market pricing. These authors argue that fuel prices, and possibly even their storage costs, should be considered when modeling electricity derivatives pricing.

The purpose of this introduction chapter is to present basic information about the Nordic electricity markets and to define the research question of this thesis. It also briefly discusses the main results and the contribution of the thesis. Finally, the last subsection of this introduction discusses the structure of the rest of the thesis.

1.1. The Nordic electricity markets

Nord Pool is the Nordic Electricity Exchange that covers Denmark, Finland, Sweden, Norway, Estonia and Lithuania. Furthermore, Nord Pool has the sole ownership over the British Power Markets. Since 2014, the Nordic markets have been increasingly integrated with North-Western European Power markets through Price Coupling Regions project that is based on European Comission's goal to harmonize the European Power Markets. (Pahkala, Uimonen & Väre 2017; Kauppalehti 2017a & 2017b)

The primary market of Nord Pool Exchange is Elspot day-ahead market. On Elspot, buyers and sellers make bids and offers for the deliveries of electricity for the following day. The Nord Pool spot is an auction-based exchange, which primary goal is to establish liquid markets for trading electricity. It does so by joining or pooling the producers and consumers of electricity into one market place. The markets form a single equilibrium price for the demand and supply of electricity for each hour of the following day. These equilibrium prices are known as System Prices, or simply as the spot prices. All trades on Elspot markets are settled against physical deliveries of electricity. Contrary to most financial markets, Nord Pool trades electricity on every day of the year. For example, Stoft (2002) argues that auction-based pools are the most efficient and cost effective way to organize electricity markets.

Day-ahead markets are supplemented by the intraday markets, called Elbas. Elbas trades electricity practically on real time. The intraday markets are open every day and around the clock, and it is possible to trade electricity even for the deliveries as close as the following hour. Intraday markets serve as important balancing markets for day-ahead Exchange. Their main goal is to provide the means to react to any sudden supply or demand shocks that could occur in the markets. Intraday markets are becoming increasingly important, as more and more electricity is generated using wind turbines and other renewable methods. Wind and solar generation methods are highly unpredictable by their nature and they need efficient balancing markets to supplement them for keeping the markets stable. As electricity cannot be efficiently stored, the excess supply of windy days has to be sold somewhere immediately. On the other hand, when renewables production is not able to meet the local demand, local power entities need to be able to buy electricity somewhere with a short notice. The purpose of Elbas markets is to provide the means for market participants to react to such sudden circumstances.

Elspot and Elbas prices are not the only important quotes to follow in the Nordic markets. In fact, the System price is only a theoretical common price that the Nordic markets would have if there were no transmission costs or bottlenecks in the electricity grids. In practice, the markets are divided into several bidding areas to establish local area prices for the spot electricity. Local area prices are needed because there are capacity restrictions for the electricity flow in some parts of the grids. Capacity restrictions, also known as bottlenecks, are resulted because each part of the grid has a maximum capacity of electricity that can be transferred through it. There are parts in the Nordic grid that have lower than average maximum capacity and these parts are known as the bottlenecks. Furthermore, there is always some loss in transporting the electricity through distances and also this loss is taken into the account in the local area prices. In other words, the market price of electricity, for example in Finland is not the System Price but the local area price of Finland. Area prices can be compared to delivery costs in many other commodities markets.

Currently the continental markets (not including the UK) has 14 separate area prices. Norway has 5 different local prices, Sweden has 4, and eastern Denmark, Finland, Estonia, Latvia and Lithuania each have one separate local area price. The local area prices become higher when electricity is delivered further from the central market (Oslo), Ceteris Paribus. Local area prices are formed by adding a premium to the System Price formed in the day-ahead markets. This premium is not constant and it is determined by the supply and demand conditions in the markets. (Nord Pool AS homepage; Nord Pool Spot 2009)

DS futures were known as forward contracts before 2013 when their names were changed to better match the international naming conventions of electricity derivatives. DS futures are cash settled Euro nominated contracts settled against the Nord Pool system price of 1 MWh of electricity. The settlement price is determined by the hourly system prices of the delivery period. (Nasdaq OMX 2013)

Yearly, quarterly, monthly, weekly and daily futures contracts are traded in the markets. Yearly and quarterly futures and DS futures are cascaded into shorter corresponding contracts. For example, Nordic Electricity Base Year Future contact maturing on 2015 is cascaded into four quarterly contracts (Q1-Q4) on the expiration day of the contract. On the expiration date, the quarterly contracts are then cascaded into corresponding monthly contracts. For example, Q1 contracts are cascaded into monthly contracts with deliveries for January, February, and March. The monthly, weekly and daily contracts are no longer cascaded and they are cash settled daily against the Nord Pool system prices during their delivery period. The length of the delivery period for monthly, weekly, and daily contracts is one month, one week and one day after the expiration day respectively. (Nasdaq Oslo ASA & Nasdaq Clearing AB 2017)

1.2. Purpose of the study

The purpose of this thesis is to study the risk premiums of futures contracts in the Nordic electricity markets. Commodities futures pricing research can be approached from two different angles and lines of literature; the Theory of Storage and the Risk Premium Theory. The Theory of Storage explains futures prices in relation to spot prices in terms of storage costs, convenience yield and time value of money lost when storing the commodity. The basic assumption of the Theory of Storage is that the supplier of the commodity has an option to sell or store the commodity he or she has produced. If the current market price does not satisfy the producer's supply condition, he / she will store the commodity and wait for more satisfying market prices. However, storing the commodity also has its expenses and the supplier has to optimize between the duration of storage and satisfactory market prices. The core assumption behind the Theory of Storage is that the commodity can be stored. The Risk Premium Theory on the other hand explains the futures pricing by splitting the futures price into an expected risk premium and forecast of the spot price in the maturity of the contract. A fundamental assumption behind this theory is that futures prices contain information about future spot prices and that futures prices contain observable risk premiums. (Fama & French 1987)

Electricity futures pricing is mostly studied from the perspective of the Risk Premium Theory as electricity is almost a perfect example of a commodity that cannot efficiently be stored. However, there is a new concept in the recent literature considering electricity markets; indirect storability. According to the modern line of research, storable fuels, such as gas and oil, introduce inventory like options for electricity producers. Even though the producers do not have economically feasible ways for storing electricity, they can relatively cost efficiently store fuels that can be used for generating electricity. However, this idea is nothing new in the literature, for example Routledge, Seppi and Spat (2000) develop an equilibrium pricing model for electricity futures, which acknowledges the storing option in form of fuels. However, most of the research has considered electricity as a perfectly unstorable commodity. I think that models utilizing the concept of indirect storability could have much to offer, especially for the research studying the Nordic markets. Storability could play a crucial role in the markets because of the vast Nordic water reserves.

The most characteristic feature of the Nordic electricity spot markets is the dominant role of hydropower reserves in the area. Over 50% of the electricity generated in the markets originates from the Nordic hydropower reserves. Unlike with other fuels, such as gas and coal, it is practically cost free to generate power using hydro reserves. However, the producers still face opportunity costs when using their hydropower reserves. Future water inflows and rainfalls are practically impossible to predict, and every time electricity is generated using the reserves the producer has higher risk of running out of reserves in the future. These opportunity costs are called the shadow costs in the literature. Utilizing the concept of indirect storability Botterud, Krisiansen & Illic (2010) try to model the Nordic

Electricity markets from the perspective of the Theory of Storage. Their results are promising and show that water reserves in fact seem to provide similar storage options for producers that exist with most of the other commodities. However, their results have not been able to close the dispute the academics have considering the relevance of the Theory of Storage considering electricity futures pricing. For example, Weron & Zator (2014) criticize their approach as it may have some simplifying assumptions that lead to pitfalls in the overall results of the article. They show that linear regression models are biased when studying the relationship between electricity spot and futures prices because electricity prices are so seasonal and volatile. They apply more advanced GARCH methodology to test the robustness of Botterud et al. (2010) results and find very limited evidence to support their results. However, also Weron et al. (2014) find that deviations from the past water levels have strong explanatory power on the risk premiums in the markets.

Altogether, most studies approve the Risk Premium Theory in electricity markets as a given fact. However, from the modeling perspective the risk premiums can also be considered as prediction errors in the models. For example, Gjolberg & Brattested (2011) find that the futures prices overshoot the spot prices on average by 7,4%-9,3% on monthly bases. They further argue that this is much larger than in any other markets and it is thus hard to explain it just being risk premium.

This thesis aims to contribute to the polarized discussion considering the correct way of modeling the electricity futures pricing. By using daily data set of spot prices, and both daily and monthly observations of monthly futures contract prices, the thesis aims to identify key factors that drive the spot and futures pricing in the markets. 15 different factors are included in the models from the following five categories; statistical characteristics of the spot price distribution, the Nordic water reservoirs, Nordic temperature variables, fuels used for generating electricity, and market risk variables.

In the first empirical part of the thesis, I study how the factors perform in explaining the spot prices observed in the Nordics. Electricity spot prices are known for being highly seasonal, volatile, positively skewed. The nonstorable nature of electricity and demand side price inelasticity causes the markets to be highly prone to price spikes. During these price spikes, spot market prices are extremely high for a short period of time. Traditional linear regression models perform poorly in explaining electricity pricing because of the unique characteristics of market prices (Weron et al. 2014). For this reason, I study the distribution of spot market prices using a more sophisticated econometric tool called quantile regression methodology. The use of quantile regression framework and the large data set collected, allows me to study how electricity prices are formed in different sections of the spot price distribution. The quantile regression model enables me to also study the tails of the spot price distribution. For example, by studying the right tail of spot price distribution I can identify factors that explain the market prices at top 5% of the whole distribution. This methodology could provide important insights for understanding the nature of price spikes observed in the markets.

Following papers, such as Bessembinder et al. (2002), Longstaff et al. (2004), and Huisman et al. (2012), I study risk premiums in the futures markets. At the first stage, I use the standard reduced form model to study the risk premiums and relationship between spot and futures prices. The reduced form model only uses the statistical characteristics of the spot price distribution to explain the risk premiums. I assume that the results of the reduced form model can be greatly improved by utilising the findings of the first hypothesis. The purpose of the final empirical testing of the thesis is to combine the results of the first and second hypothesis. I assume that by identifying factors that have strong explanatory power on different sections of the spot price distribution, I am able to obtain better results in modelling the risk premiums. In the final hypothesis special interest is focused on the factors that have significant explanatory power on the tails of the spot price distribution. The assumption is that those factors that increase the risk of price spikes in the spot markets should also have better explanatory power of risk premiums.

The research question of the thesis can be summarized as follows: Can risk premiums in the Nordic electricity futures markets be more accurately modelled by introducing components that explain the tail distribution of electricity spot prices?

1.3. Results and the contribution of the study

The results of the thesis provide insights into the complex pricing processes of the Nordic markets. The quantile regression model is proven to be a powerful tool in studying which factors explain the spot prices in different sections of the price distribution. The model is also able to identify highly significant factors in the tails of the spot price distribution. These factors could be crucial in understanding the causes of the price spikes in the markets. Variables indicating the state of Nordic Hydropower reserves are proven to be highly significant across the distribution. Also, the weather temperature variables have highly significant results in all sections of the distribution. Coal and LNG are found to be the most important fuel factors affecting the pricing. The VIX index is the most significant proxy of systematic risk / market sentiment. The overall fit of the model is reasonably high.

The results of the second hypothesis indicate that the reduced form model does not explain risk premiums in the Nordic Markets. This finding is in line with Lucia & Torro's (2011) paper, who observed that the reduced form models did not perform well in the Nordic markets after the market fundamentals changed due to an extremely severe price spike that occurred in 2002.

The third hypothesis combines the results of previous two hypotheses to develop a better performing model in explaining the risk premiums in the Nordics. Even though these models obtain highly significant results, the third hypothesis is rejected. The reason for rejection is that the results cannot show causality between the factors that explain the tails of the spot price distribution and risk premiums in the markets. Overall it seems that the water deviation and temperature deviation factors are the most important in explaining both spot and futures pricing in the markets.

The thesis provides contribution to the existing literature in several ways. With the quantile regression methodology, it studies the spot price distribution in detail and tries to apply this information in studying the futures pricing in the markets. However, it seems that risk premiums are determined largely by different fundamentals than the risk premiums in the markets. Moreover, the thesis tries to contribute to the discussion regarding the concept of indirect storability in electricity markets. It seems that the Nordic water reserves have high explanatory power on the risk premiums and that the water reserves could provide storage -like options for the producers of electricity. Other fuel prices obtain surprisingly weak results in explaining the futures premiums. Finally, the thesis provides the literature with a new way of measuring weather temperatures in the Nordic Countries. Constructing a single population weighted weather temperature index, from the data obtained from 58 different weather stations across the Nordic countries, allows me to study the effects of weather temperatures on electricity demand in a new and innovative way. The weather temperature index performs well especially in explaining spot pricing in the Nordic Markets.

1.4. The structure of the study

This paragraph describes the structure of the rest of the thesis. The following chapter provides the literature review and hypothesis development for the thesis. Chapter 3 presents more thorough look into the theoretical background necessary for understanding electricity spot and futures markets. Furthermore, at the end of Chapter 3 is discussion about the model specification. That is an important subsection as the hypotheses development and the data set of the thesis is specified there. The fourth chapter describes the data used in the regression analysis and it also provides some descriptive statistics of the data. It also discusses how the raw data is modified to better suit the research methodology of the thesis. The fifth chapter presents the methodology used in this research. Moreover, it includes a detailed description of every regression model used to test the hypotheses with. The sixth chapter presents the empirical findings of the regression models. At the end of the sixth chapter, all the hypotheses are answered based on the obtained results. The last chapter concludes the thesis. It summarizes the key aspects of this thesis and provides additional discussion and my own conclusions considering the subject and the results. Furthermore, it evaluates how well has this thesis fulfilled its purpose and are all the hypotheses answered conclusively. Moreover, the discussion section aims to specify how the findings and methods of this thesis could be utilized in future research.

2. LITERATURE REVIEW AND HYPOTHESIS

This chapter provides the literature review considering electricity spot and futures pricing. The following subsection discusses the statistical characteristics of electricity spot market prices. It presents the five stylized facts of the spot market prices and what kind of issues the characteristics present from the researcher's point of view.

The second subsection discusses previous literature considering commodities futures pricing and why the properties of electricity present some unique challenges for research. It also presents the most relevant research papers that have been published considering the relationship between the spot and futures prices in the Nordic markets.

The final section of Chapter 2 focuses on the hypotheses development. The hypotheses are formulated based on the findings of previous literature. Chapter 3.5 is also closely related to the hypothesis development. The explanatory variables used in the empirical models are chosen based on the discussion provided in that chapter.

2.1. Properties of Nord Pool Spot prices

Simonsen, Weron, and Mo (2004) conduct a detailed analysis of the statistical properties of Nord Pool Spot prices. Based on their findings they constitute five stylized facts considering the properties of Nord Pool System prices. These stylized facts are presented below:

1. Seasonality. *"Consumption of electricity have (at least) three types of periodicities: daily, weekly, and annual ... By comparing the system spot price with the consumption data, one indeed observes similar cycles for the price and corresponding consumption.… It is fair to say that consumption drives electricity prices".* (Simonsen et al. 2004: 6-7)

2. Mean reversion. *"The spot electricity price process is a (non-Markovian) anti-correlated, or equivalently mean-reverting process."* (Simonsen et al. 2004: 8-9)

3. Price spikes. *"One of the most pronounced features of spot electricity market are the price spikes present in the spot price. ... The price spikes are mainly a result of supply shocks. They are triggered by increased demand and/or the short term disappearance of major production facilities, or transmission lines, due to failure or maintenance, or simply abuse of market power by central market players."* (Simonsen et al. 2004: 9-11)

4. Return Distribution. "*It is rather apparent that the distribution of daily returns is highly non-Gaussian and that its tails are fat… Returns do not show long term correlations."* (Simonsen et al. 2004: 12-13)

5. Volatility; level, correlation, and clustering. *"Electricity spot market has a considerably higher volatility than many other financial and commodity markets. ... Significant temporal correlations are [word indeed omitted] present for Nord Pool up to time scale of approximately 100 days… During low price periods, the volatility tends to be high and vice versa."* (Simonsen et al. 2004: 13-14 & 16)

The first stylized fact states that the spot prices are seasonal. The seasonality of the spot prices originates from the seasonal nature of the demand for electricity. Seasonality is differently observable with different time scales. Electricity prices have at least three different periodicities; intraday-, daily, and annual seasonality. These seasonalities are observable in practically any electricity market globally. The temperatures in the Nordics vary greatly during the course of one year, and the weather conditions have strong effect on demand for electricity. Consumers also have many other behavioral patterns that make the electricity prices seasonal. For example, a study using hourly spot prices does not observe the same seasonal characteristics that a study using monthly prices would observe. The seasonality of hourly electricity demand originates from the daily routines of the people demanding electricity. The seasonality of daily prices also originates from the behavior of consumers. People mostly work during the week and stay home or go to summer cottages during the weekends. These behavioral patterns have strong influence on the electricity demand. Longer term patterns, such as those observed in weekly or monthly data, have more to do with the weather conditions in the Nordics. The highest electricity prices are observed during winters. High demand, during winter periods, can be explained by the heating demand originating from households. In addition, the water reserves in the Nordics start to deplete during winter months and this might also increase the prices.

The second stylized fact considers the mean reversion of spot prices. It states that the Nord Pool prices follow non-Markovian mean reverting processes. This means that Nord Pool prices cannot be modeled using Brownian motion, a commonly used method used in stock market price models. This also means that random walk hypothesis does not apply for the Nord Pool prices. Prices are anti-correlated and mean reverted; in other words, a price increase over a certain period of time is more likely to be followed by a similar price decrease over the next period of time. It is more probable that the markets correct themselves after a period of rising prices and the prices revert to their long-term aggregate level. In financial literature, the Random Walk hypothesis and Brownian motion of prices are crucial for equities derivatives pricing. For example, the Nobel awarded option pricing formula, the Black-Scholes Merton model (BSM), assumes that the prices of equities underlying options follow Geometric Brownian motion. As electricity spot prices cannot be modelled using Markowian processes, the BSM model cannot be used for pricing electricity options. Simonsen et al. (2004) argue that the fundamental reason for non-Markowian properties of electricity prices is the lack of arbitrage opportunities in the markets. (Simonsen et al. 2004; Black & Scholes 1973)

The third stylized fact considers price spikes in the electricity markets. It is important to take the price spikes in to the consideration when modeling the spot prices of electricity. Price spikes are defined by extremely rapid price changes that are reverted back to normal levels within a short period of time. Price spikes are present in the Nordic markets mainly because of the nonstorable nature of electricity and unique demand and supply characteristics that are caused by it. Price spikes are also important considering electricity futures pricing, as equilibrium pricing theory assumes that the main reason for market participants to use derivative contracts is to hedge their risk against price spikes. (Simonsen et al. 2004)

Simonsen et al. (2004) find that the daily returns in the markets are positively skewed and have high kurtosis. This means that the return distribution of spot market prices is not comparable to standard normal distribution. The distribution is leptokurtic and has fat tails. In other words, the spot market returns have much higher standard deviation and there are more extreme values that we would observe with data with normally (or log-normally) distributed returns. The non-normality of the return distribution has to be taken into account in many econometric applications. (Simonsen et al. 2004)

Simonsen et al. (2004) observe that the volatility of daily returns is on average 16%. This is much higher than observed in most other markets. The typical values for the volatility of stock market returns are 1-1,5 % and for individual stocks around 4%. They also find that the volatility is clustered. This means that there are clear periods of low and high volatilities. On average, these periods change in the cycles of 100 days. It is somewhat counterintuitive that they observe that volatility of spot prices is at the highest during summer months, when the spot prices are at the lowest. They argue that this might be due to forced production. During times when the Nordic water reserves are full, and more rainfall is expected, the producers are forced to generate electricity using the reserves even though the current market price does not satisfy their supply condition.

Many authors approve these stylized facts when studying the electricity prices in the Nordics. For example, Escribano, Peña, J. and Villaplana (2011) prove that these characteristics are highly important to consider when modelling electricity spot prices. They develop a model that simultaneously takes the seasonality, mean reversion, volatility clustering and time-dependent jumps into account. Their result show that the electricity spot prices are significantly mean reverting, exhibit volatility clustering, and have time-dependent jumps for all the eight markets they study. These characteristics are robust even after adjusting the prices for seasonal patterns. Their findings are robust across all the 8 different electricity spot markets they study, including the Nord Pool markets.

2.2. Risk premiums and indirect storability in the Nordic electricity markets

This chapter discusses the key concepts related to electricity futures pricing. It begins by introducing the reader to the basic commodity futures pricing and to the concept of risk premiums. It also describes the essential literature relating to risk premiums in electricity markets and discusses research that studies the futures pricing in the Nordic electricity markets. Understanding these concepts is essential for developing the research question and the hypotheses of the thesis. Furthermore, this chapter presents the concept of indirect storability, which has an important role in the Nordic electricity markets. Indirect storability is an important concept in the markets, as hydrological power generation is a unique example of indirect storability. In the Nordic electricity markets, over 50 % of the total capacity is produced by utilizing the Nordic hydrological reserves (Botterud et al. 2010). Hydropower generation is a unique production method as it is practically cost free to utilize and can be used to substitute high cost traditional Peaker Power generators, such as oil powered condensing power plants and gas turbines (Savolainen & Svento 2012: 1133-1134).

Forwards and futures are financial derivative contracts that are fundamentally agreements to buy or sell certain goods with a certain price at the certain time in the future. Forward and futures contracts can be used to trade financial underlying instruments, such as stocks, bonds, or commodities. Taking a long or short position in these contracts does not cost anything for the investor, so these contracts do not include premiums as is the case for example with options. Because of this, the value of futures or forward contract at the trading date is 0. The yield or the loss for the participants can only be determined after the expiry of the contract, as it is based on the market prices of the underlying at the expiry of the contract. The following example explains the basics of the valuation of futures contracts.

A participant willing to buy the underlying at certain moment in the future takes a long position in a forward or futures contract. Taking a long position in the contract binds the purchaser of the contract for buying the underlying at a specified future date with a fixed price. On the other hand, taking a short position in the same contract obliges the counterparty to sell the good with the same maturity and price. Forward contracts are usually financial contracts with non-standardized terms. They are most often intermediated by brokers and traded Over the Counter (OTC). Futures contracts are derivatives traded in exchanges and they have standardized terms. Forward and futures prices are close to each other, as the price development of the underlying is basically the only factor that affects the price. However, forward contracts can be considered to slightly riskier because of the counterparty risk. However, many authors argue that difference between the two types of contracts is so small that it does not have to be considered in most cases. (Geman 2005: 9; Geman & Vasicek 2001; Cox, Ingersoll & Ross: 348-438)

The yield of a long position in relation to the price of underlying is defined by the following formula $S_T – K$. Where S_T means the spot price of the underlying at the maturity of the contract and K means the price that is fixed at the level agreed during the trading day of the contract. Similarly, the yield of the short position is defined by $K- S_T$. As entering the contract is cost free and forward and futures contracts do not include any premiums, the yield between the counterparties is a zero-sum game at the trading date of the contract. Figure 1 describes the profits and losses of short and long positions in forward contracts. The profits and losses of futures contracts are determined in the same manner.

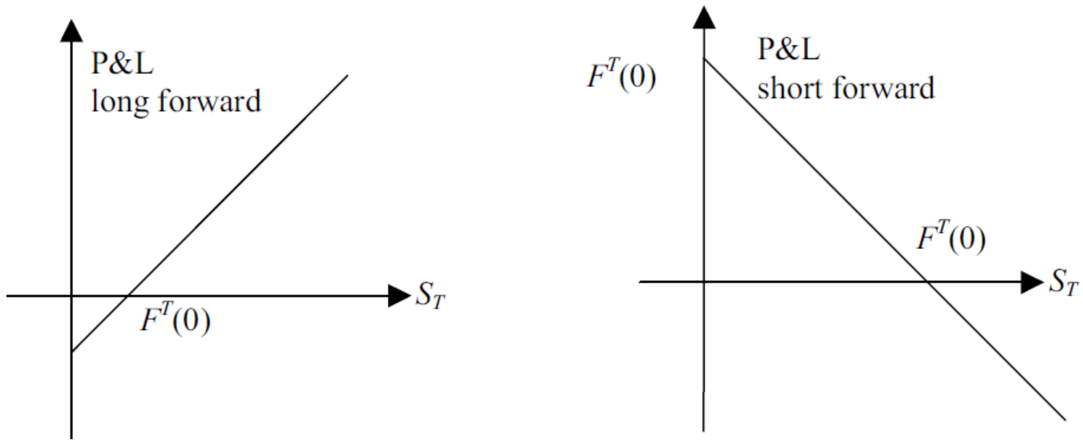


Figure 1. Profit and losses of long and short forward contracts. (Geman 2005: 5)

Futures markets have a crucial role for commodities pricing. According to Black (1976), one of the most important roles of futures contracts in commodity markets is to provide a reliable estimate of the spot price of the commodities at the certain point in the future. Based on the price information contained in the futures prices, it is easier for market participants to make informed decisions and back up their other decision-making processes. For example, a farmer could benefit from the price information provided by the futures markets, even if he/she did not do trading on the financial markets. If for example the farmer is pondering whether or not to invest to new harvesting machinery, estimates of the future prices of his/her crops are essential for making informed decisions regarding the investment. If the value of the farmer's crops is to plummet in the future, and the farmer is not able to predict this, his/her investment might become unprofitable in the end. Following this logic, it is easy to see that if we expect the futures prices to be perfect estimates of the future spot prices at the settlement date, it would be easy for the market participants to make well-informed decisions in their day to day business. (Yang, Bessler & Leatham 2001)

In reality the futures prices are rarely perfect estimates of the future spot prices. Certain general concepts must be explained before focusing solely on the electricity markets. Commodities derivatives are traded with several different maturities. The contracts that are closest to settlement are usually the most liquid ones and closest to the actual spot prices. As the time for maturity gets longer, the derivative prices usually get further away from the actual spot price. This is called the term structure of the futures contracts. The term structure can be either backwardated or contango. Backwardation means that the term structure of the futures contract is downward sloping. In other words, the future prices are further above the current spot prices as the maturity of the futures contracts is longer. The opposite situation of this is contango. It means that the term structure of futures contracts is upward sloping. As the maturity of the contracts gets longer futures prices are further below the current spot prices. (Ilmanen 2012: 114-118)

There are two separate disciplines of theories relating to commodity futures pricing; *The Theory of Storage*, and *Risk Premium Theory*. The Theory of Storage assumes that producers can store the goods in their inventories. This storage option is especially important for the producers when the current spot prices are low. By stacking the goods in their inventories, they can wait the spot prices to rise and then sell their inventories when the spot price satisfies their marginal supply price criteria. However, it is not free for the producers to hold their goods in their inventories and thus the theory introduces the concept of storage costs. The producers are faced with an optimization problem between the expected rise in the future spot price and the running costs of the inventories eating away the ultimate profit of their production. The Risk Premium theory does not require the goods to be storable but assumes that the pricing of futures contracts depends on the demand and supply factors for hedging against the price changes of the commodities.

According to the Theory of Storage, the relation between spot and futures contracts depend on storage costs and convenience yields. The following formula (1) has to be true:

$$(1.)\ F_{t,T}e^{yT} = S_t\ e^{(r\,+\,c)T}$$

Where:
t: The current date
T: The maturity date of the futures contract
F: Futures price
S: Spot price
Y: Convenience yield
c: The relation between storage costs and spot price
r: The risk-free rate

By dividing both sides of the equation with the convenience yield factor, e^{yT}, and applying the properties of logarithmic calculus we have the following equation (2):

$$(2.)\ \ F_{t,T} = \ S_t e^{(r+c-y)T}$$

From Equation 2, we can see that the current futures price maturing at date T can be explained by risk free interest rates, the storage costs, and the convenience yield.

Keynes (1971) [the original text is from 1930] found out that the futures prices for commodities are usually backwardated and based on that phenomenon he developed the Theory of Normal Backwardation. Authors such as Carter, Rausser & Scmitch (1983), Chang (1985), Bessembinder (1992), and De Roon, Nijman & Veld (2000) have since studied the phenomenon and improved the theory. Probably the most important addition to the original theory is the concept of hedging pressure. According to the Theory of Normal Backwardation, the main reason explaining the backwardation of futures prices is the demand and supply factors for hedging. The demand for hedging is caused by the risk aversion of producers. Risk averse producers have demand for futures contracts because they want to hedge their future returns by freezing the commodity price for the desired time period. The speculative investors and other market participants do not provide this possibility for the producers for free. They require risk premium for bearing the downside risk of price fluctuations and for providing the markets for hedging. Hedging pressure literature further explains the backwardation by introducing certain other factors to the demand and supply functions of derivative contracts. Such factors can be for example asymmetric information and transaction costs. These sorts of factors are often included in more sophisticated regression models.

According to the Risk Premium Theory, futures price equals the expected future spot price at the maturity plus the required risk premium charged from the hedgers. Accordingly, we have the following formula (3.):

$$(3.)\quad F_{t,T} = E_t(S_T) + P_{t,T}$$

Where:
$E_t(S_T)$: Expected spot price at Maturity (T)
$P_{t,T}$: Risk premium

Futures' basis is a widely used concept in research related to risk premiums. The basis is simply the difference between the futures price and the spot price at the present time. The concept of the basis is easy to further explain by modifying Equation 3 slightly. In risk premium literature, the basis is usually presented in the following form:

$$(4.)\quad B_{t,T} = F_{t,T} - S_t$$

Where:
$B_{t,T}$: The basis for a futures contract at t, and maturing at T

By reducing the present spot price (S_t) from the both sides of Equation 3, we get:

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

By applying Formula 4 to the above equation, we have the following equation:

$$(5.)\quad B_{t,T} = E_t(S_T) - S_t + P_{t,T}$$

The concept of the basis is clearly explained in Formula 5. The basis explains the difference between the expected spot price and the current spot price added by the risk premium charged from the hedgers at the time t. (Huisman et al. 2012: 894)

To contribute to the discussion between the Theory of Storage and the Risk Premium Theory Fama et al. (1987) study 21 different commodities. They find out that the Theory of Storage performs relatively well for the most of the commodities they study, but for some commodities the Risk Premium is superior in explaining the futures pricing. Based on their extensive research they are able to draw the following conclusions:

1. *The standard deviation of the basis and predictability of spot prices.* Those commodities that have the highest standard deviation of the basis have strong forecasting power on the future spot prices. Examples of commodities with strong forecasting power on future spot prices are broilers, eggs, and soybeans.

2. *The* s*torage costs and predictability of spot prices.* The Theory of Storage assumes that there is relation between the high storage costs and the seasonality of spot prices. The futures basis of those commodities that have high storage costs seem to also have strong ability to forecast future spot prices. Examples of commodities with high storage costs and predictable future prices are hogs and cattle.

3. *Seasonality of the basis and predictability of spot prices.* Fama et al. (1987) assume that the key factor explaining forecasting power is the seasonality of the basis. Seven out of ten commodities that are found to have strong seasonality have statistically significant forecasting power on the future spot prices. However, corn and wheat are also found to be seasonal commodities, but instead of having forecasting power of spot prices, the futures contacts seem to predict the risk premiums of futures contracts. Moreover, it seems that the pricing of orange juice, which is also found to be a seasonal commodity, is better explained by the Theory of Storage for some of the maturities and by the Risk Premium Theory for other maturities.

Fama et al. (1987) conclude that the Theory of Storage seems to be a superior modeling approach for the most of the commodities they study. However, the pricing of for example, lumber, soy oil, cocoa, corn, and wheat seems to be better explained by the Risk Premium Theory. Hence, they cannot conclude that the assumptions of the Risk Premium Theory would be unrealistic for all the commodities futures.

As electricity is a perfect example of a commodity that cannot be efficiently stored, electricity futures pricing is traditionally approached from the perspective of the Risk Premium Theory. The pioneering papers of Bessembinder et al. (2002) and Longstaff et al. (2004) use reduced form models to explain the electricity futures prices in the US markets. These papers aim to explain the risk premiums by assuming that the level of demand for electricity and the skewness of spot prices are the key factors driving the hedging demand. Increased demand and high skewness of the spot price distribution are assumed to be signs of increased risk of price spikes. Bessembinder et al. (2002) find that the risk premiums in both the Pennsylvania, New Jersey, and Maryland (PJM) and California (CALPX) -markets are positive on average and change seasonally. The premiums they observe are high compared to those observed in other commodities markets, for example those studied in Fama et al. (1987) paper.

A major shortcoming in the paper of Bessembinder et al. (2002) is the adequacy of the data. They also note that the high standard deviation of their time series makes it hard to find significant results. Longstaff et al. (2004) use similar methodology, but instead of studying monthly contracts they study futures for hourly deliveries (intra-day futures). They are able to find positive and significant risk premiums in the PJM markets and observe that the variance of the spot price has negative impact on the risk premiums whereas the skewness of spot prices has a positive impact. Furthermore, they find that the risk premiums are seasonal also in intra-day data. The reduced form model that Longstaff et al. (2004) use is discussed in Chapter 3.4.

This thesis also studies the concept of indirect storability in the electricity markets, an idea developed by Routledge et al. (2000). They argue that there could be storage like options for market participants, as electricity can be in fact indirectly stored in form of fuels. Indirect storability of electricity is especially interesting subject in the Nord Pool markets because the vast hydro power reserves in the Nordic area. This concept is discussed in more detail in Chapter 3.4.

2.3. Hypotheses

This chapter presents the hypotheses used in this thesis for the purpose of answering the research question formulated in Chapter 1.2. The model specification, which is discussed in Chapter 3.5, is also an integral part of the hypotheses development. Based on the previous literature, discussed in the model specification chapter, this thesis studies spot and futures pricing in the Nordic markets by including explanatory variables from five categories into the models. Those categories are the following: 1. Statistical characteristics of the spot price distribution 2. Nordic Water levels 3. Temperature variables 4. Fuels that can be used for generating electricity 5. Global market risk / sentiment variables. All these variables, and other data used, is described in detail in Chapter 4.

The purpose of the first hypothesis is to test the most important factors affecting the system prices in the Nord Pool markets. The theory seems to suggest that especially the factors that cause or affect the spot prices in the tails of the distribution are important also considering the futures pricing. To better understand the extreme movements of the spot prices, I use quantile regression analysis to study the first hypothesis. The quantile regression framework allows me to study how the explanatory variables explain the spot prices during different market conditions. Regular OLS regression would only study the mean of the distribution, whereas with the quantile regression I am able to study both tails of the distribution and also everything between the tails (including the mean of the distribution).

The first hypothesis states that using quantile regression analysis, I am able to find variables that explain the daily spot prices in the both tails, and also in the mean of the distribution. It also states that the model has high explanatory power on the spot prices. If this hypothesis is accepted, it would suggest that the quantile regression analysis fits my study better than the regular OLS framework would. The first hypothesis is formulated below:

H_1: The model used is able to explain the pricing in Nord Pool spot markets reasonably well. Furthermore, by using quantile regression analysis, I am able to identify variables that explain the extremely low and high market prices.

The purpose of the second hypothesis is to test the reduced form equilibrium model of Bessembinder et al. (2002) and Longstaff et al. (2004) on the Nordic futures premiums. The reduced form model only considers statistical characteristics of the spot price distribution and I am interested to see whether they have any explanatory power on Nordic futures premiums. Lucia et al. (2011) provide some evidence that the reduced form model has not been able to explain the futures premiums on the markets after a big price spike that occurred in 2002. Based on the findings of Lucia et al. (2011), I do not expect the reduced form model to perform especially well. Regardless, I think that the main goal of the second hypothesis is to provide a benchmark on which to compare the results of more advanced models used to test the final hypothesis of the thesis. The second hypothesis is formulated below:

H_2: The reduced form model of Bessembinder et al. (2002) and Longstaff et al. (2004) cannot be used to explain the risk premiums of the monthly futures contracts on Nord Pool Spot electricity.

The objective of last hypothesis is to combine the information obtained from testing the two previous hypotheses. The last hypothesis uses the whole data set collected based on the model specification chapter for explaining the risk premiums in the Nordic markets. Assumption is that the last model outperforms the standard reduced form model and that factors that were found to affect spot market pricing are also important considering the futures pricing. I assume that especially the variables that were found to explain the spot market prices on the tails of the distribution are significant in explaining the futures premiums. I hypothesize that the market participants are closely following any factors that could be able to cause price spikes on the spot markets and that those factors would play a crucial role in determining the hedging demand on the markets. Based on the economic theory, the factors that significantly explain the extremely high spot market prices should also have pronounced effect on the futures premiums on the market. The final hypothesis is presented below:

H_3: The model used has high explanatory power on the futures risk premiums. The factors that affect the market prices on the spot markets also explain the futures premiums. Especially the variables that were found to be significant on the tails of the spot price distribution have significant ability to explain the futures premiums.

The empirical part of this thesis is assembled to test the three hypotheses presented above. All the hypotheses are either accepted or rejected based on the empirical results of these testes. The solutions and the final discussion about the hypotheses is presented at the end of Chapter 6 and in the Conclusions chapter.

3. THEORETICAL BACKGROUND

This chapter presents the theoretical background of the thesis. It begins by explaining the long-term equilibrium relationships of electricity markets. After that, it concentrates on explaining the demand and supply conditions of electricity pricing. In subchapter 3.4. the spot pricing in the Nord Pool markets is discussed in more detail. Subchapter 3.5. considers futures pricing in the electricity markets. It discusses the Risk Premium Theory, indirect storability and recent research concerning the Nordic markets. Finally, subchapter 3.6. represents the model specification of the thesis. This subsection discusses recent research regarding the explanatory variables used in my models and argues why the chosen variables could be interesting in the scope of this thesis.

3.1. Long term equilibrium spot market price

If the markets are assumed to be competitive, the producers are willing to sell their production with a market price exceeding their marginal costs of production. The marginal cost represents the expenditure that the producers face by producing one extra unit of goods. In the spot markets for electricity, the marginal costs of the producers are defined by the variable and fixed costs of electricity generation. Variable costs include fuel costs, emission permit costs, taxes, and any operational or maintenance costs that are dependent of the total production volume. Fixed costs include for example the original investment to the production facility and any development expenditures to it or its machinery. The fixed cost per unit produced is a decreasing function of the total production volume. If a producer increases the volume generated in the facility, the fixed cost per unit is decreased. (Borenstein 2000)

The marginal cost of electricity varies greatly between different methods of production. For example, a wind or solar production facility has comparatively small variable costs because the production method does not include any fuel costs. On the other hand, their fixed costs are high in comparison with many other production methods. This is further explained later when the supply function of electricity is discussed. Electricity produced with nuclear power is another extreme compared to wind power. The fixed costs of nuclear power are high, mainly because of the high original investment cost of building the plant. However, the fixed cost per unit produced during the economic lifetime of the plant is far lower than with wind power because of the high volume of production that this method enables. (Borenstein 2000)

If it is assumed that the producer of electricity does not have any market power, the producer is always willing to sell electricity if the marginal costs of generation are covered. In other words, producer is always willing to sell one extra unit if the marginal costs of generating the unit are smaller or equal to the market price of electricity. The aggregate supply function in the electricity markets is considered stepwise instead of linear. The irregular shape of the supply function is a result of the varying cost structures of different generation methods. (Borenstein 2000)

The suppliers always aim to satisfy the current market demand with the production method that has the lowest marginal costs for them. When the market demand increases above the capacity of the cheapest available generation method, suppliers are forced to start producing electricity with more expensive methods and fuels. However, they are not willing to sell electricity before the marginal costs of the new production method are covered. This causes the market price of electricity to jump on a higher step on a marginal supply function curve. Admittedly, the stepwise form of the supply function is an important factor behind the price spikes that can be observed in the electricity markets. (Borenstein 2000)

Another important factor behind the price spikes in the electricity markets can be explained with the attributes of the demand function of electricity. If the demand for a good was elastic, rational consumers would not necessarily be willing to pay for the higher price that the suppliers ask for their increased marginal costs. In markets that have elastic demand, the consumers would need something back for the increased price or they would reduce the level demanded. In other words, the utility of an additional unit demanded would need to be higher than the cost of producing the extra unit. However, the price elasticity of electricity is considered extremely low compared to other markets (Geman 2005). Hence, the consumers in electricity markets are willing to pay basically anything the producers ask for the extra unit generated if there is demand for the extra unit. Therefore, the long-term equilibrium price of electricity is assumed to be the marginal cost of the most expensive unit produced. (Borenstein 2000)

3.2. The demand of electricity

According to basic microeconomics, the demand for any good is at the level defined by equilibrium, where the marginal utility of the consumer equals the price of the good. Ceteris Paribus, when the price of a good increases, the demand for the good will reduce to a smaller level defined by the equilibrium condition. For example, if the price of electricity stays at high level for a long period of time, rational consumers will try to optimize their consumption. Households might for example buy new, more energy efficient, devices for their homes to save from the electricity bills. Alternatively, another example would be a CEO of an industrial factory who might try to make his production line more efficient to save in the energy costs. The consumers are more responsive in reducing their demand in some goods than in others, if the price is increased. The level of responsiveness to the price changes is called the price elasticity. (Kirschen & Strbac 2004:73-78)

Electricity is considered as an almost perfect example of a good, that has low price elasticity. It is essential for the consumers that electricity is available at any time of the day. In addition, they are not usually aware of the current market price of electricity. An important factor behind the inelastic demand is that consumers usually do not buy electricity from the spot markets. When illustrating the long-term equilibrium price of electricity, the demand function is usually assumed to be almost vertical. (Kirschen et al. 2004:73-78)

However, there have recently been important fundamental changes in the markets which might affect the price elasticity of electricity. One of such change is the remote reading of electricity meters. In the past, consumers might have gotten information about their electricity consumption only once a year when a representative of the local electricity distribution company came to read their meter. Nowadays, the meters are read with a remote connection and consumers are able to get practically real time data about their consumption.

For example, in Finland a statute given by the Council of State about the settlement and meter reading practices required that 80% of the metering points maintained by the local distribution companies are remotely readable by the end of 2013. The distribution companies are also required to provide real time consumption data for their customers. It is assumed that the real time metering of electricity consumption will increase the elasticity of electricity demand. Academics believe that this will increase the market efficiency of electricity markets. For example, Borenstein and Holland (2005) present a model that predicts that the benefits of real time metering far out weight the costs associated with the transformation that it requires. (Pahkala et al. 2009)

For example, Bye and Hansen (2008: 27-28) find out that the electricity prices in the Nordics are nowadays more elastic than they used to be. Also, the elasticity seems to be seasonal in intra-day, weekly, and yearly cycles. The authors conclude that the elasticity of electricity demand can be reasonably modeled in the long term, but the short-term modeling actually encumbers the capacity of modern computation.

The effect of real time metering on the price elasticity of electricity is an interesting field of research. However, the subject is fairly new because of the resent advances in the technology. Bye et al. (2008) conclude that there is yet only limited amount of relevant research information available today.

Despite the findings of Bye et al. (2008) considering the changing nature of demand elasticity, markets are usually modeled based on the assumption that demand is inelastic and does not change seasonally. For example, Borenstein and Holland (2005) and Savolainen et al. (2012) model the market demand based on the load-duration curves obtained from the electricity distribution companies.

3.3. The supply of electricity

For the consumers, electricity is always a standard product and they are indifferent, or unconscious, about how it is currently produced. However, the producers face different optimization problems when considering how to meet the current market demand. An important consideration is the production costs of different methods. Tarjanne and Kivistö (2008) estimate the production costs of Finnish producers with different fuels. The estimated costs are presented in Figure 2. For simplicity, the figure does not take the costs of emission trading or any government subsidies in to the account. In reality these subsidies and emission disincentives increase the costs of fossil fuels in comparison to more environmentally sustainable production methods. (Tarjanne et al. 2008)

Figure 2 presents the structure of the generation costs of different Finnish power plants. Fuel costs are illustrated with the yellow color, operating and maintenance (O&M) costs are presented the with orange color, and fixed costs with the blue color. Both, O&M and fuel costs qualify as variable costs. The generation methods studied are the following; Nuclear production, gas turbine production, coal plants, peat plants, wood plants, and wind power production. It is assumed that the annual limit of wind power production is 2200 hours, as the wind turbines cannot operate at all conditions. Fixed costs vary greatly based on the assumptions made in the estimation. Most of the fixed costs constitute of the original investment in the power production facility and hence the chosen market interest rate plays a significant role. Fiqure 2 assumes that the risk-free interest rate is 5 %. (Tarjanne et al. 2008:8-10)

Nuclear production is the cheapest generation method, 35 € per MWh produced. The Fuel and O&M costs of nuclear production are relatively cheap, even though the original investment is high in comparison with the other production methods. The tremendous amount of electricity generated during the economic lifetime of the plant decreases the fixed costs per unit produced. Furthermore, the economic lifetime of a nuclear plant is assumed to be 40 years, whereas for other production facilities it is assumed to be only 20 years. In addition to the typical costs of operation and maintenance, the O&M costs of nuclear costs include also the expected costs associated with processing and the final disposal of the fuel spent. The expected costs of waste treatment are based on the annual costs nuclear producers pay to national nuclear waste fund. (Tarjanne et al. 2008)

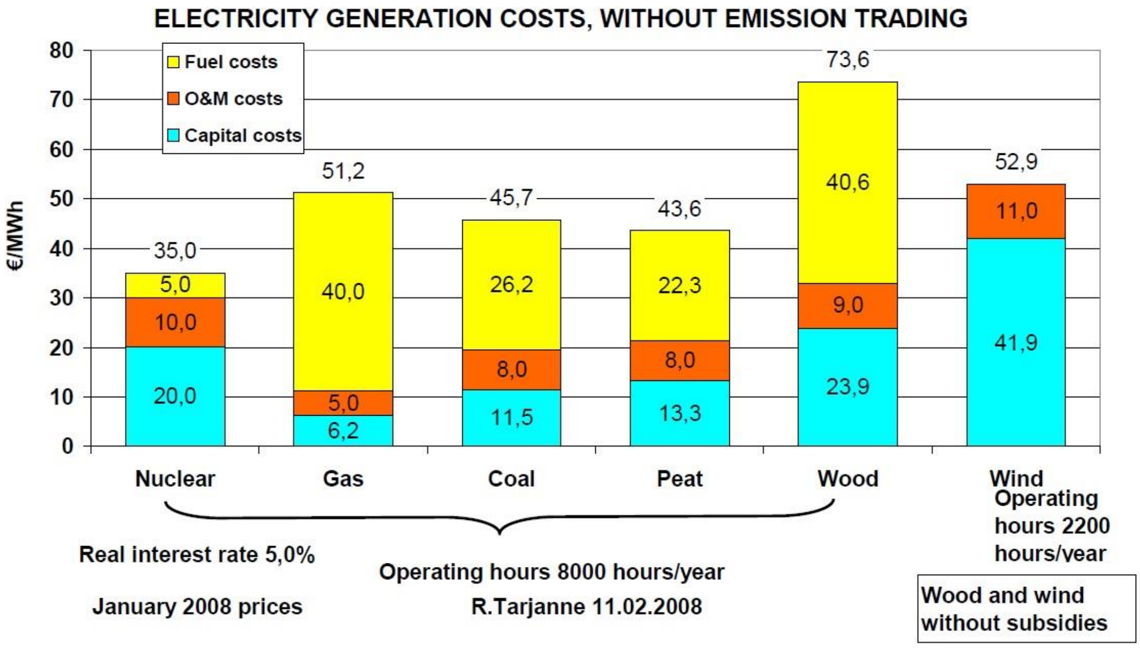


Figure 2. The cost structure of Finnish generation methods. (Tarjanne & Kivistö 2008:8)

Low O&M and fixed costs are characteristic for gas, coal, peat, and wood. Fuel costs are the most significant factor in determining the total cost of generation for these generation methods. For example, 78% of the total production cost of electricity generated in gas plants is determined by the fuel price. Even tough, there are no fuel costs in wind production, the fixed costs of the generation method are nearly double compared with other forms of production. (Tarjanne et al. 2008)

Savolainen et al. (2012:3-5) model the Nordic long-term equilibrium pricing based on the different generation cost estimates provided by Tarjanne et al. (2008). In addition, they also estimate the costs of electricity produced with the Nordic water power generation. They conclude that the variable costs of water power generation are at least three times lower than for example with nuclear production. They also estimate that the fixed costs are one of the lowest of the generation methods studied.

Electricity producers aim to satisfy the market demand with the cheapest available generation method. As the market demand increases and the maximum capacity of the cheapest production facilities are exceeded, the producers are forced to start generating electricity with more expensive fuels. The total costs of production are determined by the fixed costs, variable costs, and the capacity factor of production. The capacity factor of production measures the percentage of hours during the year that the production method in question produces electricity to the grid. When the capacity factor is high, the fixed costs of the production facility are spread over a higher number of annual hours and are therefore lower per unit generated. (Savolainen et al. 2012)

The model of Savolainen et al. (2012) simplifies the Nordic markets to consist only of four different generation methods. Generation methods are divided to following categories based on their cost structure:

- Nuclear power: Nuclear power represents the baseload production facilities in the model. Steady load and low variable costs are usual characteristics of the base load facilities. It requires high input to adjust nuclear power production to lower or higher level and it is not usually economically rational. Therefore, the producers aim to optimize the output to satisfy the demand that is assumed to always be present in the markets. This amount is called the baseload demand.

- *Conventional Thermal Power.* This generation category consists of coal and peat generation facilities. These methods of generation are typical mid-merit facilities. The generation volume can be easily and cheaply adjusted based on the demand conditions. Electricity producers use these plants when the baseload facilities are not able to satisfy the market demand.

- *Peaker Power Facilities:* This category consists of the generation facilities that are designated by high variable costs. This category consists of facilities that burn oil and gas. Peaker Power facilities are designed to rapidly respond to demand shocks in the markets.

- *Hydropower:* This category utilizes the Nordic water reserves. Hydropower generation has low variable costs and the level of generation is easy to adjust. However, the availability of generation is limited to the existing water reserves. The recovery of reserves is dependent of water inflow in the Nordics. The water inflow is generated by rainfall and melting of snow and ice in the mountains. The recovery rate of water reserves is thus highly seasonal and random to some extent. For these reasons, the supply conditions of Nordic water generation are especially hard to predict.

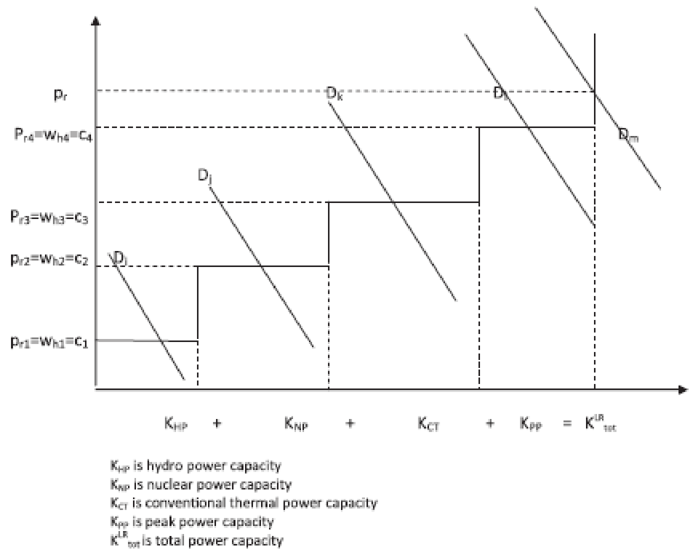


Figure 3. The long-term market capacity in the Nordics. (Savolainen et al. 2012: 1135)

By modeling the costs of these generation methods and proxying the demand by using past load duration curves, Savolainen et al. (2012) derive the long term market capacity for the Nordic markets. Figure 3 illustrates this market capacity.

The Y-axis of Figure 3. illustrates the price of electricity with different levels of demand and the X-axis illustrates the long-term aggregate supply of electricity in its long-term equilibrium. The figure illustrates the stepwise form of aggregate electricity supply curve. The stepwise form of the aggregate supply curve stems from the different cost structures of different generation methods. As the demand for electricity increases, producers are forced to start generating with more expensive fuels and power plants. The long-term equilibrium price in competitive markets should always equal the marginal cost of the fuel used to produce the last unit of electricity to meet the current market demand. The generation methods in Figure 3 are presented from left to right in acceding order based on their total production costs per unit. On the left are the inexpensive nuclear and hydropower plants and the expensive peaker-power plants are in the right corner of the figure. (Savolainen et al. 2012)

3.4. Spot pricing in the Nordic markets

The price of electricity in the Nordic markets is determined in Elspot -markets. In Elspot -markets, the Nordic market participants trade electricity for the physical deliveries of the following day. A typical seller in the markets is a producer of electricity, for an example a generation facility owner, and a typical purchaser is a local electricity transfer company. The deliveries are determined for each hour of the following day and are settled following auction principles. This chapter discusses the determination of the Elspot -prices and the local area prices.

During the forenoon of each day (08.00-12.00 CET) sellers and purchasers have time to place their buy- and sell-orders for the physical deliveries of the following day. Purchasers assess the amount (volume) of electricity they want to buy from the exchange during each hour of the following day. Based on their assessed demand they place the buy-market orders to the Elspot-trading portal. The market orders specify the volume of the electricity the buyer is willing to buy with different prices. The producers also place similar market orders about their willingness to produce electricity to the market with different prices.

At noon (12.00 CET), Nordpool closes the trading and market participants are no longer allowed to place the market orders. Based on the received buy- and sell- orders, Nordpool constructs the market demand and supply curves for each hour of the day. The hourly Elspot price and volume is determined at the intersection between the supply and demand curves.

Figure 4 illustrates the Elspot system price and volume for delivery on 11.12.2014 at 12 CET. The purple line illustrates the market supply curve and respectively, the blue line illustrates the market demand curve. The curves are formed as explained in the previous paragraphs. The X-axis of the figure illustrates the volume of deliveries and the Y-axis determines the price per MWh delivered. The equilibrium price for the hour in question is determined at the intersection between the demand and supply curves. The equilibrium price in the figure is 31,04 € / MWh. The figure shows that when the volume is between 30 000 MWh and 50 000 MWh the supply curve ascends only moderately, but when the volume closes 60 000 MWh the supply curve turns extremely steep. This is because the maximum capacity of the regular power production facilities is starting to get exceeded and the producers are forced to start generating electricity with the expensive peaker-power generation facilities.

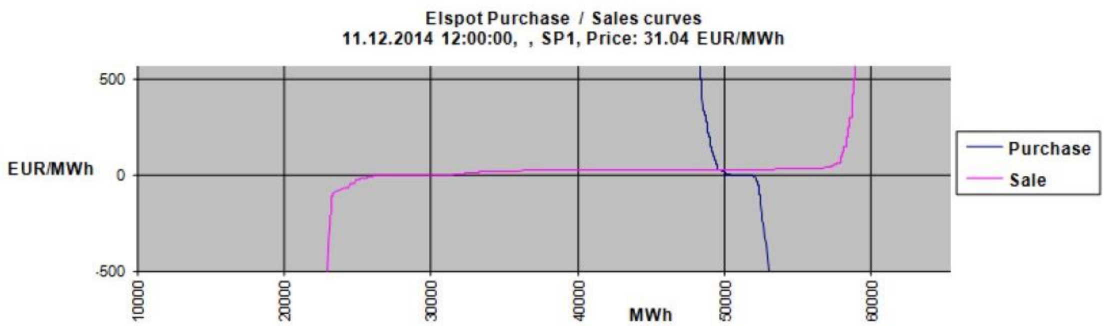


Figure 4. Elspot sytem price 11.12.2014 12:00 CET. (Nord Pool As online)

During the afternoon, purchasers pay the arranged deliveries to the sellers. The trade is settled when the sellers start delivering electricity, based on the hourly volume agreed in the auction, to purchasers. Deliveries start at 00.00 and the price is changed on the hours.

The changes in the hourly Elspot prices originate from changes in the fundamentals affecting the market demand and supply. Rothovius, Nikkinen, Sihvonen & Klemola (2013: 53-55) characterize four reasons that can explain the changes in the equilibrium prices:

1. *Changes in the production costs of electricity.* For an example, when the production costs increase, the slope coefficient of the market supply curve steepens. Particularly, the elasticity of the demand function decreases. When the supply of electricity is inelastic, small changes in the demand can result in tremendous increases in the electricity prices.

2. *Changes in the production capacity.* For an example, when the market capacity decreases, the market supply curve moves towards the origin of the curve. This causes the equilibrium price to increase.

3. *Changes in the level of demand.* As the level of demand for electricity increases, the market demand curve moves further away from the origin of the curve. As a result of this, the equilibrium price for electricity is increased.

4. *The marginal utility of purchasers is changed.* For an example, when the marginal utility of electricity is increased the demand curve steepens. This increases the equilibrium price of electricity.

By examining the changes in the market price of electricity at hourly level, Rothovius et al. (2013) observe that the changes in intraday market prices can be largely explained by the changes in the demand curve. Figure 5 presents their findings about the hourly price changes within a particular day of their data set. It is notable that Figure 5 illustrates a different date than Figure 4. Moreover, the two figures are scaled differently.

Figure 5 demonstrates that hourly equilibrium prices and volumes change significantly within a day. Furthermore, it is evident that the hourly prices are distributed close to the

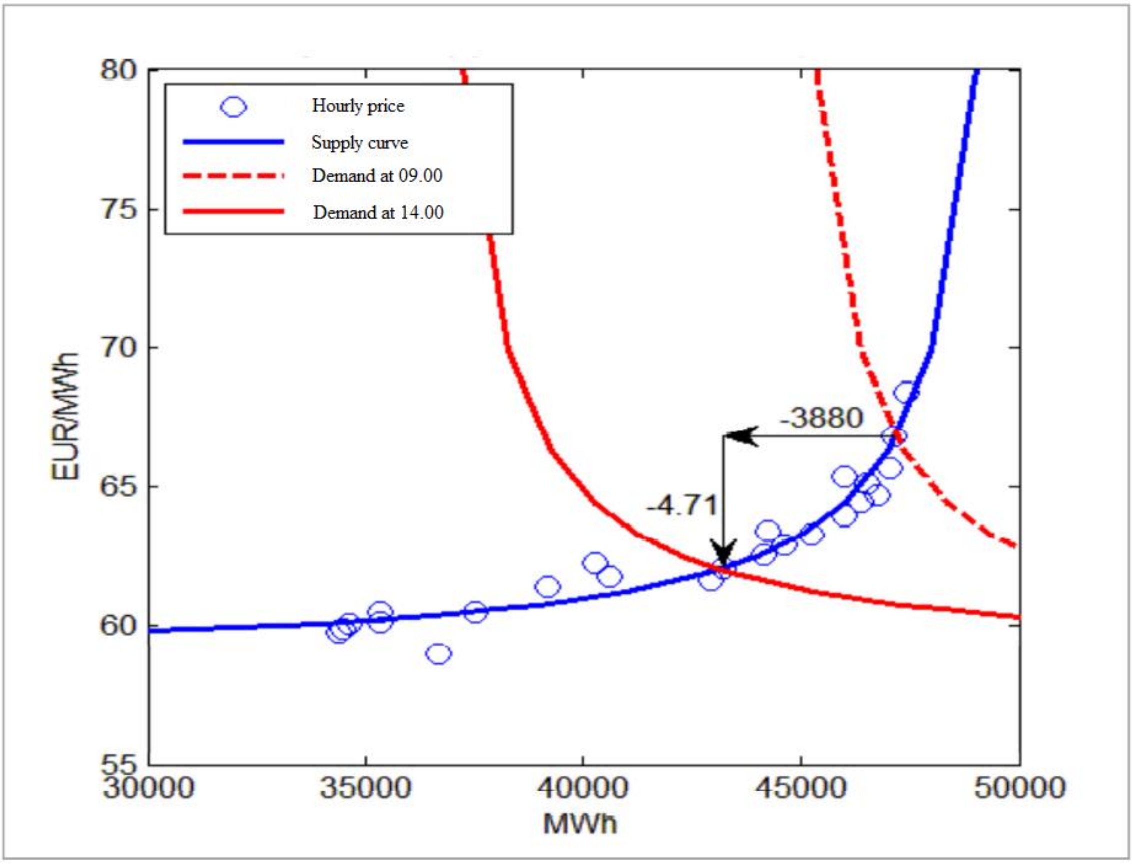


Figure 5. Changes in the hourly system prices on January 31, 2011. Rothovius et al. (2013: p. 56)

market supply curve. The hourly prices thus seem to be explained largely by the changes in the level of demand, in other words moving demand curves. This observation is consistent with the theory discussed in this chapter.

The consensus regarding Nord Pool is that it is a well-functioning market and almost a textbook case of successful market liberalization. Although there have been considerable price spikes at times, the markets cannot be considered having failed since its birth in 1996. However, recently across Europe, there has been intense debate regarding whether current electricity market designs are always able to ensure a sufficient electricity supply. Some major European countries, such as Germany and France, have decided that they need additional measures to secure the capacity adequacy of electricity. These supplementary designs for modern spot electricity markets are called Capacity Remuneration Mechanisms. The inelasticity of electricity demand is one of the root causes of fear for capacity inadequacy in the electricity markets. On the other hand, as an increased proportion of electricity is generated using renewables, in other words highly volatile and unpredictable generation methods, it is feared that also the price inelasticity of the supply side would increase. The increased volatility of supply side factors increases the exposure of electricity producers and thus poses an increased risk of market failures. Although there have been some studies considering whether some capacity remuneration mechanisms should be included to supplement the Nordic electricity markets, there does not seem to be consensus yet in the academic literature regarding whether these measures would be well-grounded or not. (Lindboe, Hagman, Christensen 2016)

3.5. Futures pricing in electricity markets

Research regarding futures pricing in the electricity markets mainly follows the assumptions of the Risk Premium Theory. The key assumption behind the Theory of Storage is the arbitrage rule. The arbitrage rule cannot be directly applied to electricity markets, as electricity cannot be stored. Whereas the Theory of Storage explains the differences between current futures prices and future spot prices with storage costs and convenience yields, the Risk Premium Theory explains the differences with supply and demand conditions for derivative contracts.

The following example applies for any commodities market with liquid secondary derivative markets. If the future volatility of the spot price of the commodity is assumed to increase, the producers have higher demand for hedging contracts. The increased volatility of the market prices poses an increased operational risk for the suppliers of the product.

Different kind of hedging products can be used to fix the price of goods at the present level, in the purpose of managing the operational risks associated with the fluctuations of the market prices. The counterparties of these hedges are investors or institutions who take for example a short position in a futures contract for the future delivery of the commodity in question. Both participants, the short and long side of the contract, are assumed to have access to the same information at the time of the investment. Thus, also the participant who is betting short assumes high future volatility of market prices and requires a higher price from the hedger, for providing the possibility for hedging. This higher price is called the risk premium in the literature. The case mentioned above is an example of the equilibrium pricing relationship between the demand and supply conditions for commodities derivatives. This equilibrium relationship is central to the risk premium literature. (Pirrong & Jemakyan 1999; Eydeland & Geman 1999)

As mentioned earlier, Routledge et al. (2000) were one of the first authors to study risk premiums in the electricity markets. They developed the first equilibrium pricing model for electricity markets. Their model tries to be in line with the key empirical findings regarding electricity pricing observed by Kaminski (1997). Kaminski (1997) argues that any electricity derivatives pricing model should take some features of electricity prices in to account. The first feature to be considered in models should be price spikes and the skewed distribution of the spot prices of electricity. Secondly, also the heteroscedasticity of electricity prices should be considered. The volatility of prices should be high when the prices are high and vice versa. Finally, the conditional correlations between electricity prices and different fuels used for electricity generation should change with different levels of market demand. The first two rules are consequence of supply conditions for electricity. The supply curve is relatively flat at low demand levels, but at some point, it becomes practically vertical at maximum production capacity. The correlation between different marginal fuels and electricity prices is assumed to change with different market conditions. When the demand for electricity is low, the correlation between prices and expensive peaker power fuels is assumed to be low. However, when the demand for electricity increases, the prices of marginal fuels are assumed to be highly correlated with electricity prices.

Routledge et al. (2000) argue that even though the electricity is not a storable commodity, the convertibility of fuels to electricity makes the markets behave much like markets that trade in storable commodities. Their equilibrium pricing model aims to model the supply and demand sides of the electricity and the option to convert fuels to electricity. In their model, the realized option to convert certain fuels to electricity is called "the spark spread".

The paper of Routledge Seppi and Spatt (2001) is the first in the long line of equilibrium pricing models of electricity derivatives pricing. However, their paper falls short on the empirical side. They do simulate the pricing of electricity with their equilibrium pricing model, but do not test the model's accuracy with real out of the sample data.

Bessembinder et al. (2002) were one of the first researchers to empirically test the equilibrium pricing relationship in the electricity markets. Their study can still be considered as a benchmark study of electricity derivatives pricing. Their model aims to identify the demand and supply conditions that explain the risk premiums in the US electricity markets. They assume that markets are not participated by outside speculators and thus electricity derivatives pricing should only be determined by the hedging demand of electricity companies. They study hedging pressure and risk premiums empirically in Pennsylvania, New Jersey, and Maryland markets (PJM) and in California's markets (CALPX).

They model the futures pricing by considering the hedging demand of market participants. They assume that the producers and vendors of electricity both aim to optimize the relationship between the mean and variance of their returns. In other words, they aim to maximize their returns with as reasonable as possible variation of future returns, in other words risk. This optimization problem generates demand for hedging and thus also the demand for derivatives contracts. Market participants trade in derivative contracts to avoid unwanted and unexpected changes in the market price of electricity.

By estimating the supply and demand conditions of spot electricity, they derive a cost-based estimate of spot market prices. In their empirics, the risk premiums are defined as subtractions between expected spot prices and current forward prices for the same delivery period. Thus, the researchers assume that the forward prices are biased estimates of the future spot prices.

Bessembinder et al. (2002) assume that the risk premiums can be explained by the level of demand for electricity and the skewness of the spot price. The spot price distribution is assumed to be skewed because of the convexity of the production function and on the other hand also because of the unstorable nature of electricity. During the months of high demand, the spot price is more volatile and the risk of exceeding the capacity of the markets is higher, in other words the risk of price spikes is elevated. This risk makes the spot price distribution positively skewed, in other words convex. The months that have convex spot price distributions are assumed to exhibit the highest risk premiums because of the increased demand for derivatives contracts for hedging purposes. On the other hand, during the months of low demand, the risk premiums are assumed to be small because of the decreased demand for hedging. The skewness of spot price distribution is assumed to be close to zero and the risk of price spikes is low.

Bessmebinder et al. (2002) find out that both studied markets exhibit large seasonal variation in their risk premiums. The risk premiums are especially high during the summer months. This is consistent with their assumption that the demand is at the highest during summer months because of the increased demand for cooling down the apartments and office buildings.

Bessembinder et al. (2002) note that their results should be only considered as preliminary. The critical shortcoming of their empirics is data availability. Their data set consists of monthly observations between 1997 and 2000, thus the sample size is relatively low. Moreover, the unusually large variance of spot market prices, compared with many other markets, decrease the reliability of their estimations.

Longstaff et al. (2004) aim to increase the explanatory power of Bessembinder et al.'s (2002) equilibrium pricing model by increasing the sample size. Instead of using monthly data, they use intra-day risk premiums in their empirics. They study hourly forward prices traded for the deliveries of the following day, the so-called day-ahead forwards, and compare the prices with the realized spot prices of the following day. Their data set ranges from 1.6.2000 to 30.1.2002. It includes the hourly forward and spot prices of 913 days, and thus the data set is much larger than the one of Bessembinder et al. (2002). Their dataset is collected from the US PJM markets. (Longstaff et al. 2004)

By comparing the day-ahead forward prices with the realized hourly spot prices, they present the hourly mean premiums for each hour of the day. These hourly mean prices are presented in Figure 6. (Longstaff et al. 2004)

Figure 6 illustrates the average hourly risk premiums of 913 days. The risk premiums are presented in the Y-axis of the figure and are calculated as the difference between the day-ahead forward price and the realized spot price of the delivery hour. The figure illustrates that the risk premiums change systematically throughout the day. During the night time

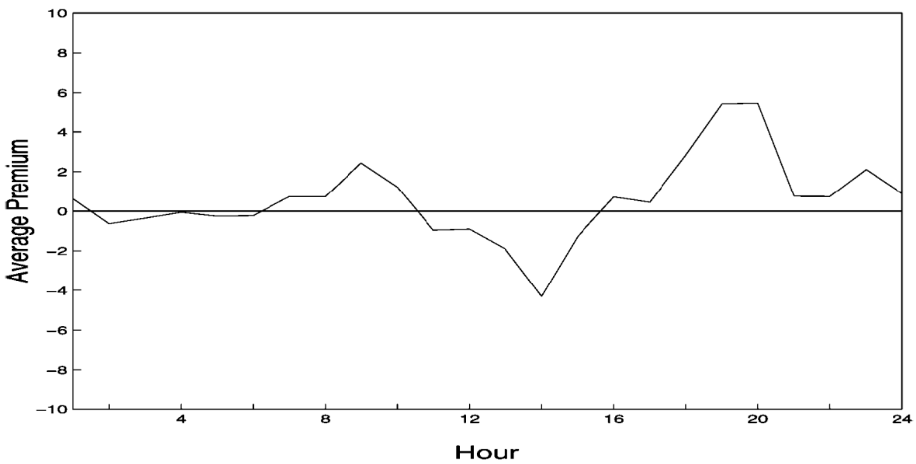


Figure 6. Average hourly risk premium in the PJM markets. Figure presents the average risk premium for each hour of the day. (Longstaff et al., 2004: 1890)

the premiums are close to zero. In the morning and after 4 p.m. the premiums are clearly positive. During the work hours the risk premiums are clearly negative. The risk premiums seem to exhibit similar intraday seasonality as the spot prices do. During the peak demand hours, the risk premiums seem to be at the highest levels. This can be argued to stem from the increased risk of price spikes. This is consistent to the findings of Bessembinder et al. (2002), who find out that the risk premiums increase during the months of high demand. Risk premiums seem to change seasonally based on the same fundamentals that make the electricity spot prices seasonal. This seasonality is observable from both monthly and intra-daily data. (Longstaff et al. 2004)

Risk premium is at the highest at 7 p.m., when the positive risk premium is 5,44 $/MWh. The risk premium is at the lowest at 2 p.m. when the negative premium is -4,31 $/MWh. Similarly to the findings of Bessembinder et al. (2002), Longstaff et al. (2004) observe that the risk premiums are extremely high in comparison to other commodities. The average risk premium 0,59 $/MWh and 10 out of 24 of the hours exhibit statistically significant risk premiums.

Longstaff et al. (2004) also try to model the risk premiums with the equilibrium model of Bessembinder et al. (2002). However, contrary to original paper they do not estimate the cost based expected future spot prices, but only consider the realized spot prices. The model used by Longstaff et al. (2004) is presented in Formula 6.

$$(6.)\ Avg.FP_i = a + \beta_1 Var_i + \beta_2 Skew_i + \varepsilon_i$$

Where:
Avg. FP_i*:* The average risk premium of each hour.
Var_i*:* The sample variance of each hour divided by 100
$Skew_i$: The skewness of each hour.

The purpose of the model is to estimate how the hourly variance and skewness perform in explaining the hourly average risk premiums. Their results clearly show that the variance of spot price has a negative impact on the risk premium whereas the skewness has a positive impact on the premiums. In their results, variable for the variance of spot prices is significant at 5% level, whereas the variable for skewness is significant at the 10% level.

Douglas et al. (2008) continue to study the equilibrium pricing model of Bessembinder et al. (2002) in the PJM markets with hourly data. They also include some elements of the Theory of Storage and findings of Routledge et al. (2001) regarding the convertibility of fuels to electricity in their model. More specifically, they try to link the electricity spot price skewness and the risk premiums to the weather temperatures and gas storages available for the electricity producers. Natural gas is an important marginal fuel in the PJM markets used by producers for meeting the high demand for electricity during the hot summer months.

Douglas et al. (2008) find out that the risk premiums in the electricity markets seem to increase (decrease) as the gas reserves decrease (increase). They also find out that the performance of the reduced form model is increased when the indirect storability is included in the model. Furthermore, they find out that the effect of weather temperatures is pronounced during times when the gas reserves are low. They argue that the sufficient gas reserves reduce the risk of price spikes in the markets during times that the temperatures in the area are hot. Thus, the reserves seem to act as a buffer against demand side shocks at the markets.

Van Treslong et al. (2010) test the robustness of Douglas et al.'s (2008) results with the same data, but slightly different methodology. Instead of using Bessembinder et al.'s. (2002) reduced form model as the base of their regression, they use the same models as Fama et al. (1987) use in their much earlier paper regarding risk premiums of commodities futures. In other words, as Douglas et al. (2008) extend the Bessembinder et al.'s (2002) equilibrium model by including fuel prices and temperatures in it, Van Treslong et al. (2010) do the same thing for Fama et al.'s (1987) model. Their results are similar to the results of Douglas et al. (2008), which proves that the Indirect Storability has a strong effect on electricity futures prices in PJM markets and that the results are robust also using different methodology of studying the risk premiums.

Huisman et al. (2012) extend the Fama et al. (1987) framework to further study Indirect Storability in the electricity markets. As the equilibrium spot price of electricity is defined by the marginal cost of the most expensive fuel needed to satisfy the current demand, the authors expect that those fuels that are used for adjusting to increased demand could also drive the risk premiums in the markets. They study the forward pricing in two markets that have very different supply conditions, the Endex -markets of the Netherlands and Nordic Electricity markets. In Netherlands, the electricity supply is to a large extent generated using fossil fuels. Natural gas is the most important marginal fuel in the markets. The Nordic markets on the other hand use hydro power reserves as the primary marginal fuel. The authors define two alternative forms of Indirect Storability, Perfect Indirect Storability and Imperfect Indirect Storability. Natural gas is argued to be a good example of Perfect Indirect Storability. It is easy to store, quick to transform into electricity, and there is active derivative markets for trading it. An electricity producer that holds a short position in the electricity futures contract can thus easily store the needed equivalent of gas and reduce the risk of price spikes in the electricity markets. Alternatively, the producer can also hedge the short position in the futures contract by taking a long position in a gas future or option. The authors use the Nordic hydropower reserves as an example of Imperfect Indirect Storability. Water can be stored for future electricity generation in water reserves. However, in the long term the water reserves are dependent on external factors such as rainfall and temperatures. Moreover, it has to be noted that there are no active derivative markets for the Nordic rainfall. Because future rainfall is hard to hedge and predict, it is also hard for producers to optimize the moment they want to use their existing reserves for producing electricity. This sort of optimizing problem is well described by the Optimal Stopping Theory described for example by Siegmund (1967) and solving these sorts of problems often require advanced mathematical methods such as Monte Carlo simulations.

The results of Huismann et al. (2012) show that the pricing processes of futures contracts in the Netherlands and in the Nordics are very different from each other. Compared with the findings of Fama et al. (1987), the Nordpool futures are priced similarly to cattle and hogs. Cattle and hogs are known to be commodities where futures contracts have significant ability to forecast the future spot prices. High storage costs, the seasonal variation of the basis, and high standard deviation of the basis are common characteristics of these sorts of markets. The futures prices in the Netherlands seem to be more risk premium oriented. However, for some maturities the prediction of the future spot prices seems to be more important factor. Netherlands' results are similar to orange juice and plywood in Fama et al.'s (1987) paper. The results of Huismann et al. (2012) show that the concept of Indirect Storability is important when modeling futures pricing in the electricity markets. When the majority of the marginal production is generated using fossil fuels, it seems that the market participants consider both future risk premiums and predicting future spot prices when pricing electricity derivatives. The pricing process in the Nordics seems to be much more oriented on predicting the future spot prices of electricity rather than trying to predict futures risk premiums.

Lucia et al. (2011) study the futures pricing in the Nordics solely from the perspective of the Risk Premium Theory. They use the reduced form model of Longstaff et al. (2004) with a data set of weekly observations between 1998-2007. They find out that the reduced form model performs relatively well before the year 2002. It seems that after 2002 the reduced form model has not been able to explain futures pricing in the Nordics. It seems that the statistical characteristics of the spot price distribution have not been able to describe the risk factors market participants in the Nordic markets face.

3.6. Model specification

The purpose of this subsection is to provide the theoretical background about the basis and reasons about the chosen explanatory variables used in the empirical part of this thesis. The variables used can be roughly categorized into five categories: 1. Statistical characteristics of the spot price distribution 2. Nordic Water levels and deviations 3. Temperature variables 4. Fuels used for electricity generation 5. Market risk variables. Research about the groups one and two has already been presented in the previous chapters so the focus of this subsection is to provide background regarding the weather temperature variables, energy commodities, and market risk / investor sentiment variables.

There has been a number of studies analyzing the effects that the weather has on Nordic Spot Market prices. However, literature concentrating on the effect of observable weather, or weather forecasts, on futures pricing is much more infrequent. Especially interesting study for my purposes on the role weather conditions on spot market pricing is Mosquera-Lopez, Uribe & Manotas-Duque's (2017) paper. They study the effect of weather temperatures, wind speeds, precipitation, and solar irradiance on spot prices and local area prices in the Nordic Electricity Markets. They conduct their analysis using quantile regression framework, which provides interesting results considering my research. My main interest, regarding spot market prices, is to study which variables have the largest effect on spot prices in the tails of the spot price distribution (in other words, what are the causes of extremely low and high spot prices), and the quantile regression methodology serves this interest well. Mosquera-Lopez et al. (2017) find out that the role of the weather conditions is the most significant during times when the spot prices are extremely low or high. The authors rationalize that the role of weather is pronounced in the extremes, because of the demand and supply conditions. For example, they assume that the weather conditions have the strongest effects on the supply side during a market state of high prices, because producers are forced to start generating electricity with more expensive marginal fuels as the prices rise. However, the authors are not able to prove the effects of weather on the supply and demand conditions as their study consists of only price data. Altogether, their paper is able to prove that the weather conditions are fundamental and structural factors affecting spot market prices. They also show that during some market states, whether conditions have even higher effects on the spot prices than for example price changes in the marginal fuels that are used for generating electricity. The authors argue that weather conditions could also play a significant role in futures' market pricing of Nordic electricity.

Considering the fourth category, I am interested whether the changes in energy commodity prices are linked to the electricity prices and risk premiums. Emery and Liu (2002) study the relationships between fuel prices and electricity prices by focusing on the concept of inter-commodity spreads in two US electricity markets. Inter-commodity futures spreads are a trading tool that commodity traders and industrial organizations use to compare price relationships between two commodities that are linked to one another by their production process. For example, an oil refinery that buys crude oil for the purpose of refining it into more valuable gasoline and heating oil and selling it to the markets, might be interested in crack spreads. Crack spread is an example of inter-commodity spread, it is formed by taking a long (short) position in crude oil future and a short (long) position in gasoline future with the same expiration dates. Oil market participants use crack spreads for estimating the profitability of their refining processess, speculating, and for hedging the future revenues of the refineries. Emery et al. (2002) study the effect of Natural Gas futures prices on electricity futures prices in California–Oregon Border (COB) and Palo Verde (PV) power markets. Especially interesting element in their study is that the production methods used in the COB markets resemble the Nordic markets, whereas the PV markets resemble more Central European markets. Majority of electricity in the COB is produced by using hydropower plants, whereas PV markets are mostly producing by using coal, oil and natural gas. On the other hand, PV markets resemble the Nordic markets more considering the demand characteristics of electricity. Locating in the hot state of Arizona, the PV markets have high seasonal variation in the demand for electricity because of the demand for refrigerating houses during the hot summer months. Even though the PV markets use much more natural gas for generation on average, Emery et al. (2002) find out that the electricity prices on both markets are highly co-integrated with natural gas. They draw a conclusion that the co-integration is high on both markets because natural gas is used to provide peak power on both markets. Thus, it seems that natural gas is an important factor also on those markets that have high water reserve capacity. Natural gas seems to be a superior Peaker Power fuel as it is easily available and there are liquid derivative markets for trading it; and thus, it can be also more easily hedged. Again, the unpredictability of weather conditions makes it hard for the producers to decide the optimal timing for using their existing reserves.

Also Murat and Tokat (2009) study the crack spreads in the US markets. Even though their research does not consider electricity markets, their results regarding the predicting power of crack spread on spot fuel prices are interesting for the purposes of this paper. Their paper studies how the crude oil futures and crack spreads perform in forecasting the spot prices of oil. Both of the derivative instruments outperform the Random Walk model in predicting oil market prices. They also find out that after 2003 the forecasting performance of the crack spread is greatly improved. They conclude that the increase in the predicting ability of the crack spread is probably due to increased volatility in the markets. Moreover, the increased number of speculators in the markets might have affected the predicting performance of crack spreads. The spread has become a better predictor in the increasingly volatile markets as oil refineries are more willing to hedge their positions in crude oil. Because of the increased proportion of speculation in the markets, the market prices have started to become speculation driven. As speculators frequently use the spreads as metrics in their trading activities, the spreads have become better predictor of oil markets.

Another important consideration when studying the relationship between different fuels and electricity markets is how the different fuels are co-integrated and correlated with each other. Bachmeier and Griffin (2006) study the integration between crude oil, coal, and natural gas markets and whether there is a single global market for any of the fuels. The authors show that the markets for oil are globally integrated in such degree that it can be defined as a single global market. Also shocks at one local oil market decouple to other oil markets in an instant. For natural gas, there is some evidence of the market integration whereas the signs of market integration for coal are found to be weak. The weak co-integration of the coal markets contradicts with the findings of Wårell (2006), who find some integration for the coal markets, at least for cooking coal. However, Wårell (2006) also note that the markets for cooking coal are much more integrated than the ones for the type of coal used in electricity production called steam coal. Moreover, Bachmeier et al. (2006) show that the oil, gas, and coal markets are very weakly correlated with each other. They further argue that while oil, gas and coal markets could be almost perfect substitutes in electricity or heat production in the long term, the assumption is not valid in the short term. For an example, if the markets knew that toil price rocketed in the long term, they could be able to optimize their production methods so that they would use more gas and coal in their future production. This would change the long-term equilibrium of the markets and also the fuel mix the producers use would change. However, this long-term optimizing assumption does not apply in the short term. The producers are not able to react to sudden and unpredictable changes in oil prices and cannot substitute oil with other fuels.

Mjelde & Bessler (2009) study the relationship and price dynamics between electricity markets and four major electricity generating fuels; coal, oil, uranium, and natural gas. They use data from two major US electricity markets for their research. Their findings show that both electricity markets are highly linked with all the fuel prices studied and there is a dynamic link between the fuel and electricity prices. Electricity prices can in some circumstances affect the fuel prices and more often fuel prices do affect electricity prices. In line with the findings of Emery et al. (2002), they show that both markets studied react heavily and instantly to price changes of natural gas. They also show a phenomenon where changes in peak load electricity prices on either of the electricity markets creates a shock on natural gas markets. The shock then further transfers from gas markets to oil markets. They also show that the coal prices are a big driver on both markets, as it is considered an important base load generation method on both markets.

Frydenberg, Onochie, Westgaard, Midtsund, & Ueland (2014) study the relationships between close to maturity electricity futures and fuel prices in Nordic, German, and UK markets. They find out that the British electricity markets are highly linked with gas and coal prices, whereas only coal prices are significantly linked to German and Nordic markets. They consider that the weak link between Nordic electricity prices and gas prices could be explained by Nordic hydro reserves that reduce the need for using Peaker Power fuels to meet peak demand.

I am also interested in whether electricity pricing in the Nordics is linked with other financial markets and market fundamentals than just energy commodity markets. There has been a lot of research considering the links between stock prices and commodities prices. However, these studies rarely include electricity prices in their analyses as electricity is often considered an oddity compared with many other commodities.

Creti, Joëts & Mignon (2013) do include electricity in their paper in which they study the links between commodity prices and stock market prices. With GARGH -modeling approach they observe statistically significant negative correlation between electricity markets and the S&P 500 stock prices, a similar link is also found between natural gas and S&P500 prices. The authors conclude that while most of the commodities are linked with the stock markets, at least to some extent, gas and electricity markets seem to function by completely different fundamentals.

S&P 500 Stock Index Option Implied Volatility (VIX) is often regarded as the key indicator of global and cross-market risk perception and financial distress. Chicago Board Options Exhange (CBOE) publishes the VIX index to measure the observable level of uncertainty about future stock market prices. The VIX index is based on the implied volatility of options, in other words it is the price of risk that the market participants consider when they price options. VIX has proven to be a good estimator of future volatility in stock markets globally, but there has been a recent interest to study how it affects non-equity markets such as commodities or currencies. For example, Broadstock and Filis (2014) show that there is a time varying link between the VIX and crude oil prices. Also, Sari, Soytas & Hacihasanoglu (2011) provide evidence that there is an equilibrium relationship between the global crude oil prices and VIX. Zhang, Chevallier & Guesmi (2017) study whether there is a spillover effect from VIX to American and European gas and oil prices and whether the relationship between them has changed during the period of 1999-2015. They also study the assumption stating that the links between commodities and stock markets have weakened after the financial crisis of 2008. They find out that during the onset of global financial crisis in 2008, all the fuel prices started to have high correlation with VIX. After the peak in correlation in 2008, the correlation between oil and VIX remained high. However, the correlation between gas and VIX was much lower. The authors conclude that oil markets are highly linked to uncertainty observed in the stock markets whereas regional factors are much more significant considering the price of gas. Moreover, they argue that gas prices are highly dependent on oil prices, but the uncertainty that transforms from equity markets to oil markets is often diluted before it affects the price of gas. They also show that the correlation of oil prices with stock market uncertainty has persisted since the financial crisis on both European and American markets. The gas prices were integrated with uncertainty during the onset of the financial crisis, but this integration did not endure after the crisis.

Since 2008, CBOE has also published a similar uncertainty index to VIX measuring the option implied volatility of crude oil derivatives. This Oil VIX could be an interesting tool for studying the Nordic electricity markets. Liu, Ji & Fan (2013) study the links between Oil VIX and other published implied volatility indexes that are; VIX, EVZ (Euro/Dollar Implied Volatility Index), and GVZ (Gold Price Implied Volatility Index). They find out that the Oil VIX is mainly Granger caused by the uncertainty information of other volatility indexes. They find out that the impacts of other volatility indexes on oil VIX are significant, but short lived. Although it is a common view in the literature that that volatility prediction models using information content of VIX outperform the models using historical volatilities, it is a little surprising how little the Oil VIX has been studied. Dutta (2017) is one of the only authors to study whether Oil VIX can be used to improve the prediction accuracy of models trying to estimate the future volatility of the oil markets. His findings show that the using oil VIX increases the prediction accuracy of volatility models and that the model utilizing the implied volatility information outperforms the traditional models in many cases. Considering his results, it is probable that the use of Oil VIX will gain more popularity in the relating literature in the future.

The last uncertainty factor that I am interested to study is the TED -spread. The TED -spread is considered as a measure of counterparty risk in financial markets. It is the difference between risk-free and interbank rates. Therefore the TED -spread proxies the markets' view on how banks and financial institutions are able to pay back their short-term loans. The TED -spread is a widely used measure of investor sentiment and market liquidity in many markets, so I assume that it might also have some implications for the Nordic electricity derivatives markets.

Marshall, Nguyen & Visaltanachoti (2013) study whether the liquidity between different commodity markets is linked. For this purpose, they study 16 commodities from the following categories; energy, industrial metals, precious metals, agriculture, and livestock. They find strong evidence of common inter-market liquidity, for each of the commodity studied. They also find support that there have been cross-market liquidity crashes in commodity markets that could be explained by investor sentiment. Speculators withdraw liquidity from commodity markets simultaneously in certain market states when the prices of commodities are in a decline. These kind of "liquidity dry ups" have been previously reported to exist on stock markets for example by Hameed, Kang & Viswanathan (2010). Hameed et al. (2010) find liquidity dry ups that are observed between different stock markets and also dry ups that can be observed across different industries within a one market.

However, Marshall et al. (2013) do not provide any actual explanations or causes on what could cause the sudden dry up of liquidity in multiple commodity markets at the same time. By using quantile regression methodology Koch (2014) studies the extreme price changes in energy commodities. He provides results showing that the TED -spread is related to the “liquidity dry up” –phenomenon in the energy commodities markets. His results show that when the TED -spread increases, there is significantly higher probability of sudden and extreme price falls in more than one energy commodity price. In other words, the results of Koch (2014) show that the counterparty risk and tighter credit conditions, proxied by the TED -spread, do have an effect on energy commodities markets prices. This finding motivates the use of TED -spread in my thesis.

4. DATA

Chapter 4 describes the data used in this thesis. The core data of the thesis consists of the daily observations of Nord Pool Spot system prices and OMX commodities futures markets data. Even though the spot market data used is of daily frequency, the daily prices are actually averages of hourly prices. The time period of the data collected ranges from the beginning of 2005 to the end of 2015. The thesis also uses a number of explanatory variables to test the impact of different factors on the electricity spot and futures pricing. This chapter provides a detailed description of all the data used, how it is adjusted and some descriptive statistics and illustrative figures regarding the data set.

4.1. Nord Pool system prices

The daily system prices are calculated from hourly high frequency data. The hourly system prices are formed in the markets as described in Chapter 3.3. The daily prices are obtained by simply averaging the hourly prices of the day. The total number of daily prices in the data set is 4017 and the daily prices are calculated from 96 408 hourly observations.

Furthermore, the daily logarithmic returns of spot prices are used in this thesis. The daily returns are compounded from the daily spot prices with the following formula (7):

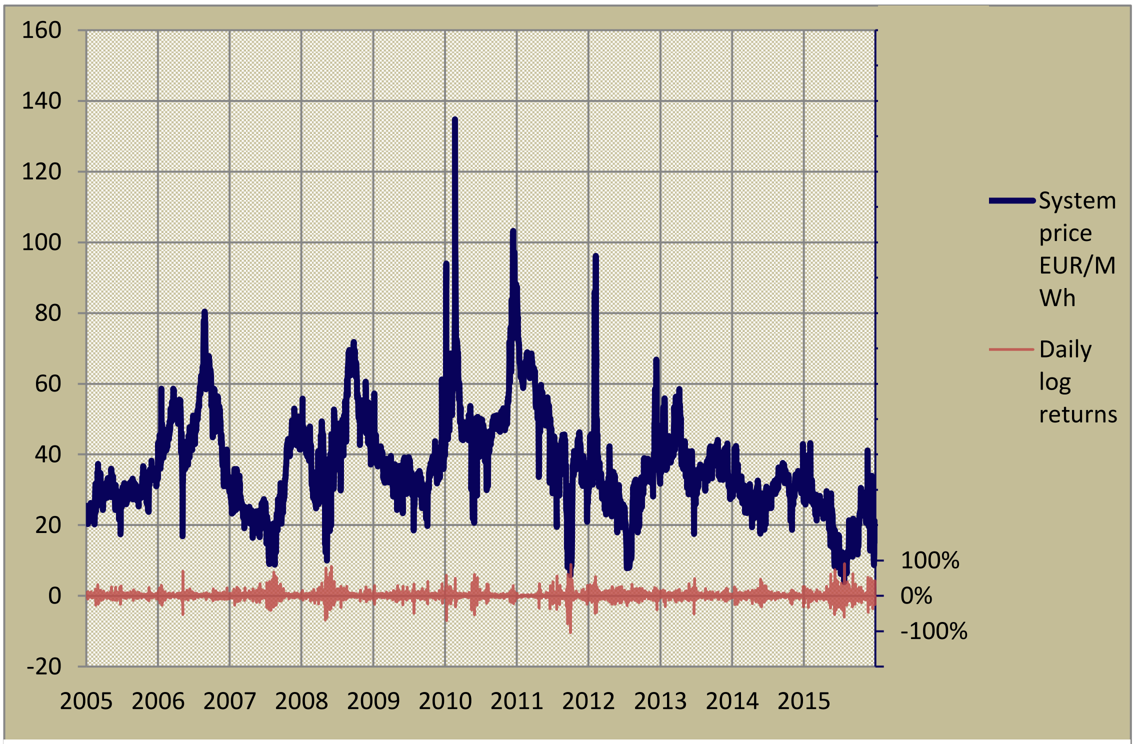


Figure 7. The daily spot market prices (EUR/MWh) and the logarithmic returns.

$$(7.) \quad r_t = \ln(p_t / p_{t-1})$$

Where, r_t is the daily index return of day t, and $\ln(p_t / p_{t-1})$ is the (natural) logarithmic difference in index price between the days t and t-1. (Sengupta 2004: 295-297)

Figure 7 illustrates the whole time series of daily spot market prices and the daily returns of these prices. The spot market prices are illustrated with the blue line and the scale is presented on the left side of the figure. The daily returns are presented with the red line and the scale is presented on the right side of the figure. For illustrative purposes, the scale of daily returns is presented with a much smaller scale than the spot prices. The high volatility of spot prices and the occurrence of high price spikes are clearly visible from the figure. Both high prices and the high positive price spikes seem to occur mostly during the winter time. This further strengthens the assumption of seasonality of spot market prices.

When discussing the price spikes in the data, it is important to consider whether the resolution of daily prices can capture the nature of these spikes. According to Simonsen's (2004) third stylized fact the time periods of these extreme prices are usually short, and it takes only hours for prices to revert to normal levels. Hence, it is interesting to study the price spikes in hourly resolution to truly understand the severity of this phenomenon in the markets. The largest daily prices in the data were reached in 22.02.2010. Figure 8

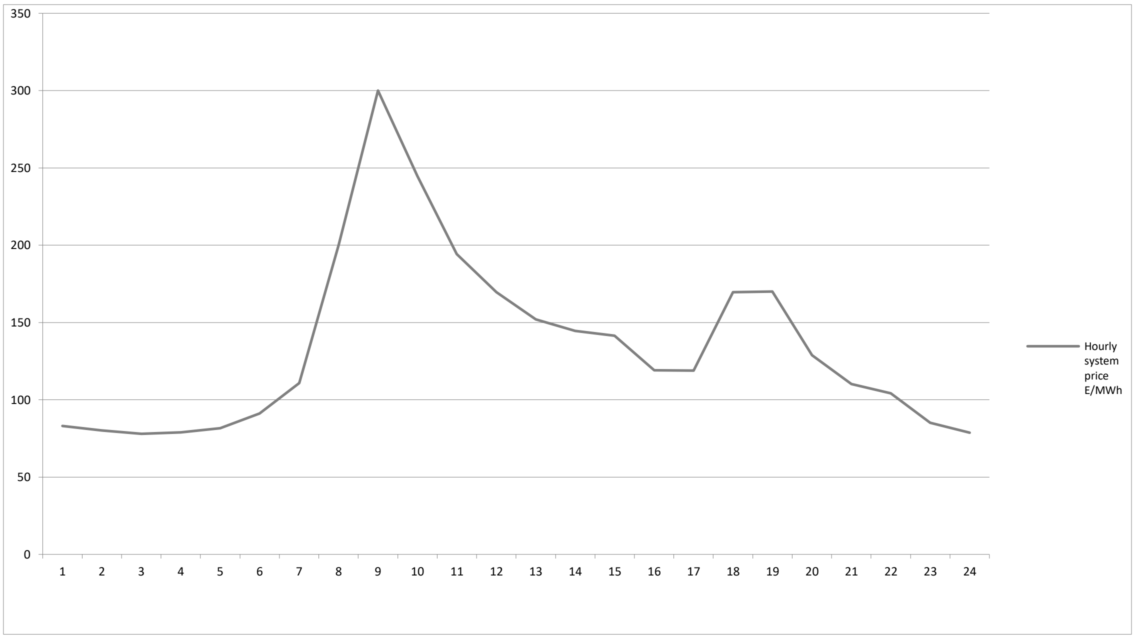


Figure 8. The price spike that occurred on the 22 February 2010. Hourly prices on the Nord Pool spot markets.

illustrates the hourly prices during the 22nd of February 2010. This figure supports the third stylized fact of Simonsen et al. (2004).

It is evident that the price spike occurs between the hours 8-10 A.M. The price spike seems to be sudden and reverts back to normal levels within several hours. This indicates that the daily resolution might not be accurate enough for identifying the real price spikes in all cases. If the price spikes last only for several hours the method of averaging the hourly prices might leave some price spikes unidentified.

Moreover, the seasonality of electricity prices can be observed in the data. Figure 9 illustrates the hourly means of the entire time series. The intra-day seasonality is clearly visible from the figure. The demand is at its lowest during the night time and increases when people use electricity at their home. The so called two headed peak occurs in the morning and in the evening. The two-headed peak is caused by the daily routines of the people consuming electricity.

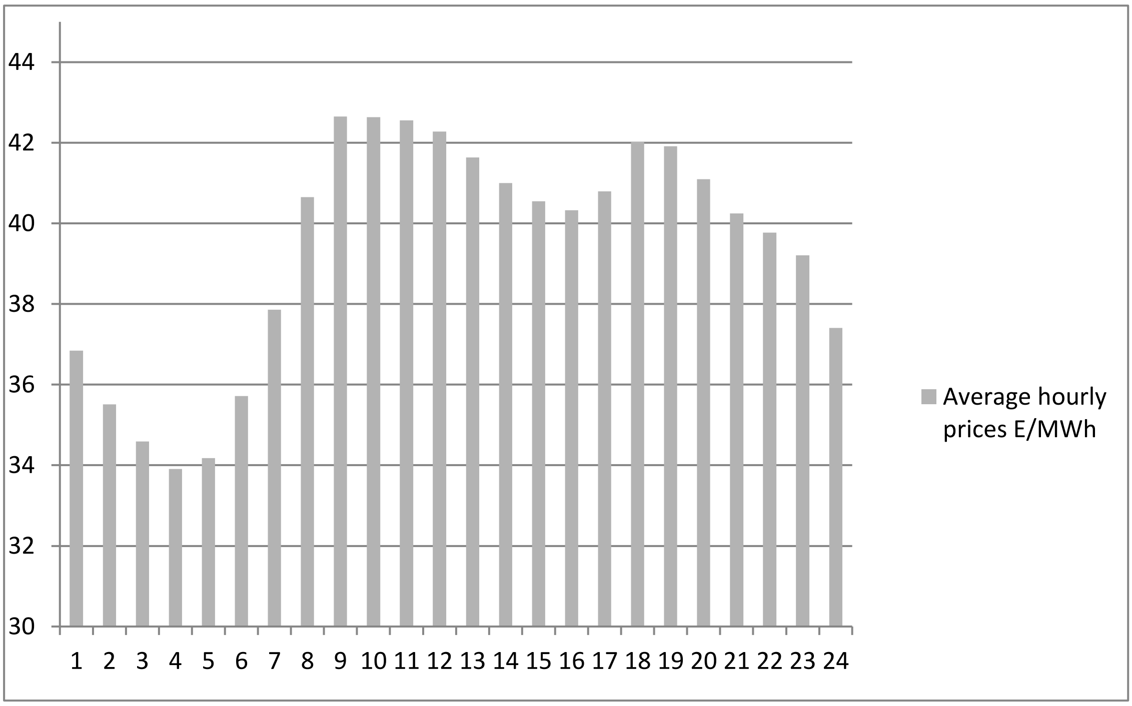


Figure 9. The average hourly spot prices of the whole sample period.

4.2. Futures market prices

The futures market data of the thesis is collected from the Thompson Reuters DataStream. There are only monthly, quarterly, and yearly contracts available on the DataStream. The focus of the thesis is on monthly contracts, as they have the largest number of observations and they are the most liquid contracts on the markets. There is separate data on the normal base load contracts and the peak load contracts. (Peak load contracts are no longer traded in the Nord Pool, the trading ended during the year 2015). Because of the better availability of baseload contracts data, this thesis concentrates on them.

The futures data from the DataStream is in daily continuous index form. There are also several traced indices (TrC1-TrC6) available. The traced indices allow me to easily study the risk premiums at different stages prior to the settlement of the contract. For example, comparing the last trading day of the month of TrC6, TrC3, and TrC1 allows me to study what is the basis of the contract 5 months, 2 months and one day before the settlement of the contract. Because of the indexed data there is no need to rolling the contracts over as would be required if the data was just raw futures price data.

As discussed in the theoretical background chapter, there are several ways of defining risk premiums in empirical research. This thesis follows the common ex post premium approach to avoid the pitfalls of estimating expected future spot prices. This approach is taken in the literature for example by Geman et al. (2001), Shawky, Marathe, and Barret (2003), Longstaff et al. (2004), and Lucia et al. (2011).

Since the studied futures are monthly contracts, the most straightforward way to study the risk premiums is to use monthly spot price observations. The ex post monthly risk premiums are calculated by using the following formula:

$$(8.)\ \hat{P}_{t,T} = F_{t,T} - \bar{S}_T$$

Where
$\hat{P}_{t,T}$: Is the proxy of the ex post risk premium during month t. Hat is included to the premium term as the random noise term is not included in the formula. However, the random noise is included in the error term of the regression models presented in the following chapter.

$F_{t,T}$: Is the futures price at t for a contract that is settled at T. The thesis studies risk premiums for six different times from the maturity. They are the following: one day-, one full month and one day-, two full months and one day-, three full months and one day, four full months and one day, and five full months and one day prior to the first settlement day of the contract.

$\bar{S}_T$: Is the average spot price during the settlement month of the contract. The average price is calculated as the arithmetic mean of the daily spot prices during the delivery month.

As discussed in the background chapter, relative risk premiums are also common approach for studying electricity derivatives pricing. This approach is also studied in my thesis for examining the robustness of the results. The relative risk premiums are calculated by using the following formula:

(9.) $\widehat{rP}_{t,T} = \frac{\hat{P}_{t,T}}{F_{t,T}}$

Where:

$\widehat{rP}_{t,T}$ Is the relative risk premium. Again, the relative premium is defined as estimate because the random noise is omitted from the formula.

My major concern with this method of defining risk premiums is the sample size of the models, especially because I am using monthly futures contracts data. In my research period, the number of monthly risk premium observations is only 132. The sample size might not be large enough for observing the subtle features and key drivers behind futures pricing in large multifactor regression models. In aim to increase the sample size of my analysis, I try to utilize the daily continuous indices for performing the analysis also with daily frequency data.

The traced continuous indices of Thompson Reuters DataStream provide natural means for doing daily frequency analysis. However, the underlying of the contracts is one month's delivery of spot electricity, so the average price of the delivery month of the contracts must be used also for daily frequency analysis. This means that all the daily closing prices of the traced indexes are subtracted by the same monthly mean spot price of the delivery period. In other words, the daily premiums are the difference between the daily futures price and the average monthly price of the delivery month.

Figure 10 illustrates the process of obtaining the daily realized risk premiums from the six traced futures indices. Each one of the traced indices are settled on November 2011. The traced indices in the figure are basically rolled over at the end of the month so that on the first trading day of the month the figure starts to the track index that shows the price of the contracts that are one month closer from the settlement than the previous index. For example, during April 2011 the traced index TRc6 tracks monthly futures contracts that are due to settlement on November 2011. On May 2011, the figure starts to track TRc5 index that shows again the price of monthly futures contracts that are settled on November 2011. This pattern is repeated for all the 6 traced indexes used in this thesis. On the 31st of October, the last day of TrC1, all trading for contracts with deliveries for November is seized.

The red line in Figure 10 illustrates the current daily system price of Nord Pool. It is shown in the figure to visualize the dependencies between current futures prices and current spot prices in the markets. The green dotted line represents the average spot price during the delivery month, which is the average daily system price on November 2011 including the weekends. For illustrative purposes about the behavior of the futures prices, another futures price index is presented in the figure. This time the settlement period for contracts is December 2011. The second futures price time series is presented with the purple color and is displayed for the following months: August, September, and November. The difference between the futures price (blue line) and the average spot price of the delivery month (green dotted line) is the realized ex post risk premium in the markets.

The figure illustrates that as the settlement of the contract gets closer, the futures price seems to be more affected by the current spot price. At the end of May, the futures price practically ignores the large and sudden collapse in the spot price because the delivery of

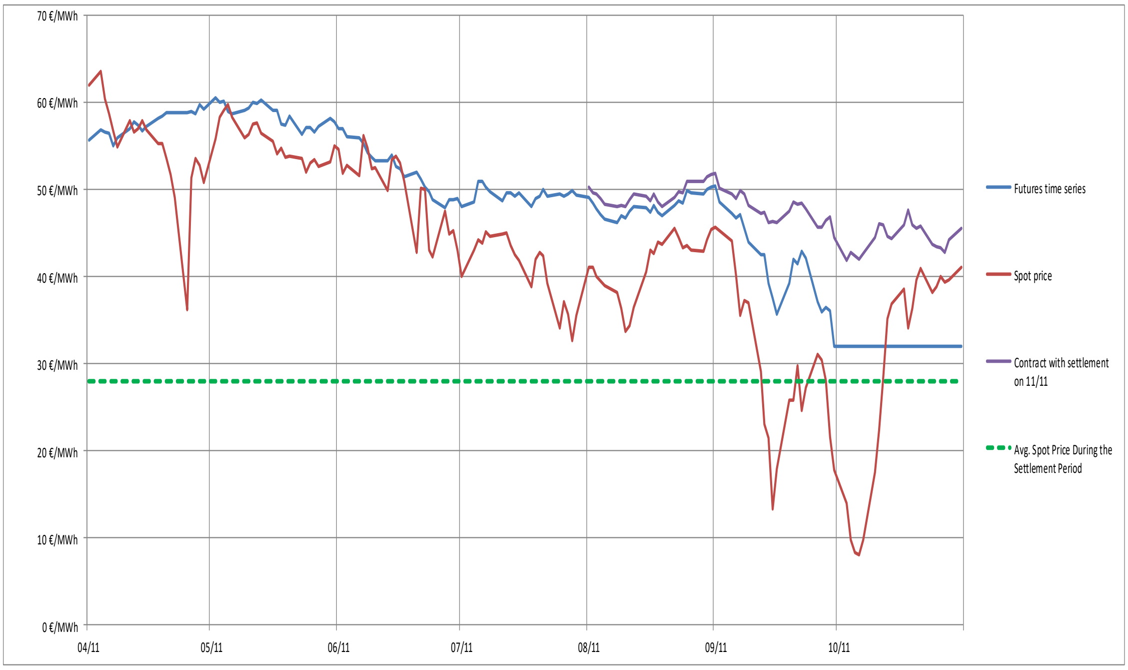


Figure 10. The illustration on how daily risk premiums are calculated using the six traced monthly futures indexes for contracts that are settled on November 2011.

the contract is five months away. However, the even more severe plummet of spot prices at the beginning of September seems to have influential effect on the futures prices.

Furthermore, the futures contracts that are due to settlement on December 2011 do not react to the sudden decline in spot prices during September. This indicates that the futures prices have stronger correlation with the spot prices when the settlement period of the contracts is closer. This might also indicate that contracts closer from the settlement are more prone to speculative trading. In general, the futures prices in the figure are consistently higher than both the current spot price and the average spot price of the settlement month. This indicates that during the period displayed in the figure, the risk premiums were positive, and that the markets had positive basis.

As seen from Figure 10 the daily ex post risk premium is calculated for each traced futures index by subtracting the realized average system price of the delivery month from the daily futures prices. The futures are traded on every weekday of the year whereas the spot electricity has 365 or 366 trading days in a year. Thus, all the analyses in this thesis about the futures prices omit the weekends from time series used. However, the average monthly spot prices of the delivery period do take weekend spot prices into account, because futures contracts are settled against seven days a week delivery.

Tables 1 and 2 present the descriptive statistics for both monthly and daily realized risk premiums. Similar table for the daily relative risk premiums is presented in Appendix 1. Relative risk premiums are treated as robustness checks for the results throughout this thesis and they are given less focus on the discussion. All the regressions are also run using relative risk premiums, but the results are not presented in this thesis due to space constraints.

Following Lucia et al. (2011), the statistical characteristics of the risk premiums are also studied at the seasonal level to see whether there is seasonal variation in the risk premiums. The seasons are defined in the data set by the following classification; Winter consists of observations from December to February (12-2), Spring from March to May (3-5), Summer from June to August (6-8), and Autumn from September to November (9-11). The tables study characteristics of the risk premiums by expressing the following features of the distribution of the time series; arithmetic average, sample standard deviation, skewness, kurtosis, the smallest value, and the largest value of the risk premium. Moreover, the number of observations in the sample is demonstrated with symbol N. Furthermore, a simple t-test is presented in the table that test whether risk premiums in the sample are significantly different from zero. The formula of the t-test used is presented below:

$$(10.)\ t_{stat} = \frac{\bar{P}-H_0}{S\,/\sqrt{n}}$$

Where;
$\bar{P}$: Is the arithmetic sample mean of the risk premiums
H_0 : Is the zero hypothesis that is tested. In this case the zero hypothesis is that the average risk premium in the market equals zero. Therefore, $H_0 = 0$
S : Is the sample standard deviation of the observed ex post risk premium.
n : Is the number of observations in the sample. (Azcel & Sounderpandian 2008: 272-278)

As demonstrated on Table 1, the risk premiums are highly significant and positive in the monthly level when the seasonal dummies are not included in the analysis. This applies for all the times from settlements studied. The only case where the zero hypothesis cannot be rejected at one percent significance level, is for the contracts closest to settlement. The t-tests of monthly premiums with different seasons are not nearly as significant as they are for the whole time period. The seasons with premiums most significantly different from zero are winter and autumn. The reason behind insignificant results for the seasons is clearly the low sample size of only 33 monthly observations. The results for daily premiums presented in Table 2 are totally different with the sample size of 2869 observations and around 720 observations for each of the seasons. The daily risk premiums are positive and significantly different from zero for all the seasons and all the different maturities studied.

The differences in t-statistics between the tables 1 and 2 clearly demonstrate the difficulties of studying monthly risk premiums with only monthly observations in case of Nordic electricity markets. With the sample size being so small the uncertainty increases and this reduces the accuracy of empirical tests. A major problem with doing empirical tests with small sample size is consistency. As this paper considers a large number of explanatory variables for studying the risk premiums in the markets, large sample sizes decrease the likelihood of inconsistent variables. With inconsistent data, t-values and p-values used in hypotheses testing become worthless as the sampling distribution does not represent the actual distribution of the population. For further discussion considering inconsistency and too small sample sizes I refer to Law of Large Numbers and Wooldridge (2013:757-761). (Azcel et al. 2008:243-245)

Table 1. Statistical characteristics of risk premiums in monthly contracts. Ex post premiums are measured in monthly frequency. The table reports the statistics for whole time period studied and the same statistics for different seasons. Seasons are defined as follows: Winter: December-February, Spring: March-May, Summer: June-August, and Autumn: September-November.

		Months to the settlement date of the futures contract					
		0	1	2	3	4	5
Whole Period							
	Average Premium	0,9130	2,0280	2,7388	3,3940	3,6712	3,9311
	Standard Deviation	5,0430	8,5733	10,3685	12,1067	13,2285	13,5754
	T-test	2,0801 **	2,7177 ***	3,0348 ***	3,2209 ***	3,1885 ***	3,3269 ***
	Skewness	0,8336	-0,3426	-0,0110	0,2766	0,3164	0,3534
	Kurtosis	6,5717	2,8306	2,6905	1,8351	1,7613	1,1118
	Smallest Value	-19,9402	-33,8002	-32,7239	-29,9202	-36,2702	-31,3002
	Largest Value	23,8400	26,5696	40,0696	46,9278	46,1778	44,9335
	N	132	132	132	132	132	132
Winter							
	Average Premium	1,1253	2,8511	4,3978	6,4823	6,9896	7,5644
	Standard Deviation	6,5639	12,0496	15,1855	17,6954	18,6777	17,4290
	T-test	0,9849	1,3592	1,6636 *	17,6954 ***	18,6777 ***	17,4290 ***
	Skewness	-0,2882	-1,1425	-0,3166	0,0829	-0,0633	-0,0959
	Kurtosis	4,5337	2,5262	1,5822	0,4068	0,8264	0,6614
	Smallest Value	-19,9402	-33,8002	-32,7239	-29,9202	-36,2702	-31,3002
	Largest Value	23,8400	26,5696	40,0696	46,9278	46,1778	44,9335
	N	33	33	33	33	33	33
Spring							
	Average Premium	0,6870	1,1592	1,5837	2,5437	3,5352	4,4498
	Standard Deviation	4,9977	7,1488	8,0841	10,4915	12,7506	15,1488
	T-test	0,7897	0,9315	1,1254	1,3928	1,5927	1,6874 *
	Skewness	3,1650	0,8961	-0,2383	-0,3608	0,0974	0,3602
	Kurtosis	14,4713	1,3053	0,0567	-0,1260	-0,1070	0,2175
	Smallest Value	-5,5667	-9,5467	-15,7700	-22,9200	-19,7700	-24,9900
	Largest Value	23,8400	23,0839	20,3024	20,7566	33,9335	44,9335
	N	33	33	33	33	33	33
Summer							
	Average Premium	0,1295	1,3313	1,5534	1,1664	1,0873	1,6183
	Standard Deviation	3,6008	5,9955	7,7543	8,9941	8,5909	9,4305
	T-test	0,2065	1,2756	1,1508	0,7450	0,7271	0,9858
	Skewness	0,3910	-0,3297	-0,6468	-0,6829	0,0001	-0,2505
	Kurtosis	1,1386	0,8942	1,1959	0,7877	-0,4404	-0,0576
	Smallest Value	-7,7379	-15,2779	-20,8479	-24,4779	-16,6162	-21,4779
	Largest Value	9,9401	13,8688	15,6688	15,9112	19,0501	21,8001
	N	33	33	33	33	33	33
Autumn							
	Average Premium	1,7103	2,7703	3,4203	3,3836	3,0727	2,0918
	Standard Deviation	4,6577	8,1307	8,8249	8,9579	10,6071	10,4573
	T-test	2,1094 **	1,9573 *	2,2264 **	2,1699 **	1,6641 *	1,1491
	Skewness	0,9204	0,9290	0,8133	0,4591	0,4445	0,5438
	Kurtosis	3,2111	0,2442	0,3085	1,3317	2,3209	2,1873
	Smallest Value	-6,8588	-8,7674	-11,3278	-17,0778	-22,1578	-23,7874
	Largest Value	17,6106	22,3028	23,4033	28,3106	29,8528	31,2528
	N	33	33	33	33	33	33

For both, monthly and daily, data sets it is visible that risk premiums increase as the time from the settlement increases. This is practically true for all the seasons and all the maturities studied. This could be partly caused by backwardation, a market state that introduced in the theory section of the thesis. However, backwardation, by definition, means decreasing term structure of futures contracts compared with current spot prices. Definitive conclusions about this can not be made from the tables as they do not consider futures prices, but ex post risk premiums. Another possible reason for increasing risk premiums as a function of time from the settlement is that the counterparties with short positions in the futures contracts require larger risk premiums from the hedgers. It is presumable that the market participants accept that the uncertainty about future spot prices increase as the

Table 2. Statistical characteristics of risk premiums in monthly contracts. Ex post premiums are measured in daily frequency. The table reports the statistics for whole time period studied and the same statistics for different seasons. Seasons are defined as follows: Winter: December-February, Spring: March-May, Summer: June-August, and Autumn: September-November.

		Full months prior to the settlement date of the futures contract					
		0	**1**	**2**	**3**	**4**	**5**
Whole Period							
	Average Premium	1,3846	2,2245	2,8357	3,4146	3,6618	3,7583
	Standard Deviation	6,6809	9,2546	11,1033	12,5670	13,2833	13,5632
	T-test	11,1008 ***	12,8749 ***	13,6797 ***	14,5536 ***	14,7659 ***	14,8421 ***
	Skewness	-0,2488	-0,0679	0,2456	0,4306	0,4844	0,4052
	Kurtosis	3,1225	2,6214	2,4455	2,0521	1,8176	0,9632
	Smallest Value	-33,0502	-33,8002	-33,7739	-35,6702	-37,0002	-31,3002
	Largest Value	26,9300	38,8196	47,3196	53,6778	58,9278	60,6767
	N	2869	2869	2869	2869	2869	2869
Winter							
	Average Premium	0,9360	1,3316	1,7571	2,1499	2,1867	1,3733
	Standard Deviation	7,4763	9,6503	8,7235	7,6984	7,8610	9,7433
	T-test	3,3334 ***	3,6741 ***	5,3633 ***	14,5536 ***	14,7659 ***	14,8421 ***
	Skewness	-0,3329	-0,8018	-0,3892	-0,0124	0,5116	-0,3778
	Kurtosis	1,2400	1,7012	0,1340	0,2134	-0,1329	-0,4683
	Smallest Value	-24,2739	-31,6239	-21,8400	-16,2312	-12,1352	-25,3179
	Largest Value	26,9300	26,8339	22,2024	23,8010	22,4310	21,8301
	N	709	709	709	709	709	709
Spring							
	Average Premium	0,8467	1,7126	1,4309	1,3550	1,2516	1,9023
	Standard Deviation	4,6067	5,5465	8,0023	10,3053	10,8704	10,1678
	T-test	4,9387 ***	8,2966 ***	4,8046 ***	3,5330 ***	3,0937 ***	5,0270 ***
	Skewness	0,9999	0,3484	-0,6938	0,1414	0,4949	0,4308
	Kurtosis	2,1326	0,2462	1,0259	0,3247	1,1491	1,9414
	Smallest Value	-12,2165	-12,5840	-27,4779	-27,8674	-25,2174	-28,2174
	Largest Value	18,9066	17,7315	17,7112	31,2606	32,6528	31,8028
	N	722	722	722	722	722	722
Summer							
	Average Premium	1,0643	1,6409	2,9885	4,4072	5,6563	6,5179
	Standard Deviation	5,7403	7,9715	8,9623	12,1443	14,3864	16,4702
	T-test	4,9854 ***	5,5350 ***	8,9662 ***	9,7580 ***	10,5717 ***	10,6408 ***
	Skewness	0,3315	0,4278	0,8037	0,1970	0,2655	0,1130
	Kurtosis	1,1673	1,0004	1,0405	3,3582	2,2606	0,5988
	Smallest Value	-15,7879	-21,0779	-17,7478	-35,6702	-37,0002	-31,3002
	Largest Value	18,3722	28,0666	38,2533	51,5196	58,9278	60,6767
	N	723	723	723	723	723	723
Autumn							
	Average Premium	2,6965	4,2170	5,1694	5,7446	5,5418	5,2071
	Standard Deviation	8,1726	12,2877	16,2860	17,5190	17,4142	15,7211
	T-test	8,8224 ***	9,1768 ***	8,4875 ***	8,7680 ***	8,5094 ***	8,8567 ***
	Skewness	-0,8185	-0,1533	-0,0015	0,2271	0,1991	0,3469
	Kurtosis	3,8928	1,4976	0,6830	0,1121	0,0906	-0,3459
	Smallest Value	-33,0502	-33,8002	-33,7739	-35,4239	-34,6739	-26,0700
	Largest Value	25,9696	38,8196	47,3196	53,6778	52,2767	46,1835
	N	715	715	715	715	715	715

time from the settlement of the contract gets longer. In addition, the fact that the standard deviation of risk premiums increase as the function of time, speaks for this interpretation. (Ilmanen 2012: 114-118)

Altogether, comparing statistical characteristics of daily and monthly risk premium distributions yield similar outcomes. The average premiums, standard deviations, and measures of skewness and kurtosis are fairly similar. The key difference between the two distributions is the results of the t-tests. The small number of observations in monthly data decreases the significance of the test results drastically compared with the highly significant results of daily premiums. This could indicate that while the two methods of defining ex post risk premiums are comparable, daily risk premiums should be superior for empirical research purposes because of the larger sample size. Relative risk premiums yields similar results.

4.3. Hydro power reservoirs

The time series for the Nordic water reservoirs is obtained from the Thomson Reuters DataStream. DataStream collects the data provided by the Norwegian Water Resources and Energy Directorate (NWRED). The NWRED provides water reserves data for all the Nordic countries. Their data is divided into seven geographical areas. It includes five Norwegian areas, one area for Sweden, and one area for Finland. Data is provided on daily frequency, but it is actually updated only once per week basis. The new reserve situation is updated by NWRED on every Thursday.

Following Botterud et. al (2010) I calculate weekly deviations from the average water reservoir levels. The weekly average water reserve capacity is calculated from a time series ranging from 3.1.2002 to 31.12.2015. The deviation from the weekly average is calculated from the time series described above. Figure 11 presents the average weekly water reservoir levels, the realized weekly water reservoirs, and the current deviation from the weekly average level for this thesis' study period.

This method of calculating the weekly average reserves might bias the results. The problem is that this method assumes that there is a clear seasonal (annual) trend in the water reserve levels and that the levels are normally distributed. However, if there is seasonality and the distribution is not normally distributed, the arithmetic means of weekly reserves might not give accurate results. More advanced models such as rolling estimations and larger data set would be required. If the average reserve levels were biased estimators, this would be problematic also because of the overlapping time series. For an example, (Ceteris Paribus) Electricity Company X making hedging decisions in the year 2006 does not have the full information used in this study, because the time of which the average reserves are calculated ranges from the year 2002 to 2015. If the Company X (in the year 2006) has used different proxies of average reserves, they could have a different hedging demand that my model would assume. This would affect the risk premiums and weaken the explanatory power of my model. However, I argue that the seasonal trend and close to normal distribution of reserve levels are reasonable assumptions. Similar assumptions have been made in the previous literature for example by Botterud et al. (2010).

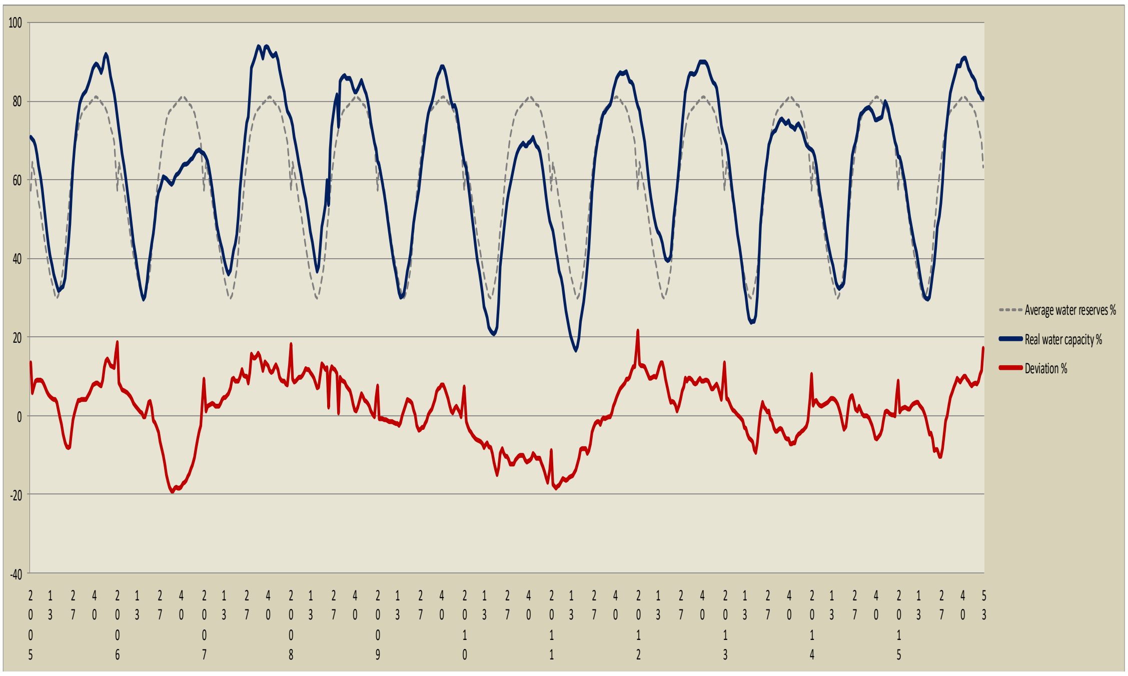


Figure 11. Average annual water reservoir levels and the realized deviation from the average weekly level.

Figure 11 illustrates the water reservoir level data used in this thesis. Weekly average reservoir levels are presented with a grey dashed line, realized reserves are illustrated with a solid blue line, and the deviations from the average levels are illustrated with a bolded solid red line. The average reserves and realized reserves should be interpreted as percentage deviations from the full Nordic water level capacity.

It is interesting to study the relationship between the Nordic water reservoirs and spot market prices. Figure 12 presents a scatter plot diagram of water reservoir deviation and

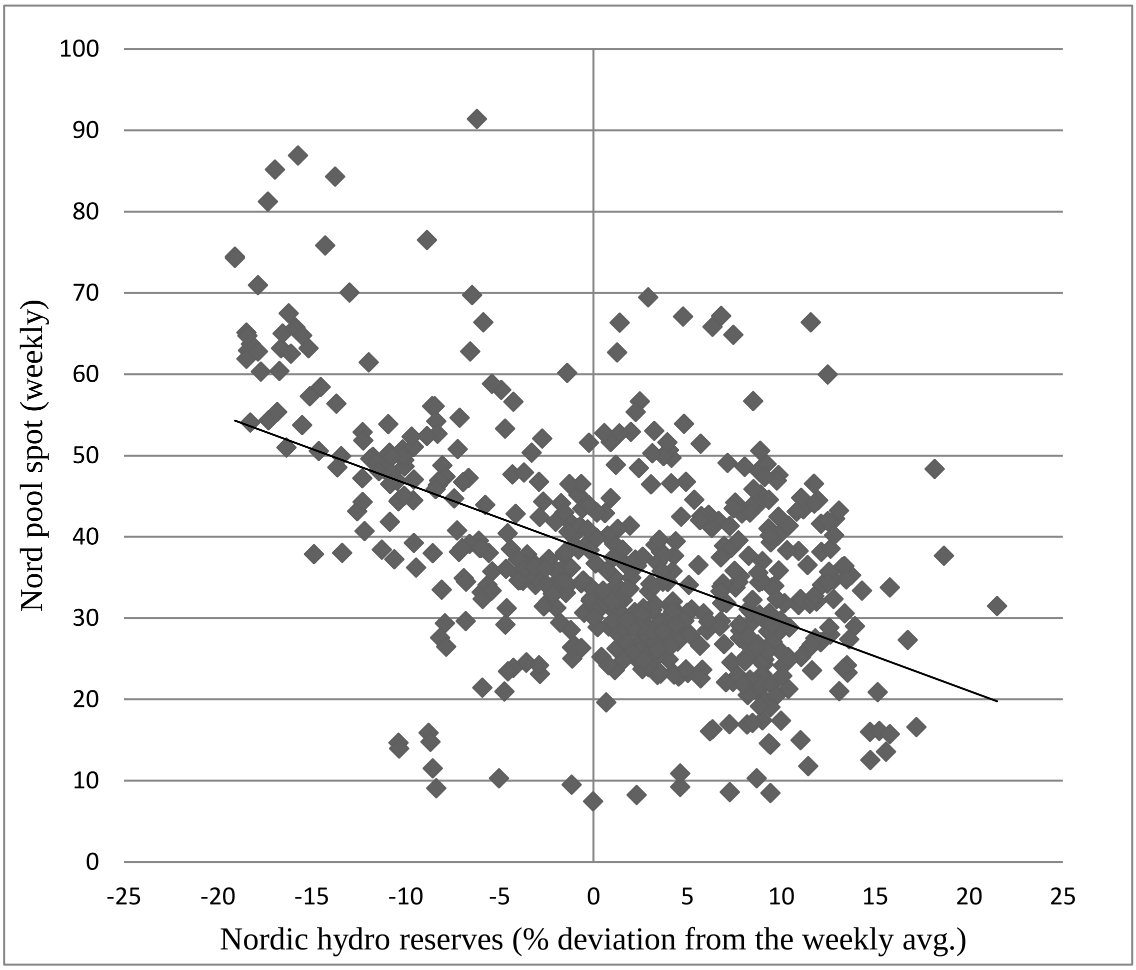


Figure 12. Scatter plot diagram of the Nordic Hydropower reserves and weekly average spot prices.

electricity spot market prices. As water reservoir data is only updated once a week the spot market data is modified to fit the purposes of the diagram better. Figure 12 has the weekly average spot prices in the Y-axis and the deviation from the average water reservoir levels are represented in the X-axis. A similar scatter plot diagram is presented in Appendix 2, but instead of the weekly average prices every Thursday's spot price is presented in the Y-axis. Thursdays are chosen because new water level data is updated on every Thursday. Furthermore, a linear trend line is fitted to the both figures to better illustrate the decreasing nature of the observations.

The scatter plot diagram illustrates that the highest weekly prices occur during times when the water balance is below its normal levels (negative deviation). Also, the trend line is decreasing. However, high positive prices still occur during the weeks when the deviation is positive. Most observations scatter between -5 and +5 and the prices being modestly between 20 and 60 €/MWh. Because Figure 12 illustrates the weekly average prices it might smoothen the extreme values, thus it is interesting to observe the scatter plot diagram in Appendix 2. The figure is fairly similar, perhaps a little more scattered. Nevertheless, the clear decreasing trend, extreme values occurring mostly at the negative tail, and concentration around 0 deviation are the most interesting similarities observed between the figures.

4.4. Energy commodities prices

Several Energy Commodities prices are analyzed to study their effect on the Nordic Electricity Market prices. Commodities are chosen so that they would proxy as well as possible the fossil fuel prices the Nordic Electricity producers face in their operations. The studied fossil fuels are the following: Oil, Coal, and Liquefied Natural Gas (LNG).

All the Energy commodities data is downloaded from the Thompson Reuters DataStream. ICE Low Gasoil Futures Contracts are used to proxy the fuel oil price in the Nordics. These futures contracts are settled against 100 tons of diesel barges delivered to the ARA region. The ARA region includes the harbors of Amsterdam, Rotterdam, Antwerp. This commodity derivative contract is a widely used pricing benchmark for all oil distillate products in the Europe. It is hence assumed to be a good proxy of oil prices in Nordic Region.

Merril Lynch's Global Commodities Price Indexes are used as the proxies of coal and LNG prices in the Nordics. Both indices represent the global spot prices of these commodities, so they do not include possible freight costs to the Nordics. Because of the limited availability of data, the approximations for the freight costs regarding coal and LNG are omitted from the analysis of this thesis. All the proxies included in this thesis are originally nominated in US dollars and transferred to Euro currency with daily $/ € exchange rate obtained from the Thompson Reuters DataStream.

Figure 13 illustrates the time series of all the fuel proxies used in this thesis. The proxies are illustrated in their absolute values. All the fuel prices seem to be highly volatile and correlated with each other at least to some extent. It is notable that all the prices exhibit a large jump during 2008. This is assumed to be caused by the shock that ignited the global financial crisis.

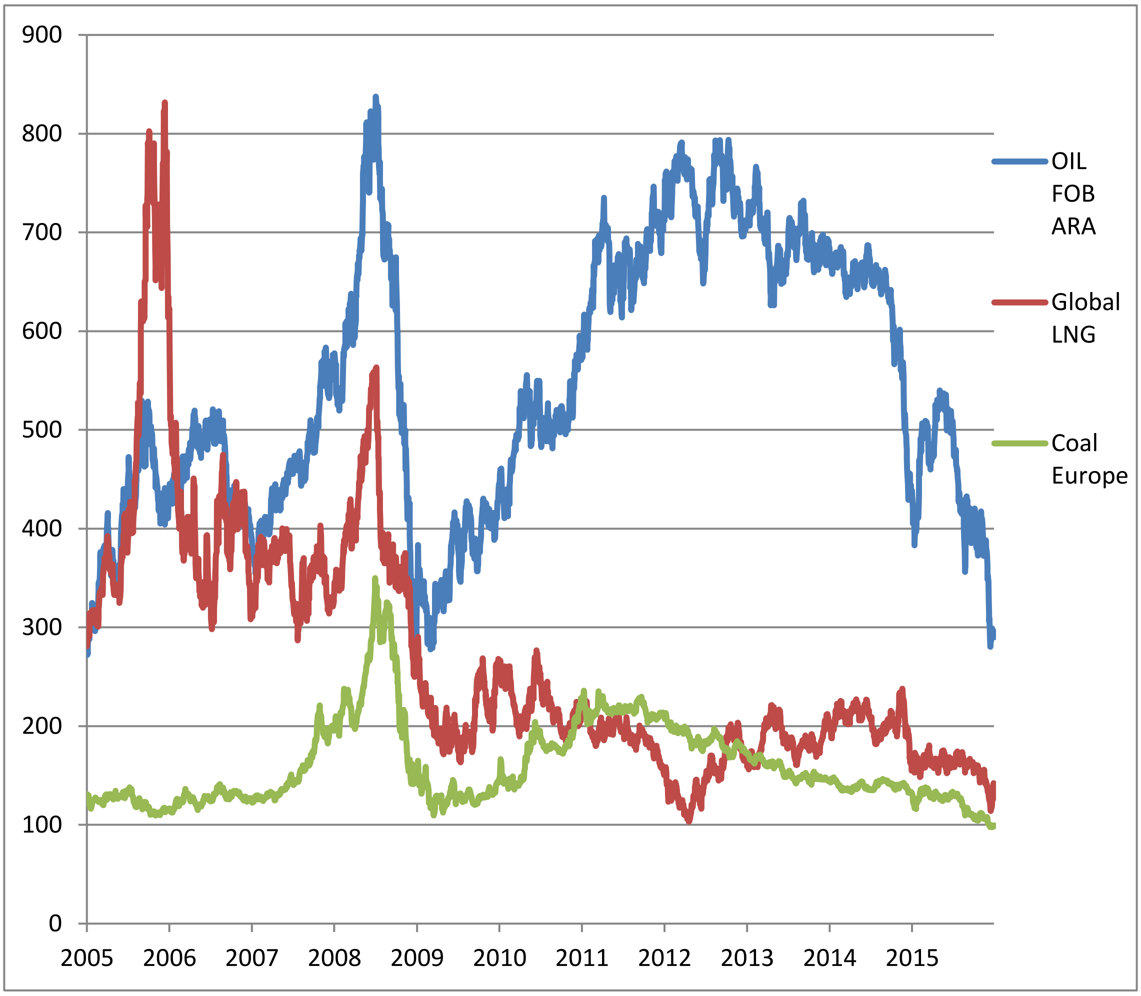


Figure 13. The daily prices of the fuel price proxies used in the empirics.

4.5. Market risk variables

To test the effects of the global market conditions on the spot prices and risk premiums on the Nordic Markets; several market variables are used. These variables are the following: Chicago Board Options Exchange (CBOE) Volatility Exchange Index (VIX), CBOE Crude Oil Volatility Index (Oil VIX), and the TED -spread. The time series for VIX and Oil VIX are downloaded from the CBOE homepage (2016) and the TED -spread is obtained from the Thompson Reuters DataStream.

VIX is a widely used benchmark indicator of the financial distress in the global equity markets. It indicates the implied volatility of option contracts in the S&P 500. Although, it represents the uncertainty of S&P500 stock markets, it might have some implications also in commodities and even in electricity markets. (CBOE's homepage)

However, the Oil VIX might provide to be more useful on electricity markets since it proxies the uncertainty of the global oil markets. Oil represents a significant proportion of fossil electricity production in the Nordics. Therefore, the global uncertainty in the oil markets might affect the hedging demand and supply conditions in the Nordic Electricity Markets. To test this also the Oil VIX is included in the regression analysis. The Oil VIX is obtained with similar methodology as VIX, but it measures the CBOE's market expectation of 30-days volatility for oil. The implied volatility is calculated from option contracts that have United States Oil Fund LP (USO) as the underlying security. USO is an ETF contract, which is designed to track near month futures contracts on West Texas Intermediate (WTI) Crude Oil. WTI is the most important reference price for the global oil markets. (CBOE's homepage, USO's homepage, Amic 2005)

The third Market Risk variable included in the analysis is the TED -spread. The TED -spread is the difference between three-month London Inter-Bank Offered -rate (LIBOR) and three-month U.S. Treasury Bill -rate. The TED -spread is a widely used measure of liquidity risk (or counterparty risk) in the economy. As LIBOR rates are considered as benchmark rates for risky inter-bank loans and T-Bill -rates are considered as benchmark rates for risk free investments, the spread between the two rates represents the fear that banks have for loaning assets to other banks. In general, it represents the risk of banks defaulting on their loans. As the TED -spread played an important role during the recent financial crisis, it might be interesting to see if the tight credit conditions also had an effect on the Nordic Electricity markets. (Brunnenmeier 2009; Cornett, McNutt, Strahan & Tehranian 2011)

VIX is the only market risk variable that is available for the whole time period studied in this thesis. The time series for Oil VIX is available from 10.5.2007 and the TED -spread is available from 18.7.2006. In the regressions, the observations prior to the availability of the time series are treated as missing observations. This should make sure that the missing observations do not bias the results. However, the significance of TED -spread and Oil VIX variables might be reduced because of the large number of missing observations in the time series. This should be considered when interpreting the results.

Figure 14 plots the market risk variables from 10.5.2007 to 31.12.2015. The financial crisis around 2007 and 2008 is clearly visible in all of the time series. However, the TED -spread variable peaked most heavily during the crisis. After the initial crisis, all the variables are highly integrated. Oil VIX is at a higher level than VIX for almost the whole time period. Moreover, there is a peak in Oil VIX during the first months of 2015 that is not visible in the other market uncertainty variables. At the beginning of 2015, market uncertainty about future oil prices rose heavily as the crude oil prices plummeted to the lowest levels since the ending of global financial crises. Global crude oil prices faced decreasing oil demand and heavy global excess supply. The excess supply in the markets persisted for the whole year and this increased the uncertainty in the markets. As seen in the figure the oil options where highly turbulent during 2015. (US Energy Information Administration 2016)

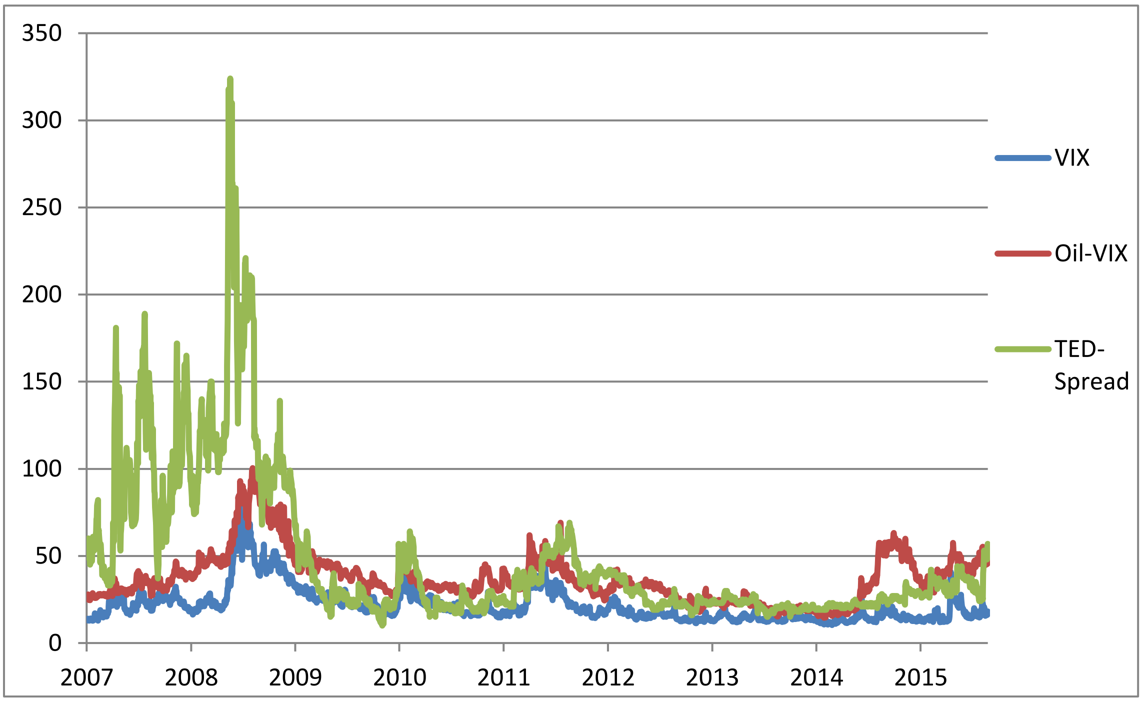


Figure 14. The Market Risk Variables from 10.5.2007 to 31.12.2015.

4.6. Weather temperature data

This study aims to provide contribution to the existing literature by using extensive weather temperature data to test the effects of the weather conditions on spot prices, price spikes, and risk premiums. To my knowledge as extensive temperature data has not been included in any of the published papers relating to the Nordic Market prices. It is understandable since collecting the data from different Nordic Meteorological Institutes requires either advanced database programming or time-consuming manual labor. As the temperature is considered an important driver for the demand for electricity, this data could provide some interesting results regarding electricity pricing in the Nordics.

The weather data consists of daily temperature observations for Finland, Sweden, and Norway for the whole research period. The data is collected from the National Meteorological Institutes of each country; The Finnish Meteorological Institute for Finnish data, The Swedish Meteorological and Hydrological Institute for Swedish data, and the Norwegian Meteorological Institute for Norwegian data.

Probably the simplest way to proxy the weather conditions in the Nordic area would be to use the average temperatures of each country. However, these sorts of broad averages might heavily bias the results and I don't think they are good estimators of the effects that the weather conditions have on the demand for electricity. As the coldest temperatures in the Nordics usually occur in the northern parts of the countries but the population is much more concentrated on the southern latitudes, I think that the population densities of different latitudes should be somehow taken in to account when modeling the effects of weather conditions on the demand for electricity. To obtain better estimates for the weather conditions, I want to take the geographical demographics of each country into account. To my knowledge, this is the first study that takes population demographics into account in such accuracy, when using weather temperature to analyze the electricity pricing in the Nordic Markets.

To estimate the effects of geological demographics on the electricity demand, I choose to use population living in each of the administrative counties of the countries studied. In total, Finland has 18 (the county of Åland is not included in the data), Sweden has 21, and Norway has 19 administrative counties. The population living in each of the counties is collected from the National Statistics Authorities of each country (Statistics Finland, Statistics Sweden, and Statistics Norway). The counties of each country and the population living in it is presented in the Appendix 3.

After obtaining the demographics data, I collect the daily time series of weather temperature observations for each county. This is done by using the databanks of National Meteorological institutes. Instead of providing mean temperatures for counties, they provide observation time series for each weather station within the county. I choose the most relevant weather station based on the Administrate Center of each county. Each county has an Administrative Center, which is usually the largest city / town in the area. If there are many weather stations in the Administrative Center, I choose the most relevant one based on the following criteria: location, data quality, and elevation. This means that I firstly try to use the weather station closest to the city center. However, if the data quality of that station is poor, for example, there might be many missing observations; I use another station further from the city center but with an intact time series of temperature observations. The weakest criterion for selection is the elevation of the weather station. I try to use weather stations closest to the sea level. The table presented in Appendix 3 also provides the administrative centers of counties, weather stations chosen, the elevation of each station, and the coordinates of the stations used (Lat / Lon).

Any missing or unreliable observations in the temperature data are treated with a function that replaces the missing (or unreliable) observation with the last available observation in the time series.

The time series consisting of a single county's temperatures are combined to a single time series by using weighted average method. The weights are defined as the relative share of county's population from the total population living in the country in question. The formula used for combining the time series is presented below:

$$(11.)\ \bar{t}_t = \sum(t_{i,t} * w)$$

Where:

$\bar{t}_t$: Is the country's population weighted average mean temperature for day t.
$t_{i,t}$: Is the county i's temperature for day t.
w: Is the share of county's population of country's total population.

Figure 15 presents the daily average temperatures defined in Formula 11 for all of the countries studied. The subgraphs A-C presents the whole temperature time series for each of the countries and the subgraph D illustrates the monthly average temperatures for each of the countries. However, it must be noted that the subgraph D does not illustrate the actual monthly average temperatures, but monthly averages of the population weighted daily observations.

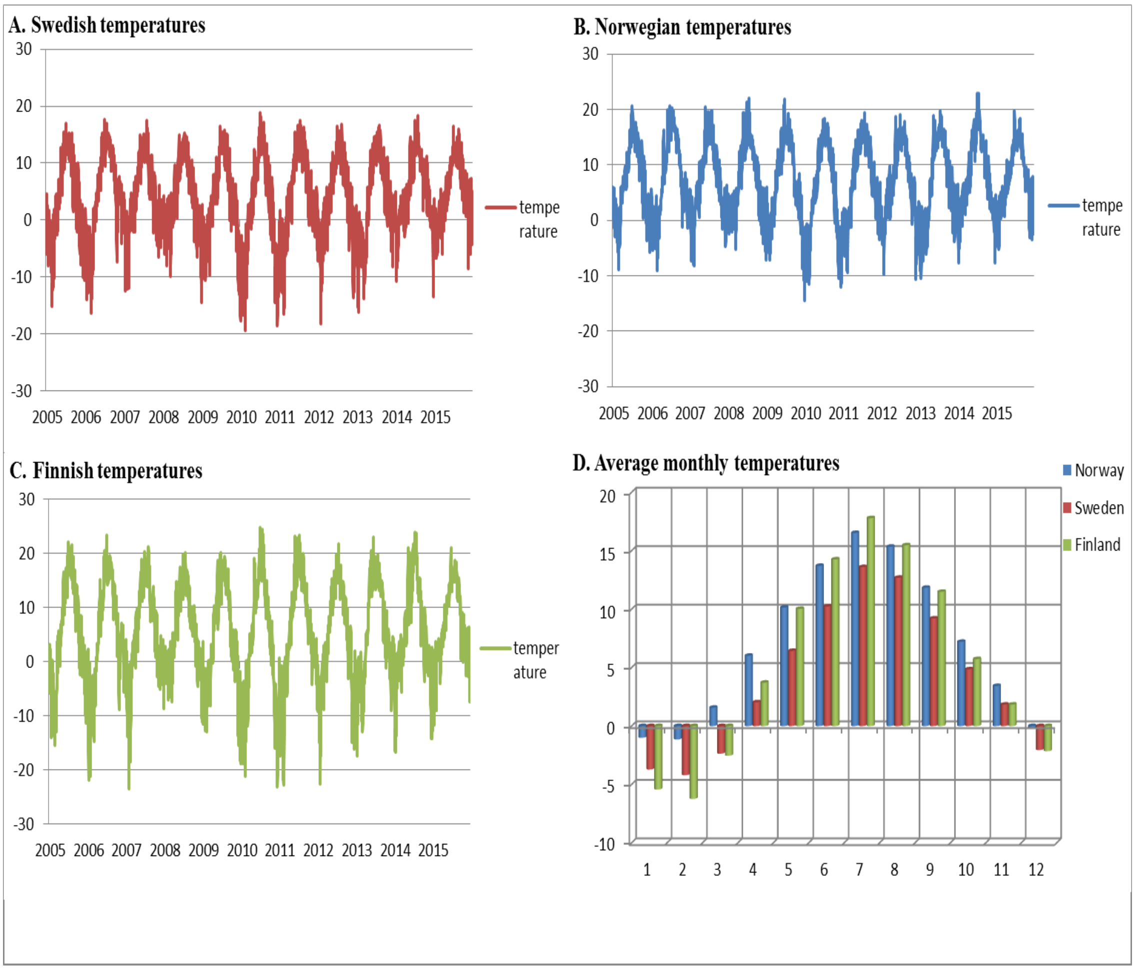


Figure 15. Weather temperature data.

It is evident from the subgraphs A-C that the time series for the population weighted temperatures are really similar between each of the countries. During the summer months, most observations for all of the countries are around 20 $°C$. During the winter months, temperatures are well beyond freezing for each country. Finland seems to exhibit the largest variation in the temperatures between summer and winter months. The climate is most stable in Norway between the seasons. The subgraph D. further explains the variation between the seasons. For all of the countries, the average temperatures are the coldest during February and the hottest during July. The coldest months in Norway are never far beyond freezing, whereas the average temperature during February is -6,2 degrees Celsius in Finland.

As with the water levels, also the weather temperatures are compared with spot market prices in a scatter plot diagram. The diagram is presented in Figure 16. A problem of comparing water level data with spot market prices was that the frequency of reservoir data was weekly whereas for spot markets daily data is available. The temperatures are collected in daily frequency so this problem is not present in this descriptive figure. Moreover, whereas the spot market prices were reported as weekly averages in Figure 12, they are daily observations in Figure 16. The weather temperature in the figure is obtained by averaging the weighted temperatures of each country, illustrated in Figure 15 A-C, by the weight of each country (based on the relative share of total population living in the Nordics). This method is also used in the rest of the thesis when using weather temperature observation data.

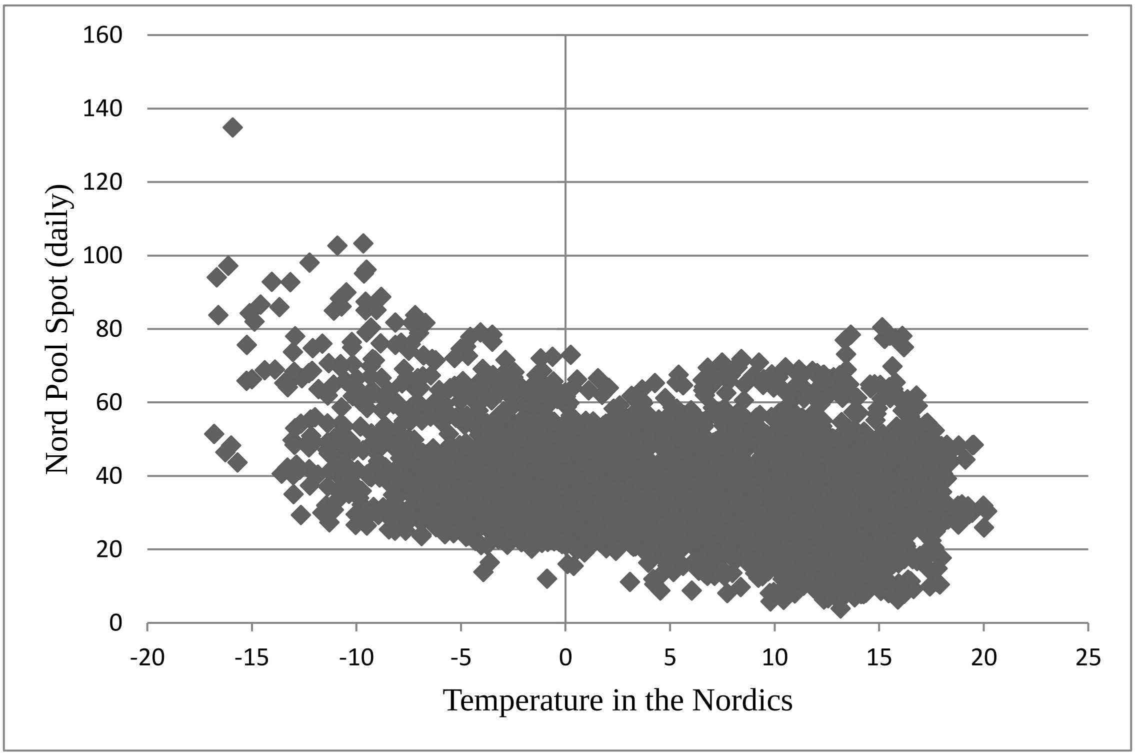


Figure 16. Scatter plot diagram of weather temperatures and daily Nord Pool Spot prices.

5. METHODOLOGY

This chapter introduces the empirical methods and the models used in this thesis. The chapter begins with a subsection that describes all the factors used in the empirical models of this paper. The remaining subsections present the empirical models used to test the hypotheses introduced in Chapter 2.3.

5.1. Description of the variables used in the empirical models of this paper

This section presents all the variables used in this thesis. The variables are the following:

$Price_t$: Current electricity spot market price. The daily average of the hourly prices of the current trading day.

$Price_{t-1}$: The one day lagged spot market price of electricity. The lagged price means the daily average price of the previous trading day. For example, when studying Friday's price, this parameter gets the value of the Thursday's price.

$Price_{t-7}$: Seven days lagged spot market price of electricity. It is the daily average price of the same trading day of the previous week. Together with the one day lagged price, this variable links the current spot price to past level of spot prices.

$\mathrm{Waterlevel}_t$: The current water level in the Nordics. The factor represents the current percentual balance of the total water capacity in the Nordics. As explained in the data section, this time series is obtained from Thompson Reuters in weekly frequency. However, in the daily regression models, this variable is transformed to the daily frequency by using linear interpolation, which is a common practice in the relating literature.

$Waterdeviation_t$: Water deviation factor explained in the data section. As with the waterlevel -variable, this is obtained in the weekly frequency and interpolated to daily frequency when used in the daily regressions.

$Temperature_t$: The Population weighted average temperatures in the Nordics. The method of collecting the temperatures and weighting them by the estimated number of people living in the area where the temperatures are collected is discussed in the data chapter in more detail. This is the average temperature of all the Nordic countries studied.

$Temeraturedeviation_{t.}$ The weekly average temperatures for the Nordic countries are calculated from the whole temperature series. Daily deviation from those averages is then calculated from those weekly averages. This variable is included in the analysis in an attempt to eliminate the seasonal variation in the temperature time series. Eliminating the seasonal variation is necessary for studying futures risk premiums with different times from maturity.

$Oilprice_t$: The daily value of the Oil FOB ARA index. It is the most prominent proxy of the oil price that the Nordic producers face, since it represents the price of oil delivered to the Amsterdam-Rotterdam-Antwerp (ARA) region. They are the closest harbors to the Nordic countries where the deliveries of futures contracts for oil can be traded.

$Coalprice_t$: The price of the Merrill Lynch Global Commodities Index for the coal traded in the European area at day t. It is the best proxy that I am aware of the coal prices that the Nordic electricity producers face when buying coal.

$LNGprice_t$: The price of the Merrill Lynch Global Commodities Index for the global LNG at day t. Global LNG is used as the proxy for gas imported to the Nordic countries.

Weekend: Binary dummy variable that obtains the value 1 if the current day (t) is Saturday or Sunday and 0 otherwise. It is used for studying the weekend effect of spot prices. According to the studies considering the spot price seasonality, the weekends are predicted to have negative effect to spot prices due to reduced electricity demand. See for example Bye et al (2008).

VIX_t, *$OilVIX_t$ & TED -$spread_t$:* The daily index values of Chicago Board Options Exchange (CBOE) Volatility Exchange Index (VIX), CBOE Crude Oil Volatility Index (Oil VIX), and the TED -spread. The time series for VIX and Oil VIX are downloaded from the CBOE homepage (2016) and the TED spread is obtained from the Thompson Reuters DataStream.

5.2. The quantile regression model used for analyzing the spot price distribution

Quantile regression estimations can be performed by using quantile regression models. Quantile regressions divide the distribution of the dependent variable in to quantiles and studies each of the quantiles separately. Quantile regressions were introduced to the literature by Koenker and Basett (1978). Quantile regression models can gain interesting insights to many research questions as they are able to capture the impact of explanatory variables at different sections of the distribution of the dependent variable. Using quantile regression framework to test the first hypothesis of the thesis serves the research question of the thesis well, as it is assumed that the variables that have the most powerful explanatory power in the tails of the spot price distribution could also be the variables that have the most powerful effect on the risk premiums in the electricity markets. (Koenker & Hallock 2001)

The main quantile regression used to study the factors affecting spot prices is the following:

$$(12.)\ VaR_t(\theta) = \beta_0(\theta) + \beta_1(\theta)price_{\,t-1} + \beta_2(\theta)price_{\,t-7} + \beta_3(\theta)waterdeviation_t + \beta_4(\theta)temperaturedeviation_t + \beta_5(\theta)Oilprice_t + \beta_6(\theta)Coalprice_t + \beta_7(\theta)LNGprice_t + \beta_8(\theta)VIX_t + \beta_9(\theta)OilVIX_t + \beta_{10}(\theta)Ted\_spread_t + \beta_t(\theta)\,Weekend + \varepsilon_t(\theta)$$

The factors are explained in the previous subsection and the sample quantile VaR_r is the solution to the following minimization problem:

$$(13.)\ RQ = \min_{VaR_t \in \mathbb{R}} \left[\sum_{t\in\{t:y_t \geq VaR_t\}} \theta|y_t - VaR_t| + \sum_{t\in\{t:y_t \leq VaR_t\}} (1-\theta)|y_t - VaR_t|\right]$$

Where y_t is the spot market price of electricity and $\Theta = 1/2$ gives the least absolute error estimate, or in other words the OLS regression median. The RQ criterion 13 is minimized on the spot prices with the explanatory variables in 12 to characterize the sensitivities of the variable coefficients over the quantiles. (Lundby & Uppheim 2011; Koenker et al. 2001)

The quantile regressions used in this thesis are run by dividing the spot price distribution into 20 quantiles. The length of each interval for the most quantiles represents 5% of the distribution, but in addition the extreme left and right side of the distribution is included to the model (the top and bottom 1%). The explanatory variables included in the model 12 are slightly varied in different tables to provide the best results regarding the first hypothesis; more on this on Chapter 6.1.

5.3. The simple multiple regression model of the risk premiums

The second hypothesis is studied with a simple multiple regression model. The model is largely based on the reduced form model of Bessembinder et al. (2002) and Longstaff et al. (2004). The model aims to prove that risk premiums depend mainly on the skewness and the variance of the spot price. The variance of spot prices should have a negative linear relation to risk premiums and skewness of spot prices should have a linear positive relation to the risk premiums. The intuition behind the skewness factor is that it represents the risk of price spikes. When the spot prices are positively skewed, markets expect price spikes to occur and the hedging demand increases. The increased demand for hedging raises the premiums required by the counterparties of these hedges. Altogether four regressions are run to test the second hypothesis.

The reduced form model has been used in the Nordic markets for example by Lucia et al. (2011). Lucia et al. (2011) finds out that the reduced form model does explain the risk premiums before the year 2002. After the year 2002 market fundamentals seem to have changed and the model did not perform well after that in their study.

The first regression used to test the hypothesis is straightforward; I use exactly the same model as Lucia et al. (2011). The only difference is the contracts studied, Lucia et al. (2011) study the risk premiums of weekly contracts, whereas I study monthly premiums. The formula of the first regression used to study the second hypothesis is presented below:

$$(14.)\ F_{t,t+i} - S_{t+i} = \beta_0 + \beta_1 * Var[S_{t+i}] + \beta_2 * Skew\,[S_{t+i}] + \varepsilon_{t,t+i}$$

Where:

$F_{t,t+i} - S_{t+i}$: Is the ex post risk premium or the realized risk premium with i months to maturity.

$Var[S_{t+i}]$: Is the sample variance of the spot price during the delivery period (month).

$Skew\,[S_{t+i}]$: Is the unstandardized skewness of the spot price distribution during the delivery period (month).

According to the equilibrium pricing model of Bessembinder et al. (2002), the coefficient for variance should obtain negative values, whereas the coefficient for skewness should obtain positive values. Moreover, Lucia et al. (2011) argue that as they study ex post premiums instead of ex ante premiums constant β_0 should be interpreted as mean prediction error. If the constant has positive (negative) value in average, it means that the market participants overestimate (underestimate) the spot price at maturity. This interpretation is followed in this study as the regression also studies ex post premiums.

Formula 15 presents the second regression model studying the second hypothesis. Formula 14 is modified to include a factor proxying the spot prices of electricity during the delivery period of the contract. The intuition behind this is that tight and loose market conditions might affect the risk premiums. I assume that the risk premiums are affected by the level of spot price. If the level of spot prices is high during the delivery period, I assume that the risk premiums are also high; and vice versa. It has to be noted that this factor is not included in the studies of Bessembinder et al. (2002), Longstaff et al. (2004), or Lucia et al. (2011) and it might disturb the interpretation of the constant (β_0) factor. Moreover, as the mean spot price of the delivery month is included to the both sides of the equation in the model, there might be some autocorrelation problems. Even though all the OLS models presented in this thesis are corrected for heteroscedasticity and autocorrelation (HAC robust estimates), the autocorrelation might bias the reliability of t and p -statistics computed for this model. Even so, I think that market tightness is crucial to take into account in studying the third hypothesis of this thesis. To make the results between the hypotheses easier to compare, the mean spot price of the delivery period is included also to some of the models analyzing the second hypothesis of this thesis. The second regression model used to study the second hypothesis is following:

$$(15.)\ F_{t,t+i} - S_{t+i} = \beta_0 + \beta_1 * Mean\,[S_{t+i}] + \beta_2 * Var[S_{t+i}] + \beta_3 * Skew\,[S_{t+i}] + \varepsilon_{t,t+i}$$

Where:
Mean $[S_{t+i}]$: Is the arithmetic mean of the spot prices during the delivery period.

Sample size is a major problem with my data when studying the risk premiums with monthly frequency observations. The sample size of monthly regressions is only 132 observations. The optimal solution for increasing the sample size would be to use the same methodology as in previous formulas but extending the scope of the study also to shorter term futures contracts. There are also weekly and even daily futures contracts traded for the Nordic electricity. However, data for these contracts is not available on the Thompson Reuters DataStream -database. Acquiring data for these contracts from Nasdaq or from another source would be costly and thus is not an option for this thesis. An alternative approach, which is taken in this thesis, is to increase the frequency of observations by utilizing the continuous daily index and the continuous traced indices (TrC 1- TrC 6) for monthly contracts. I am not sure whether this approach has been used in the literature relating to Nordic futures pricing, as researchers usually seem to acquire the futures data from other databases. However, by utilizing the continuous time series of monthly futures data, the sample size of the timeseries used is increased to 2869 observations. This is a remarkable improvement considering the multifactor models used in the rest of this thesis. The use of continuous traced indices is discussed in more detail in Chapter 4.2.

The first model that utilizes the daily continuous time series of the monthly contracts is presented in Formula 16. The model is a modified version of Formula 14, although it has to be noted that the interpretation of variance and skewness are fundamentally different. The previous two models aimed to explain the risk premiums by studying the statistical characteristics of the spot price during the delivery period of the contract, but the daily regressions study the distribution of the spot price prior to the trading date of the futures contract. Variance and skewness are calculated from the rolling sample of 22 trading days prior to the trading date of the futures contract. These variables are more interesting regarding the third hypothesis of the thesis as they use information that is available for the market participants at the moment when they trade the futures contracts. Thus, they are more realistic estimators when studying factors that affect the price of futures contracts traded in the markets.

$$(16.)\ Premium_{i,t} = \beta_0 + \beta_1 * \ Var\ \tilde{S}_{T_{22}} + \beta_2 * Skew\ \tilde{S}_{T\_22}\ +\ \varepsilon_{i,t}$$

Where:
$Premium_{i,t}$: The ex post risk premium calculated from the day t's closing price. Risk premium is calculated by subtracting delivery month's mean spot price from the closing price of the futures contract during the trading day. Subscript i indicates the TrC time series used. i=1 stands for TrC1, i=2 stands for TrC2, … and i=6 stands for TrC6. As explained in Chapter 4, TrC1 stands for future's price for next month's delivery, TrC2 stands for future's price for second sequent month and so on.

$Var\ \tilde{S}_{i,T\_22}$: 22 days rolling or moving sample variance of the spot price taken from t. Time series is formed by using spot prices prior to the trading date (past information) whereas previous two models used the observations during the settlement month of the contract (future information, not available for the participants at t). Timeseries are calculated using 5 days week.

$Skew\ \tilde{S}_{i,T\_22}$: 22 days rolling or moving skewness measure of the spot price, as with the variance observations prior to the trading date of the contract are used.

The last equation studying the second hypotheses is formed with the similar manner as Formula 16. The last model is presented in Formula 17:

$$(17.)\ Premium_{i,t} = \beta_0 + \beta_1 * Mean\,\tilde{S}_{T_{22}} + \ \beta_1 * \ Var\,\tilde{S}_{T_{22}} + \beta_2 * Skew\,\tilde{S}_{T\_22} \ + \ \varepsilon_{i,t}$$

Where:

$Mean\,\tilde{S}_{i,T_{22}}$: 22 days rolling or moving mean of the spot price taken from the time point t.

5.4. The extended multifactor model of the risk premiums

The last empirical section of the thesis attempts to answer the third hypothesis by including several explanatory factors in the reduced form models introduced in the previous subsection. The aim of these models is to gain deeper understanding about the pricing process in the Nordics by studying which factors contribute to the existence of the risk premiums in the markets. It also tries to increase the explanatory power of the daily frequency regressions defined in the previous section. Furthermore, it tries to incorporate the findings of the previous hypothesis and study how the factors that affect the spot pricing of electricity in different quantiles of the distribution perform in explaining the risk premiums in the futures markets. All the models are estimated using daily frequency data and five days week.

In addition to regular risk premiums used in the previous models, these regressions are also run using relative risk premiums introduced in the data section. Relative premiums are used to test the robustness of the model and to better understand how these models perform. However, the results of models using relative risk premiums are not presented in this thesis due to space limitations.

Overall, five different models are tested and they are run using two different definitions of risk premiums. The difference between each of the models is how they treat the distribution of spot price prior to the trading date of the futures contract. The first two models do not include any measure about the level of the spot price. The first model also omits the variance and skewness terms of the spot price distribution. The third model includes the spot price of the trading day (t), but omits the variance and skewness factors. The fourth model uses the seven days lagged spot price and omits the variance and the skewness factors. Finally, the fifth model uses the same 22 rolling mean price as the model 17 and in addition it includes the variance and skewness factors to the regression. Similarly to the previous subsection, these regressions are run with six different times to settlement. The five models used to test the third hypothesis are presented below in formulas 18-22.

1st model:

$$(18.)\ Premium_{i,t} = \beta_0 + \beta_1 * Waterdeviation_t + \beta_2 * Temperaturedeviation_t + \beta_3 * Coalprice_t + \beta_4 * Oilprice_t + \beta_5 * Lngprice_t + \beta_6 * VIX_t + \beta_7 * OilVIX_t + \beta_8 * Ted\_spread_t + \varepsilon_{i,t}$$

2nd model:

$$(19.)\ Premium_{i,t} = \beta_0 + \beta_1 * Var\ \tilde{S}_{T_{22}} + \beta_2 * Skew\ \tilde{S}_{T\_22} + \beta_3 * Waterdeviation_t + \beta_4 * Temperaturedeviation_t + \beta_5 * Coalprice_t + \beta_6 * Oilprice_t + \beta_7 * Lngprice_t + \beta_8 * VIX_t + \beta_9 * OilVIX_t + \beta_{10} * Ted\_spread_t + \varepsilon_{i,t}$$

3rd model:

$$(20.)\ Premium_{i,t} = \beta_0 + \beta_1 * S_t + \beta_2 * Waterdeviation_t + \beta_3 * Temperaturedeviation_t + \beta_4 * Coalprice_t + \beta_5 * Oilprice_t + \beta_6 * Lngprice_t + \beta_7 * VIX_t + \beta_8 * OilVIX_t + \beta_9 * Ted\_spread_t + \varepsilon_{i,t}$$

4th model:

$$(21.)\ Premium_{i,t} = \beta_0 + \beta_1 * S_{t-7} + \beta_2 * Waterdeviation_t + \beta_3 * Temperaturedeviation_t + \beta_4 * Coalprice_t + \beta_5 * Oilprice_t + \beta_6 * Lngprice_t + \beta_7 * VIX_t + \beta_8 * OilVIX_t + \beta_9 * Ted\_spread_t + \varepsilon_{i,t}$$

5th model:

$$(22.)\ Premium_{i,t} = \beta_0 + \beta_1 * Mean\ \tilde{S}_{T_{22}} + \beta_2 * Var\ \tilde{S}_{T_{22}} + \beta_3 * Skew\ \tilde{S}_{T\_22} + \beta_4 * Waterdeviation_t + \beta_5 * Temperaturedeviation_t + \beta_6 * Coalprice_t + \beta_7 * Oilprice_t + \beta_8 * Lngprice_t + \beta_9 * VIX_t + \beta_{10} * OilVIX_t + \beta_{11} * Ted\_spread_t + \varepsilon_{i,t}$$

6. EMPIRICAL FINDINGS

This chapter presents the empirical results of the thesis. First, the results of the quantile regression analyzing the spot market prices are presented in Chapter 6.1. Following that, the results of the simple reduced form model used to study the risk premiums of the futures markets are presented in Chapter 6.2. Finally, the results of more complex model explaining the risk premiums are presented in Chapter 6.3.

Chapter 6.4. provides discussion about the results in general and compares them to the existing literature and theory regarding the electricity markets. In addition, the final subsection discusses whether the hypotheses formulated in Chapter 2.3 can be accepted based on the empirical results presented in this chapter.

6.1. The results for the quantile regression analysis of the spot prices

The first hypothesis studies the variables explaining electricity spot pricing. To further analyze the extreme prices this hypothesis is studied with quantile regression model that is discussed in Section 5.2. Table 3 presents the results of this quantile regression model. In this model, the weather temperature deviation factor is also used. In Appendix 4, the same regression is studied with the normal population weighted temperature factor that simply studies the absolute level of the temperatures instead of normalized deviation factor.

From Table 3, and from the table in Appendix section, we can see that the factors *lagged spot*$_{t-1}$, *lagged spot*$_{t-7}$, and *weekend dummy* are all significant at one percent level across all the quantiles. This means that current daily prices are explained largely by recent past prices, both previous day’s price and last week’s price. Also, the weekend effect is dominant in explaining current spot prices. The Weekend dummy obtains negative values in all the quantiles of all the regressions. This means that during the weekends, prices are consistently lower than during the business days, not depending on whether the current price is at low or high level. All these findings are in line with the previous literature and the general assumptions regarding electricity spot markets.

In addition, the Nordic water reservoir deviation factor, Nordic water level factor, Nordic temperature factor, and the temperature deviation factor are highly significant across all the quantiles. The Water deviation factor is significant at 1% level for all the quantiles except at the most extreme right end of the spot price distribution (the top 1% of the distribution). However, if the Water level factor is excluded, the deviation factor is significant across all the quantiles, as seen in Table 4. This might be explained by the relatively high correlation between the level and deviation factors. When excluding the water level from the regression, water deviation factor obtains negative values for all of the quantiles. This implies that the deviation factor has negative correlation with the spot prices. In other words, during times when the water levels are below their long-term average the spot price of electricity is higher. The temperature deviation factor is significant at 1 % level for most of the quantiles. Also, the temperature deviation factor seems to have negative relation with the spot prices. In other words, when the weather temperature in the Northern Europe is colder than usually during that time of year the spot prices are at a higher level. According to the results shown in Table 3, weather temperature and water deviation factors have significant explanatory power on spot prices in all quantiles of the spot price distribution. Both temperature deviation and water reservoir deviation have negative correlation with the spot prices. Both unusually low water reservoirs and cooler than average temperatures result in higher electricity spot prices.

The fuel factors are not nearly as significant as water and temperature deviation factors in explaining the spot prices. Surprisingly, the oil price factor does not explain the spot prices in any of the quantiles. LNG does a little better being significant at 10 % level in eleven out of twenty-one quantiles. Coal is the most significant fuel price factor. It is significant at 1 % level for all the quantiles between 0,4 and 0,95. This means that the coal has significant explanatory power also on the right side of the spot price distribution. Coefficients that are significant for coal and LNG are mostly positive. This means that coal and LNG have positive relationship between the spot prices of electricity. For example, higher coal prices result in higher spot prices for electricity. This is intuitive as higher fuel prices should increase the production costs, and thus steepen the supply curve of electricity (Rothovius et al. 2013: 53-58).

The explanatory power of the market risk variables is not as significant as with other variables used in the model. VIX and Oil VIX are the most prominent factors of this group of variables. They provide significant results at least at 10 % confidence level for a just under half of the quantiles. The significant coefficients are not concentrated around the center of the distribution, instead they seem to obtain most significant results around the tails of the spot price distribution. TED -spread is only significant on the extreme left tail of the distribution on both tables. As the significance of the market risk variables seem to increase when during times when the spot prices are extremely low or high, it is going to be interesting to see how they perform in explaining the risk premiums in the markets. It is assumed that those variables that obtain significant values in this spot price model perform well also in explaining the risk premiums in the markets.

The pseudo R-squared values, indicating the explanatory power of the regression quantile, vary between the values 0,64 and 0,82. The fit of the model is at its best around the center of the distribution. Most of the pseudo R-squared values are close to 0,80, so the model seems to describe the spot pricing in the markets decently well.

The results of the first regression analyses are presented below. First, Table 3 presents the results with all the factors included in the quantile regression. Second to test the robustness of the results, Table 4 presents the results without the factors for seven day lagged price and temperature level. Finally, the results without the temperature deviation factor are presented in Appendix 4.

Table 3. The first quantile regression analysis of the spot price. All variables are included to this model as explanatory variables. Each column of the table presents the coefficient estimators, t-statistics and pseudo R-squared values for the quantile in question. Statistical significance is indicated with *, **, *** for 10 %, 5 %, and 1 % confidence levels respectively.

Quantile	0,01	0,05	0,1	0,15	0,2	0,25	0,3	0,35	0,4	0,45	0,5	0,55	0,6	0,65	0,7	0,75	0,8	0,85	0,9	0,95	0,99
c	-1,9436	-1,0360	-1,5240	-1,3518	-0,8085	-0,4394	-0,3143	0,0090	0,0774	0,2513	0,3994	0,5795	0,9113	0,8656	0,9567	1,1573	1,3306	1,8414	1,9171	2,3577	1,2700
t-statistics	(-0,88)	(-1,06)	(-2,60) ***	(-3,29) ***	(-2,36) **	(-1,45)	(-1,11)	(0,03)	(0,30)	(0,92)	(1,39)	(1,92) *	(2,88) ***	(2,64) ***	(2,97) ***	(3,50) ***	(3,46) ***	(4,05) ***	(3,18) ***	(3,06) ***	(0,27)
Lagged spot_t-1	0,6349	0,7381	0,7870	0,8155	0,8198	0,8282	0,8113	0,8069	0,8063	0,7975	0,7893	0,7806	0,7757	0,7579	0,7601	0,7476	0,7327	0,7140	0,7108	0,7175	0,6911
t-statistics	(22,20) ***	(37,27) ***	(53,00) ***	(47,56) ***	(50,92) ***	(48,97) ***	(39,04) ***	(42,66) ***	(42,26) ***	(40,88) ***	(43,05) ***	(42,89) ***	(49,79) ***	(47,11) ***	(58,61) ***	(64,60) ***	(65,08) ***	(57,27) ***	(34,75) ***	(39,86) ***	(12,11) ***
Lagged spot_t-7	0,1639	0,1625	0,1426	0,1271	0,1278	0,1230	0,1446	0,1520	0,1528	0,1602	0,1668	0,1750	0,1770	0,1866	0,1831	0,1923	0,2008	0,2107	0,2125	0,2158	0,3398
t-statistics	(5,73) ***	(16,32) ***	(11,93) ***	(8,40) ***	(9,60) ***	(8,23) ***	(7,07) ***	(8,49) ***	(8,36) ***	(8,78) ***	(9,81) ***	(9,51) ***	(10,89) ***	(11,36) ***	(12,54) ***	(15,17) ***	(16,84) ***	(15,29) ***	(11,66) ***	(10,06) ***	(4,14) ***
Water Deviation Nordics	-0,2502	-0,0817	-0,0683	-0,0608	-0,0532	-0,0432	-0,0358	-0,0326	-0,0349	-0,0343	-0,0371	-0,0335	-0,0375	-0,0488	-0,0505	-0,0559	-0,0636	-0,0687	-0,0833	-0,1018	0,0592
t-statistics	(-4,81) ***	(-3,49) ***	(-4,06) ***	(-4,09) ***	(-4,83) ***	(-4,11) ***	(-3,20) ***	(-3,14) ***	(-3,18) ***	(-3,04) ***	(-3,24) ***	(-2,88) ***	(-3,41) ***	(-4,39) ***	(-4,41) ***	(-4,50) ***	(-4,89) ***	(-4,64) ***	(-4,50) ***	(-3,51) ***	(0,49)
Water Level Nordics	0,0291	0,0207	0,0181	0,0138	0,0134	0,0098	0,0101	0,0087	0,0088	0,0092	0,0089	0,0076	0,0069	0,0073	0,0092	0,0090	0,0098	0,0096	0,0132	0,0239	0,0226
t-statistics	(1,28)	(2,67) ***	(3,46) ***	(3,14) ***	(4,05) ***	(3,49) ***	(4,07) ***	(3,85) ***	(4,00) ***	(4,14) ***	(3,95) ***	(3,36) ***	(3,01) ***	(3,16) ***	(3,94) ***	(3,47) ***	(3,39) ***	(2,73) ***	(2,92) ***	(3,22) ***	(0,93)
Nordic temperature	-0,1231	-0,0284	-0,0341	-0,0375	-0,0351	-0,0306	-0,0323	-0,0242	-0,0236	-0,0265	-0,0334	-0,0305	-0,0329	-0,0312	-0,0350	-0,0390	-0,0382	-0,0310	-0,0372	-0,0607	-0,0797
t-statistics	(-1,33)	(-1,00)	(-2,04) **	(-2,43) **	(-4,35) ***	(-3,90) ***	(-4,15) ***	(-3,44) ***	(-3,52) ***	(-3,94) ***	(-4,85) ***	(-4,20) ***	(-4,31) ***	(-4,00) ***	(-4,54) ***	(-4,76) ***	(-3,89) ***	(-2,64) ***	(-2,77) ***	(-3,27) ***	(-2,06) **
Temperature deviation	0,1366	-0,0420	-0,0430	-0,0643	-0,0970	-0,1092	-0,1280	-0,1472	-0,1463	-0,1538	-0,1612	-0,1736	-0,1783	-0,1993	-0,2114	-0,2280	-0,2697	-0,3295	-0,3806	-0,4723	-1,0142
t-statistics	(1,29)	(-1,12)	(-1,56)	(-2,95) ***	(-5,96) ***	(-7,33) ***	(-7,40) ***	(-9,72) ***	(-10,28) ***	(-10,30) ***	(-10,53) ***	(-11,82) ***	(-12,48) ***	(-13,18) ***	(-13,21) ***	(-13,60) ***	(-13,45) ***	(-13,80) ***	(-11,95) ***	(-9,88) ***	(-7,87) ***
Oil	0,0056	0,0025	0,0001	0,0005	0,0004	0,0004	0,0002	0,0002	0,0000	0,0003	0,0004	0,0002	0,0001	0,0004	0,0005	0,0006	0,0006	0,0003	0,0007	0,0005	0,0007
t-statistics	(1,22)	(1,15)	(0,14)	(0,68)	(0,84)	(0,78)	(0,50)	(0,44)	(-0,04)	(0,66)	(1,03)	(0,52)	(0,30)	(0,85)	(1,00)	(1,14)	(1,17)	(0,56)	(0,80)	(0,47)	(0,15)
Coal	-0,0213	-0,0128	0,0031	0,0031	0,0040	0,0038	0,0041	0,0035	0,0053	0,0049	0,0053	0,0059	0,0072	0,0089	0,0095	0,0117	0,0133	0,0165	0,0170	0,0178	0,0324
t-statistics	(-1,11)	(-1,47)	(0,65)	(1,04)	(1,77) *	(1,64)	(1,82) *	(1,72) *	(2,88) ***	(2,78) ***	(3,01) ***	(3,15) ***	(3,86) ***	(4,40) ***	(4,68) ***	(5,47) ***	(5,94) ***	(6,25) ***	(5,11) ***	(3,83) ***	(1,53)
LNG	0,0078	0,0022	0,0012	0,0016	0,0008	0,0009	0,0009	0,0006	0,0006	0,0005	0,0005	0,0008	0,0005	0,0011	0,0010	0,0010	0,0015	0,0013	0,0023	0,0024	0,0031
t-statistics	(1,87) *	(1,56)	(1,28)	(3,13) ***	(1,83) *	(2,21) **	(2,27) **	(1,55)	(1,52)	(1,16)	(1,10)	(1,58)	(0,99)	(2,15) **	(1,96) *	(1,74) *	(2,66) ***	(2,17) **	(2,11) **	(1,50)	(0,26)
Vix	-0,0617	0,0447	0,0398	0,0256	0,0195	0,0124	0,0069	0,0084	0,0064	0,0061	0,0133	0,0142	0,0191	0,0198	0,0223	0,0186	0,0161	0,0287	0,0225	0,0175	-0,0425
t-statistics	(-1,31)	(1,19)	(2,29) **	(1,96) *	(2,04) **	(1,34)	(0,78)	(1,11)	(0,85)	(0,74)	(1,53)	(1,59)	(2,25) **	(2,39) **	(2,64) ***	(2,14) **	(1,62)	(2,10) **	(1,49)	(1,12)	(-0,48)
Oil Vix	-0,0155	-0,0343	-0,0265	-0,0126	-0,0130	-0,0095	-0,0067	-0,0063	-0,0050	-0,0050	-0,0070	-0,0035	-0,0077	-0,0054	-0,0059	-0,0071	-0,0049	-0,0077	-0,0006	0,0096	0,0328
t-statistics	(-0,33)	(-2,31) **	(-3,73) ***	(-2,12) **	(-2,96) ***	(-2,22) **	(-1,67) *	(-1,76) *	(-1,40)	(-1,32)	(-1,77) *	(-0,89)	(-1,93) *	(-1,37)	(-1,47)	(-1,63)	(-1,04)	(-1,35)	(-0,08)	(0,93)	(0,84)
Ted-spread	0,0360	0,0071	-0,0005	-0,0030	-0,0026	-0,0019	-0,0011	-0,0012	-0,0019	-0,0014	-0,0013	-0,0021	-0,0015	-0,0025	-0,0025	-0,0014	-0,0010	-0,0025	-0,0019	-0,0033	-0,0105
t-statistics	(2,58) ***	(1,10)	(-0,10)	(-0,97)	(-1,16)	(-0,90)	(-0,69)	(-0,83)	(-1,41)	(-1,02)	(-0,88)	(-1,43)	(-1,05)	(-1,66) *	(-1,36)	(-0,60)	(-0,50)	(-1,11)	(-0,58)	(-0,44)	(-0,44)
Weekend dummy	-4,5663	-2,4038	-1,7894	-1,6196	-1,5340	-1,4983	-1,4122	-1,3396	-1,2990	-1,3378	-1,3378	-1,4336	-1,5010	-1,5993	-1,6776	-1,7818	-1,9889	-2,2122	-2,5134	-3,1796	-2,8615
t-statistics	(-3,85) ***	(-5,41) ***	(-8,91) ***	(-10,00) ***	(-14,09) ***	(-14,70) ***	(-14,45) ***	(-15,46) ***	(-16,08) ***	(-16,67) ***	(-16,67) ***	(-18,39) ***	(-19,04) ***	(-19,05) ***	(-20,11) ***	(-20,25) ***	(-20,20) ***	(-18,26) ***	(-14,81) ***	(-11,27) ***	(-4,00) ***
Pseudo R-squared	**0,6402**	**0,7303**	**0,7554**	**0,7706**	**0,7826**	**0,7913**	**0,7981**	**0,8038**	**0,8084**	**0,8122**	**0,8155**	**0,8185**	**0,8210**	**0,8228**	**0,8237**	**0,8234**	**0,8214**	**0,8185**	**0,8142**	**0,7974**	**0,7556**
Adjusted R-squared	**0,6391**	**0,7294**	**0,7546**	**0,7699**	**0,7819**	**0,7907**	**0,7974**	**0,8031**	**0,8078**	**0,8115**	**0,8149**	**0,8179**	**0,8205**	**0,8222**	**0,8232**	**0,8229**	**0,8209**	**0,8179**	**0,8136**	**0,7968**	**0,7548**

Table 4. The second quantile regression analysis of the spot price. The variables *Lagged spot _t-7* and Temperature is excluded from this regression. Each column of the table presents the coefficient estimators, t-statistics and pseudo R-squared values for the quantile in question. Statistical significance is indicated with *, **, *** for 10 %, 5 %, and 1 % confidence levels respectively.

Quantile	0,01	0,05	0,1	0,15	0,2	0,25	0,3	0,35	0,4	0,45	0,5	0,55	0,6	0,65	0,7	0,75	0,8	0,85	0,9	0,95	0,99
c	-0,6378	1,0546	-0,3842	-0,5437	-0,1767	-0,0773	0,2250	0,4637	0,5459	0,6703	0,8514	0,9112	0,9113	1,1959	1,6504	2,3440	2,3508	2,8125	3,5584	4,2507	8,2576
t-statistics	(-0,42)	(1,66) *	(-0,99)	(-1,50)	(-0,58)	(-0,29)	(0,89)	(1,78) *	(2,06) **	(2,52) **	(3,08) ***	(3,18) ***	(3,44) ***	(3,34) ***	(4,49) ***	(6,35) ***	(5,73) ***	(6,22) ***	(6,99) ***	(5,03) ***	(3,38) ***
Lagged spot_t-1	0,7484	0,8863	0,9236	0,9369	0,9537	0,9544	0,9552	0,9596	0,9548	0,9545	0,9523	0,9501	0,7757	0,9356	0,9254	0,9213	0,9169	0,9078	0,9034	0,8979	0,8856
t-statistics	(19,68) ***	(69,88) ***	(99,69) ***	(127,20) ***	(138,51) ***	(146,89) ***	(134,98) ***	(147,18) ***	(150,14) ***	(152,48) ***	(145,86) ***	(138,96) ***	(118,84) ***	(111,91) ***	(117,45) ***	(116,50) ***	(105,77) ***	(87,66) ***	(72,57) ***	(86,21) ***	(23,48) ***
Water Deviation Nordics	-0,2175	-0,0828	-0,0703	-0,0596	-0,0405	-0,0396	-0,0393	-0,0346	-0,0368	-0,0361	-0,0372	-0,0401	0,1770	-0,0541	-0,0631	-0,0710	-0,0736	-0,0934	-0,0908	-0,1112	-0,1265
t-statistics	(-5,24) ***	(-4,13) ***	(-5,23) ***	(-4,82) ***	(-3,80) ***	(-3,84) ***	(-3,93) ***	(-3,97) ***	(-4,19) ***	(-3,97) ***	(-3,90) ***	(-4,02) ***	(-4,61) ***	(-4,65) ***	(-5,94) ***	(-6,81) ***	(-5,86) ***	(-6,99) ***	(-5,66) ***	(-6,62) ***	(-3,17) ***
Temperature deviation	0,1294	0,0444	0,0164	-0,0433	-0,0602	-0,0647	-0,0780	-0,0939	-0,1096	-0,1231	-0,1276	-0,1304	-0,0375	-0,1585	-0,1749	-0,1947	-0,2210	-0,2632	-0,3294	-0,4516	-0,9359
t-statistics	(1,04)	(1,00)	(0,57)	(-1,97) **	(-3,57) ***	(-4,32) ***	(-5,27) ***	(-7,03) ***	(-8,56) ***	(-10,03) ***	(-10,02) ***	(-10,06) ***	(-10,23) ***	(-10,52) ***	(-11,27) ***	(-11,47) ***	(-12,47) ***	(-12,03) ***	(-9,70) ***	(-12,41) ***	(-5,82) ***
Oil	0,0064	0,0019	0,0004	0,0001	0,0003	0,0005	0,0001	-0,0001	0,0002	0,0002	0,0003	0,0003	0,0069	0,0003	0,0002	-0,0002	0,0002	-0,0002	-0,0007	0,0005	-0,0017
t-statistics	(1,40)	(1,14)	(0,36)	(0,11)	(0,53)	(1,15)	(0,27)	(-0,14)	(0,54)	(0,55)	(0,69)	(0,61)	(0,65)	(0,59)	(0,34)	(-0,37)	(0,32)	(-0,33)	(-0,94)	(0,40)	(-0,59)
Coal	-0,0152	-0,0134	0,0003	0,0031	0,0012	0,0014	0,0029	0,0033	0,0037	0,0040	0,0044	0,0057	-0,0329	0,0095	0,0115	0,0132	0,0150	0,0196	0,0235	0,0212	0,0442
t-statistics	(-0,64)	(-1,69) *	(0,09)	(1,20)	(0,49)	(0,63)	(1,42)	(1,76) *	(2,11) **	(2,42) **	(2,57) **	(3,15) ***	(3,53) ***	(4,14) ***	(5,12) ***	(5,18) ***	(4,81) ***	(5,49) ***	(7,54) ***	(3,54) ***	(2,53) **
LNG	0,0076	0,0018	0,0023	0,0021	0,0013	0,0013	0,0011	0,0009	0,0011	0,0012	0,0012	0,0011	-0,1783	0,0017	0,0018	0,0015	0,0016	0,0022	0,0022	0,0040	0,0035
t-statistics	(2,12) **	(1,05)	(2,52) **	(4,04) ***	(2,96) ***	(3,20) ***	(2,73) ***	(2,04) **	(2,54) **	(2,75) ***	(2,68) ***	(2,44) **	(2,75) ***	(2,93) ***	(3,51) ***	(2,77) ***	(2,39) **	(3,27) ***	(3,10) ***	(2,46) **	(1,67) *
Vix	0,0173	0,0643	0,0278	0,0363	0,0207	0,0126	0,0083	0,0040	0,0046	0,0058	0,0069	0,0142	0,0001	0,0185	0,0235	0,0203	0,0288	0,0154	0,0025	0,0208	-0,0081
t-statistics	(0,23)	(2,41) **	(2,10) **	(2,95) ***	(1,82) *	(1,49)	(1,09)	(0,57)	(0,65)	(0,76)	(0,83)	(1,59)	(1,69) *	(2,09) **	(2,53) **	(1,85) *	(2,16) **	(1,20)	(0,20)	(0,55)	(-0,15)
Oil Vix	-0,0680	-0,0492	-0,0178	-0,0126	-0,0106	-0,0038	-0,0022	-0,0016	-0,0011	-0,0003	-0,0008	-0,0035	0,0072	-0,0010	-0,0040	-0,0043	-0,0044	-0,0005	0,0025	0,0109	0,0233
t-statistics	(-1,94) *	(-3,90) ***	(-2,40) **	(-2,45) **	(-2,26) **	(-0,90)	(-0,58)	(-0,42)	(-0,29)	(-0,09)	(-0,21)	(-0,92)	(-0,51)	(-0,24)	(-0,92)	(-0,87)	(-0,82)	(-0,08)	(0,39)	(0,94)	(0,93)
Ted-spread	0,0332	0,0088	0,0002	-0,0041	-0,0017	-0,0021	-0,0021	-0,0015	-0,0011	-0,0013	-0,0007	-0,0005	0,0005	-0,0022	-0,0015	-0,0020	-0,0032	0,0004	0,0011	0,0000	-0,0092
t-statistics	(3,25) ***	(1,34)	(0,05)	(-1,48)	(-0,70)	(-1,18)	(-1,26)	(-1,06)	(-0,81)	(-0,85)	(-0,43)	(-0,34)	(-0,85)	(-1,48)	(-0,85)	(-1,10)	(-1,42)	(0,12)	(0,42)	(0,00)	(-0,59)
Weekend dummy	-4,8148	-2,7692	-2,0685	-1,9565	-1,7745	-1,6942	-1,6039	-1,6177	-1,5759	-1,6173	-1,6310	-1,6844	0,0191	-1,8691	-2,0327	-2,2535	-2,4660	-2,8229	-3,1570	-3,9723	-5,7352
t-statistics	(-3,82) ***	(-8,20) ***	(-9,65) ***	(-13,47) ***	(-13,91) ***	(-15,41) ***	(-16,81) ***	(-19,53) ***	(-21,01) ***	(-22,04) ***	(-21,60) ***	(-21,77) ***	(-21,58) ***	(-21,66) ***	(-22,00) ***	(-22,93) ***	(-23,90) ***	(-22,94) ***	(-20,02) ***	(-13,59) ***	(-3,83) ***
Pseudo R-squared	**0,6188**	**0,7190**	**0,7466**	**0,7629**	**0,7747**	**0,7835**	**0,7902**	**0,7957**	**0,8001**	**0,8034**	**0,8062**	**0,8083**	**0,8102**	**0,8111**	**0,8111**	**0,8101**	**0,8076**	**0,8042**	**0,8001**	**0,7841**	**0,7394**
Adjusted R-squared	**0,6178**	**0,7183**	**0,7459**	**0,7623**	**0,7741**	**0,7830**	**0,7897**	**0,7952**	**0,7996**	**0,8030**	**0,8057**	**0,8078**	**0,8097**	**0,8106**	**0,8107**	**0,8096**	**0,8071**	**0,8037**	**0,7996**	**0,7836**	**0,7388**

6.2. The results for the reduced form models of the risk premiums

This section presents the results of the models testing the second hypothesis. The models and the methods for these regressions are specified in Chapter 5.3. Altogether, results for four different regressions are presented in this chapter and each regression is run for 6 different times to settlement. All the studied premiums are calculated from monthly futures contracts and the terms of these contracts wary between 0 to 1; 1 to 2; 2 to 3; 3 to 4; 4 to 5; 5 to 6; and 6 to 7 -months to the beginning of the settlement period.

The first OLS -model, Formula 14, is the one most faithful to the original equilibrium pricing model of Bessembinder et al. (2002) and Longstaff et al. (2004). The results of the model are presented in Table 5 for six different times to settlement.

Table 5. The first reduced form equilibrium model of the ex post risk premiums using monthly data. The model is specified by Formula 14 and it is presented in Chapter 5.3. The regression is run for 6 different time series that are distincted from each other by the time they are traded prior to settlement date. All the regressions are run using Newey-West heteroskedasticity and autocorrelation robust estimators (HAC). Statistical significance is indicated with *, **, *** for 10 %, 5 %, and 1 % confidence levels respectively.

	Months to the settlement date of the futures contract					
	0	**1**	**2**	**3**	**4**	**5**
Constant β_0	1,0524	3,1979	4,2935	4,8133	5,3284	5,3345
t-statistics	(2,88) ***	(3,33) ***	(3,18) ***	(2,82) ***	(2,73) ***	(2,56) **
Varicance β_1	-0,0055	-0,0454	-0,0591	-0,0538	-0,0621	-0,0527
t-statistics	-(0,59)	(-1,58)	(-1,54)	(-1,28)	(-1,26)	(-1,06)
Skewness β_2	-0,2879	-1,0818	0,1994	0,3870	1,3435	1,0458
t-statistics	-(0,69)	(-1,18)	(0,15)	(0,25)	(0,85)	(0,76)
R-squared	**0,0069**	**0,0906**	**0,0699**	**0,0415**	**0,0477**	**0,0322**
Adjusted R-Squared	**-0,0085**	**0,0765**	**0,0554**	**0,0267**	**0,0329**	**0,0172**
N	**132**	**132**	**132**	**132**	**132**	**132**

The second model, specified in Formula 15, is highly similar to the previous model and it is also run using monthly data. The only difference between the two models is that the second one includes the mean of the spot price distribution during the delivery period of the contract to the explanatory variables of the regression. The results of the second OLS -model are presented in Table 6.

Constant, β_0, is the only significant factor in Table 5. It is highly significant and positive for all times from settlement studied. Moreover, the value of the coefficient increases as the time from settlement is increased. As pointed out by Lucia et al. (2011), the constant of the equilibrium model should be interpreted as the mean prediction error of the model. According to this, positive constants mean the market participants overestimate the spot price at the maturity of the contract. Another interpretation they make for the positive constant term in their results is that there are also other factors that determine the risk premium than the future variance and skewness of the spot price. Also the poor fit of the model speaks for this assumption. The adjusted R^2-measure, which can be interpreted as the measure of goodness of fit of the model, ranges between -1% and 6% is really low.

Table 6. The second reduced form equilibrium model of the ex post risk premium using monthly data. The model is specified by Formula 15 and it is presented in Chapter 5.3. Regression is run for 6 different time series that are distincted from each other by the time they are traded prior to settlement date. All the regressions are run using Newey-West heteroskedasticity and autocorrelation robust estimators (HAC). Statistical significance is indicated with *, **, *** for 10 %, 5 %, and 1 % confidence levels respectively.

	Months to the settlement date of the futures contract					
	0	**1**	**2**	**3**	**4**	**5**
Constant β_0	2,9222	10,4485	16,2789	21,7471	26,1683	28,8935
t-statistics	(2,33) **	(4,35) ***	(5,22) ***	(5,78) ***	(6,13) ***	(6,87) ***
Mean Spot Price β_1	-0,0538	-0,2087	-0,3450	-0,4875	-0,6000	-0,6782
t-statistics	(-1,39)	(-2,95) ***	(-4,18) ***	(-5,38) ***	(-6,08) ***	(-7,52) ***
Varicance β_2	-0,0011	-0,1196	-0,0306	-0,0135	-0,0126	0,0033
t-statistics	(-0,12)	(0,00)	(-1,01)	(-0,46)	(-0,37)	(0,10)
Skewness β_3	-0,2855	-1,0724	0,2149	0,4089	1,3704	1,0762
t-statistics	(-0,70)	(-1,21)	(0,18)	(0,28)	(0,92)	(0,88)
R-squared	**0,0242**	**0,1806**	**0,2379**	**0,2876**	**0,3599**	**0,4110**
Adjusted R-Squared	**0,0013**	**0,1614**	**0,2201**	**0,2709**	**0,3449**	**0,3972**
N	**132**	**132**	**132**	**132**	**132**	**132**

Even though the coefficients for variance and skewness are not statistically significant, they are mostly of predicted sign according to the equilibrium model of Bessembinder et al. (2002). The coefficient for variance, $\beta_{1,}$ is negative for all of the times from settlement studied. The coefficient for skewness, β_2, is positive for contracts that are settled on the following month and also for contracts that are about to be settled in one full month.

All things considered, the results presented in Table 5 are similar to Lucia et al. (2011) paper where they study the risk premiums of weekly contracts. They find that the equilibrium pricing model is not valid for the whole time period they study, which is 1998-2007. Moreover, they find that the constant is the only parameter with significant t-statistics. Moreover, they find that the value of the constant is increased as the time from settlement is increased. The goodness of the fit of their model is highly similar to the results of this paper with R^2 values that vary between 1% and 6%. The coefficients for variance and skewness are also of the same sign as the equilibrium model would predict. Lucia et al. (2011) also divide their sample into two sub -periods and find out that the model performs quite well with the earlier sub -period that includes the observations between 2/1998-33/2002 (week/year). They conclude that unprecedented demand shock that hit the markets on winter of 2002 changed the circumstances in the markets noticeably. Before the crisis, the equilibrium pricing model was performing relatively well, indicating that the market participants took risk considerations into account in their pricing at least to some extent. After the crisis this changed, and the equilibrium pricing model was not able to illustrate the behaviour of the market prices no longer.

Lucia et al. (2011) conclude that they are not sure whether the new situation, after the price shock, will become permanent or not. This paper provides contribution by studying the question with more recent data. As the results of Table 5 are highly similar to Lucia et al.'s (2011) complete time period and post shock sub -period, it is evident that the pre-turbulent market state has not returned. In other words, this paper provides evidence that the reduced form equilibrium pricing model does not hold for the Nord Pool markets.

While the results presented in Table 5 are interesting, they are somewhat anticipated as they only confirm the results of Lucia et al. (2011) with more recent data. The main goal of this paper is to find factors that market participants use for pricing derivative contracts. The second OLS-model starts to do this by introducing a new variable to the reduced form model. This can also be considered as a risk consideration as it includes a characteristic of the spot price distribution during the delivery period; the mean of spot price. In other words, it studies whether or not the level of spot price during the delivery period has an effect on the risk premiums exhibited in the markets.

Table 6 shows that the constant term remains highly significant and positive in the second OLS model. Furthermore, the coefficient increases steeply as the time from the settlement increases. Goodness of fit is much better than in the case of the standard reduced form model. An interesting observation is that the R^2 value rises steadily as the time from the settlement of the contract increases. The adjusted R^2 value for contract closest from settlement is only 0,1 %, but for contracts further from the settlement date it ranges between 16% and 40%.

The coefficients for variance and skewness remain insignificant and for most of the times from the settlement also of predicted sign. The mean spot price is highly significant for all the contracts except for the one closest to maturity. The sign of the coefficient for the mean price is negative for all the contracts. This indicates that high spot prices during the delivery period seem to decrease the risk premiums in the markets.

Tables 7 and 8 present the result of the models defined in formulas 16 and 17. As explained in Chapter 5.3; although they share similarities with the monthly regressions, their interpretation is highly different from them. The models also study ex post premiums but with variables focusing on the spot price distribution prior to the trading date, rather than the spot price distribution during the delivery period. The objective of these models is to study whether the spot price distribution observed before the trading date of the contract affects the ex post risk premiums in the markets, using daily frequency data.

Table 7. The first modified reduced form model with daily frequency observations. The model is specified by Formula 16 and it is presented in Chapter 5.3. Regression is run for 6 different time series that are distincted from each other by the time they are traded prior to settlement date (full months). All the regressions are run using Newey-West heteroskedasticity and autocorrelation robust estimators (HAC). Statistical significance is indicated with *, **, *** for 10 %, 5 %, and 1 % confidence levels respectively.

	Full months prior to the settlement date of the futures contract					
	0	**1**	**2**	**3**	**4**	**5**
Constant β_0	1,1764	2,0568	2,7556	3,1892	3,2009	3,3961
t-statistics	(3,20) ***	(3,84) ***	(4,26) ***	(4,36) ***	(4,08) ***	(4,23) ***
Varicance β_1	0,0136	0,0147	0,0082	0,0150	0,0254	0,0223
t-statistics	(1,58)	(2,07) **	(1,31)	(1,73) *	(2,77) ***	(2,50) **
Skewness β_2	-0,8668	-1,3707	-0,8769	-0,9781	-1,0532	-1,2513
t-statistics	(-2,37) **	(-2,70) ***	(-1,53)	(-1,51)	(-1,35)	(-1,63)
R-squared	**0,0171**	**0,0178**	**0,0049**	**0,0060**	**0,0102**	**0,0097**
Adjusted R-Squared	**0,0164**	**0,0172**	**0,0042**	**0,0053**	**0,0095**	**0,0090**
N	**2869**	**2869**	**2869**	**2869**	**2869**	**2869**

Table 7 presents the results of the model 16. The results show that the constant term remains positive and significant also in the data using daily frequency data. As with the models 14 and 15, the value of constant term keeps increasing as the time from the settlement is increased. It is interesting to see that the coefficients for the variance and skewness of the spot price prior to the trading date are significant for some of the contracts. Coefficients for the past variance are positive and significant for contracts with 1, 4, and 5 full months from settlement. The statistical significance is at 1 %-level for contracts furthest from the settlement. This indicates that the risk premium is increased when the past volatility of the spot price is at higher level at least for some times from maturities. The skewness has negative coefficients for all times from maturities. The only coefficients which are significant at least on the 5%-level are for the two closest to the maturity contracts. Adjusted R^2 measures are really low, being at least 1,7 % for only two closest to the settlement contracts. For the rest maturities, R^2 values are less than 1%. This indicates that the model does not perform well in explaining the risk premiums or futures pricing in the markets.

Table 8 indicates that including a measure of past spot price into the model increases the fit of the regression moderately. The R^2 factor is 10% for contracts with 2 and 3 months from settlement. The estimates for constant and past spot prices are highly significant for all the maturities. Including the past mean spot prices in the model turns the values of constants consistently negative for all the times from settlement studied. In all the previous models studying the second hypothesis the constants have been positive. The reason for this could be underspecified models, or in other words omitted variable bias. This finding is discussed in more detail in the discussion section of this chapter. Tables 7 and 8 are presented below. (Wooldrige 2013: 84-94)

Table 8. The second modified reduced form model with daily frequency observations. The model is specified by Formula 17 and it is presented in Chapter 5.3. Regression is run for 6 different time series that are distincted from each other by the time they are traded prior to settlement date (full months). All the regressions are run using Newey-West heteroskedasticity and autocorrelation robust estimators (HAC). Statistical significance is indicated with *, **, *** for 10 %, 5 %, and 1 % confidence levels respectively.

	Full months prior to the settlement date of the futures contract					
	0	**1**	**2**	**3**	**4**	**5**
Constant β_0	-2,9592	-4,7256	-7,2404	-8,5826	-7,9534	-8,4449
t-statistics	(-3,18) ***	(-3,46) ***	(-4,01) ***	(-3,96) ***	(-3,51) ***	(-3,94) ***
Mean Spot Price β_1	0,1152	0,1890	0,2786	0,3280	0,3108	0,3300
t-statistics	(4,02) ***	(4,33) ***	(4,91) ***	(4,90) ***	(4,46) ***	(5,13) ***
Varicance β_2	0,0030	-0,0027	-0,0173	-0,0152	-0,0032	-0,0080
t-statistics	(0,33)	(-0,32)	(-1,79) *	(-1,21)	(-0,24)	(-0,63)
Skewness β_3	-0,7797	-1,2278	-0,6663	-0,7301	-0,8182	-1,0019
t-statistics	(-2,14) **	(-2,44) **	(-1,20)	(-1,19)	(-1,08)	(-1,32)
R-squared	**0,0616**	**0,0803**	**0,0991**	**0,1080**	**0,0922**	**0,0983**
Adjusted R-Squared	**0,0607**	**0,0793**	**0,0982**	**0,1071**	**0,0913**	**0,0973**
N	**2869**	**2869**	**2869**	**2869**	**2869**	**2869**

6.3. The results for the extended models of the risk premiums

The objective of the last hypothesis is to improve the fit of the models used in testing the second hypothesis by including those explanatory variables that were used in regressions studying the first hypothesis. The regressions are run using daily frequency data with similar methodology as in models 16 and 17. Altogether, five slightly different models are tested to find the best fitting regression. Furthermore, these five regressions are also run using relative risk premiums, the results of these regressions are discussed in Chapter 6.5. Each of the five regressions are also run using relative risk premiums, however these results are not presented in this thesis due to space constraints. Moreover, the results of relative risk premiums do not deviate much from the models using standard definition of risk premiums.

Table 9. The first factor model without including any variable for the spot price with daily frequency observations. Model used is 18 in the matter specified in the chapter 5.4. Regression is run for 6 different time series that are distincted from each other by the time they are traded prior to settlement date (full months). All the regressions are run using Newey-West heteroskedasticity and autocorrelation robust estimators (HAC). Statistical significance is indicated with *, **, *** for 10 %, 5 %, and 1 % significance levels respectively.

	Full months prior to the settlement date of the futures contract					
	0	**1**	**2**	**3**	**4**	**5**
Constant β_0	-5,5893	-2,7339	0,6262	0,3145	-1,4370	-5,0548
t-statistics	(-2,72) ***	(-0,91)	(0,17)	(0,09)	(-0,45)	(-1,43)
Deviation nordics β_1	-0,1710	-0,2889	-0,4262	-0,5426	-0,5983	-0,6280
t-statistics	(-3,30) ***	(-3,72) ***	(-4,41) ***	(-4,87) ***	(-5,04) ***	(-5,54) ***
Temperature deviation β_2	0,1825	0,1816	0,4084	0,4708	0,4340	0,4221
t-statistics	(1,72) *	(1,47)	(3,46) ***	(3,66) ***	(3,08) ***	(3,12) ***
Coal β_3	-0,0068	-0,0045	0,0183	0,0337	0,0440	0,0492
t-statistics	(-0,47)	(-0)	(0,85)	(1,33)	(1,70) *	(1,93) *
Oil β_4	0,0079	0,0077	0,0048	0,0061	0,0087	0,0134
t-statistics	(2,28) **	(1,66) *	(0,88)	(1,00)	(1,42)	(2,31) **
LNG β_5	0,0077	0,0037	-0,0049	-0,0082	-0,0074	-0,0056
t-statistics	(2,91) ***	(0,85)	(-0,81)	(-1,39)	(-1,35)	(-1,05)
VIX β_6	0,0807	-0,0272	-0,1783	-0,2800	-0,3887	-0,4229
t-statistics	(1,32)	(-0,32)	(-1,78) *	(-2,38) **	(-3,30) ***	(-3,54) ***
Oil VIX β_7	-0,0169	-0,0523	-0,1139	-0,1334	-0,1211	-0,1003
t-statistics	(-0,65)	(-1,28)	(-2,27) **	(-2,58) ***	(-2,31) **	(-1,74) *
Ted-spread β_8	0,0206	0,0730	0,1326	0,1657	0,1800	0,1776
t-statistics	(1,53)	(3,74) ***	(5,35) ***	(5,88) ***	(6,27) ***	(6,60) ***
R-squared	**0,0753**	**0,1051**	**0,1964**	**0,2555**	**0,2918**	**0,3189**
Adjusted R-Squared	**0,0727**	**0,1026**	**0,1941**	**0,2534**	**0,2898**	**0,3170**
N	**2869**	**2869**	**2869**	**2869**	**2869**	**2869**

The results of model 18 are presented in Table 9. This model can be considered the simplest one tested in this phase of the empirics, as it does not include characteristics of spot price distribution into the explanatory variables. The first important finding that can be concluded from Table 9 is that the overall fit of the model is much higher than in either of the daily regressions studied in the previous chapter. The adjusted R^2 measure varies between 8% and 32% for the different times to settlement. Furthermore, the values of constants speak for better fit of the model than those tested in the previous chapter. Only the contract closest to settlement has significant value for constant. According to the assumptions of equilibrium pricing model of Bessembinder et al. (2002), constant represents the mean prediction error made by the market participants in their pricing of the derivative contracts. As the significance of the constant term is reduced in this model it means that the prediction error observed in the previous chapter can be largely explained by the factors included in this model.

The most significant factor explaining the risk premiums in the markets is the deviation from the Nordic water reservoirs. It is significant in one percent -level and negative for all times for settlement studied. This finding is in line with Bottersund et al. (2010), Lucia et al. (2011) and Fleten, Hagen, Nygård, Smith-Sivertsen & Sollie (2015). Botterud et al. (2010) find that reservoir levels have negative and significant coefficients for the both one- and six -week holding periods. Lucia et al. (2011) find that unexpectedly low water levels (negative water deviation in this thesis' framework) significantly increases the observed risk premium in the markets. Finally, Fleten et al. (2015) find that increase in water levels significantly reduce the observed returns on electricity forward prices.

The temperature deviation factor is highly significant for contracts with two to five months for settlement. It is also significant at 10% level for the contract closest to maturity. The coefficient obtains positive values for all the times to settlement studied. Therefore, it can be concluded that unexpectedly high temperatures during the trading period of the futures contract seem to increase the risk premium or the forecast error. This relationship is interesting as in the models testing the first hypothesis the relationship between the spot price and temperature deviation was found to be negative. It seems that even though the unexpectedly low temperatures result in higher spot prices, this relationship inverses for those futures contracts that are traded further from the settlement. This could mean that market participants do not consider lower than usual temperatures during the trading period to be a considerable risk factor for contracts that are settled in the future. In other words, market participants do not seem to assume that low temperatures during month t (for example June) result in lower prices during month t+2 (in previous example

August). Other explanation could be that unexpected shocks in the spot pricing caused by unexpected low (high) temperatures do not transfer to futures pricing. Therefore, market participants do not take higher (lower) spot prices during the trading period in to account when pricing futures contracts. This effect could cause the temperature deviation factor to obtain significant and positive values in explaining prediction error or risk premiums in the regression used in this thesis.

Fuel price factors are not nearly as significant as the factors previously discussed. For contracts closest to maturity Oil and LNG has explanatory power at 5 % and 1 % level respectively. Oil is also significant at 5 % level for the contract furthest from the settlement. There is also weak significance for the coal price factor for two contracts furthest from the settlement. All the significant values for fuel prices are positive which indicate that higher fuel prices result in higher risk premiums in electricity markets at least to some extent. Some authors, for example Fleten et al. (2015), use the logarithmic returns of fuels instead of closing prices when modeling risk premiums in electricity markets. The logarithmic returns of fuel prices were also tested in this thesis but they did not change the overall results of the regressions notably. Because of this, results with logarithmic returns are not presented in this thesis.

The risk factors have more explanatory power than the proxies for fuel prices. The most significant factor seems to be the TED -spread. This coefficient proxying global liquidity risk is significant at 1 % level for all contracts except the one closest to the settlement. This is an interesting observation, since according to my knowledge, the effects that the TED -spread has on electricity derivatives pricing has not been studied previously. Furthermore, the TED -spread is one of the least significant factors explaining the spot pricing as seen in the testes of the first hypothesis. The coefficient of the TED -spread seems to be strictly positive, indicating that higher liquidity risk increases the risk premiums in the markets. The second most important risk consideration for the markets seems to be VIX, proxying the global uncertainty of the financial markets. VIX is significant at least on 10% level for four out of six times for settlement and highly significant for two contracts furthest from settlement.

All the significant coefficients of VIX have negative signs which is somewhat puzzling. It indicates that higher volatility in global equity markets reduces the risk premiums in the Nordic electricity markets. This could be an interesting finding since most of the financial markets have strong positive correlation with VIX, and assets that have negative correlations could have some implications for example in portfolio diversification and risk management. The results for oil VIX are similar to VIX, but slightly less significant. The coefficient is significant at least on 10% level for four contracts furthest from settlement. The coefficient is highly significant for only contracts that are three full months from settlement. As with the VIX, all the significant coefficients are negative for all times for settlement studied.

Table 10 presents the results for Model 19. The model is highly similar to the model 18 as it omits all the proxies for the current level of the spot price during the trading period. However, the statistical risk measures of the spot price distribution are included to the

Table 10. The second factor model with rolling variance and skewness measures with daily frequency observations. Model used is 19 in the matter specified in Chapter 5.4. Regression is run for 6 different time series that are distincted from each other by the time they are traded prior to settlement date (full months). All the regressions are run using Newey-West heteroskedasticity and autocorrelation robust estimators (HAC). Statistical significance is indicated with *, **, *** for 10 %, 5 %, and 1 % significance levels respectively.

	Full months prior to the settlement of the futures contract					
	0	**1**	**2**	**3**	**4**	**5**
Constant β_0	-4,9379	-1,7290	0,7587	0,3432	-1,3577	-5,0306
t-statistics	(-2,37) **	(-0,58)	(0,21)	(0,10)	(-0,41)	(-1,40)
Variance σ^2_s_22 β_1	0,0139	0,0147	0,0055	0,0087	0,0163	0,0089
t-statistics	(1,51)	(1,88) *	(0,71)	(0,85)	(1,48)	(0,90)
Skewness_s_22 β_2	-0,5482	-0,9400	-0,0742	0,0895	0,1382	0,0973
t-statistics	(-1,64)	(-1,95) *	(-0,14)	(0,15)	(0,20)	(0,15)
Deviation nordics β_3	-0,1688	-0,2845	-0,4261	-0,5437	-0,6003	-0,6292
t-statistics	(-3,32) ***	(-3,73) ***	(-4,43) ***	(-4,91) ***	(-5,13) ***	(-5,58) ***
Temperature deviation β_4	0,1899	0,1795	0,4154	0,4877	0,4647	0,4395
t-statistics	(1,98) **	(1,52)	(3,48) ***	(3,74) ***	(3,39) ***	(3,26) ***
Coal β_5	-0,0117	-0,0109	0,0169	0,0321	0,0408	0,0476
t-statistics	(-0,80)	(-0,56)	(0,75)	(1,24)	(1,57)	(1,84) *
Oil β_6	0,0076	0,0073	0,0047	0,0060	0,0085	0,0134
t-statistics	(2,21) **	(1,59)	(0,87)	(1,00)	(1,39)	(2,29) **
LNG β_7	0,0080	0,0040	-0,0048	-0,0080	-0,0071	-0,0054
t-statistics	(2,95) ***	(0,91)	(-0,78)	(-1,35)	(-1,29)	(-1,02)
VIX β_8	0,0685	-0,0465	-0,1806	-0,2799	-0,3891	-0,4227
t-statistics	(1,12)	(-0,55)	(-1,81) *	(-2,37) **	(-3,33) ***	(-3,61) ***
Oil VIX β_9	-0,0143	-0,0466	-0,1140	-0,1354	-0,1246	-0,1024
t-statistics	(-0,56)	(-1,14)	(-2,28) **	(-2,59) ***	(-2,37) **	(-1,78) *
Ted-spread β_10	0,0233	0,0759	0,1337	0,1674	0,1833	0,1794
t-statistics	(1,72) *	(3,81) ***	(5,28) ***	(5,81) ***	(6,27) ***	(6,59) ***
R-squared	**0,0860**	**0,1146**	**0,1969**	**0,2568**	**0,2956**	**0,3200**
Adjusted R-Squared	**0,0828**	**0,1115**	**0,1941**	**0,2542**	**0,2932**	**0,3176**
N	**2869**	**2869**	**2869**	**2869**	**2869**	**2869**

regression. These measures are rolling variance and rolling skewness, from the previous chapter's model 17. As the results for the other coefficients in the regression are highly similar to the results of the previous model, discussion is mostly focused on these statistical risk proxies.

The first notable observation from Table 10 is that the R -squared measure of the regression is only slightly improved from the previous regression. The same applies for the adjusted R -squared measure. This indicates that the fit of the model is not improved much by including proxies about the risk considerations of the spot price prior to the trading date. Furthermore, the only significant coefficients for variance and skewness of the spot price is for contracts with one full month to settlement. The coefficient for variance is positive and significant in 10% -level and the coefficient for skewness is negative and also significant in 10% -level. It has to be also noted that in addition to the poor explanatory power of the statistical risk variables, the significant coefficients are of opposite signs as the equilibrium model of Bessembinder et al. (2002) would predict. Either the assumptions of Bessembinder et al. (2002) are no longer valid in the markets as Lucia et al. (2011) noted, or the rolling measures of variance and skewness of the past spot prices are not able to proxy the risk considerations of the market participants.

Next, the results of the model 20 are presented in the table 11. The model 20 is highly similar to model 18, but it also includes the trading day's closing price to the regression. The idea is to inspect whether the level of the spot price has effect on the risk premiums in the markets. As with the model 18, it does not include skewness or variance measures of the spot price in the regression.

The coefficient of the spot price during the trading day is significant for all the times for maturity except for the one furthest from the settlement. Furthermore, the coefficient is significant at 1 %-level for four contracts closest to settlement. The coefficient for the spot price is strictly positive indicating that higher level of spot price during the trading day of the futures contract increases the risk premiums observed in the markets. This could be explained by the increased hedging demand when the spot prices are higher. Also, the seasonal variation in hedging demand and spot prices might explain the significance of the spot price factor to some extent. Moreover, the constant factor is slightly

Table 11. The third factor model with trading day's spot price with daily frequency observations. Model used is 20 in the matter specified in Chapter 5.4. Regression is run for 6 different time series that are distincted from each other by the time they are traded prior to settlement date (full months). All the regressions are run using Newey-West heteroskedasticity and autocorrelation robust estimators (HAC). Statistical significance is indicated with *, **, *** for 10 %, 5 %, and 1 % significance levels respectively.

	Full months prior to the settlement date of the futures contract					
	0	**1**	**2**	**3**	**4**	**5**
Constant β_0	-6,7112	-4,0048	-0,7124	-1,5242	-2,5619	-5,8524
t-statistics	(-3,31) ***	(-1,41)	(-0,21)	(-0,44)	(-0,80)	(-1,68) *
Spot S_t β_1	0,1136	0,1287	0,1356	0,1863	0,1140	0,0808
t-statistics	(2,75) ***	(2,83) ***	(2,97) ***	(3,33) ***	(1,82) *	(1,33)
Deviation nordics β_2	-0,0501	-0,1520	-0,2819	-0,3445	-0,4771	-0,5421
t-statistics	(-0,77)	(-1,75) *	(-2,96) ***	(-3,22) ***	(-4,01) ***	(-4,78) ***
Temperature deviation β_3	0,2993	0,3140	0,5478	0,6623	0,5511	0,5051
t-statistics	(3,05) ***	(2,50) **	(4,28) ***	(4,65) ***	(3,73) ***	(3,39) ***
Coal β_4	-0,0220	-0,0218	0,0002	0,0088	0,0287	0,0384
t-statistics	(-1,44)	(-1,12)	(0,01)	(0,33)	(1,02)	(1,34)
Oil β_5	0,0078	0,0076	0,0047	0,0059	0,0086	0,0134
t-statistics	(2,28) **	(1,67) *	(0,88)	(1,00)	(1,41)	(2,29) **
LNG β_6	0,0055	0,0012	-0,0074	-0,0117	-0,0095	-0,0071
t-statistics	(2,12) **	(0,29)	(-1,23)	(-2,01) **	(-1,76) *	(-1,32)
VIX β_7	0,0543	-0,0570	-0,2098	-0,3232	-0,4151	-0,4417
t-statistics	(0,85)	(-0,67)	(-2,06) **	(-2,73) ***	(-3,48) ***	(-3,60) ***
Oil VIX β_8	-0,0064	-0,0404	-0,1013	-0,1162	-0,1105	-0,0928
t-statistics	(-0,25)	(-1,01)	(-2,09) **	(-2,34) **	(-2,16) **	(-1,63)
Ted-spread β_9	0,0195	0,0717	0,1313	0,1639	0,1789	0,1768
t-statistics	(1,47)	(3,72) ***	(5,36) ***	(5,87) ***	(6,27) ***	(6,56) ***
R-squared	**0,0977**	**0,1201**	**0,2079**	**0,2725**	**0,2974**	**0,3216**
Adjusted R-Squared	**0,0948**	**0,1173**	**0,2054**	**0,2702**	**0,2952**	**0,3195**
N	**2869**	**2869**	**2869**	**2869**	**2869**	**2869**

more significant and negative than in the previous models. The water and temperature deviation factors remain highly significant for most times for settlement, but there are some differences between the models. The significance of the water deviation factor is no longer significant for two contracts closest to maturity whereas the significance of the temperature deviation factor is increased for the contracts closest to maturity. This might imply that the spot price factor has some interdependencies with the two deviation factors. Furthermore, the explanatory power of oil, LNG, VIX, and oil VIX factors are slightly increased. Altogether, the adjusted R-squared measure is slightly improved from the model 1 for all times for settlement studied.

The only difference between models 20 and 21 is the factor used to proxy the level of the spot price in the model. Model 21 uses seven days lagged spot price instead of using the spot price of trading day of the contract. The results of Model 21 are presented in Table 12. The results are highly similar to the ones presented in Table 11. The lagged spot price is clearly less significant than the spot price of the trading day. Also, the adjusted R - squared measures obtain slightly lower values than when using model 20. This implies that the spot price of the trading day is a better proxy of the spot price level when studying

Table 12. The fourth factor model with seven days' lagged spot price with daily frequency observations. Model used is 21 in the matter specified in Chapter 5.4. Regression is run for 6 different time series that are distincted from each other by the time they are traded prior to settlement date (full months). All the regressions are run using Newey-West heteroskedasticity and autocorrelation robust estimators (HAC). Statistical significance is indicated with *, **, *** for 10 %, 5 %, and 1 % significance levels respectively.

	Full months prior to the settlement date of the futures contract					
	0	**1**	**2**	**3**	**4**	**5**
Constant β_0	-6,4032	-3,5698	-0,2074	-0,7384	-1,7863	-5,1624
t-statistics	(-3,18) ***	(-1,25)	(-0,06)	(-0,21)	(-0,56)	(-1,50)
Lagged spot S_t-7 β_1	0,0814	0,0836	0,0834	0,1053	0,0349	0,0108
t-statistics	(2,22) **	(2,15) **	(1,90) *	(1,96) *	(0,60)	(0,20)
Deviation nordics β_2	-0,0766	-0,1920	-0,3295	-0,4205	-0,5578	-0,6156
t-statistics	(-1,19)	(-2,25) **	(-3,36) ***	(-3,67) ***	(-4,32) ***	(-5,02) ***
Temperature deviation β_3	0,2055	0,2053	0,4320	0,5006	0,4439	0,4251
t-statistics	(2,05) **	(1,71) *	(3,65) ***	(3,89) ***	(3,18) ***	(3,14) ***
Coal β_4	-0,0175	-0,0155	0,0074	0,0199	0,0394	0,0478
t-statistics	(-1,17)	(-0,80)	(0,32)	(0,73)	(1,40)	(1,70) *
Oil β_5	0,0077	0,0075	0,0047	0,0059	0,0086	0,0134
t-statistics	(2,27) **	(1,65) *	(0,87)	(0,99)	(1,41)	(2,31) **
LNG β_6	0,0062	0,0022	-0,0064	-0,0101	-0,0080	-0,0058
t-statistics	(2,36) **	(0,51)	(-1,05)	(-1,71) *	(-1,45)	(-1,06)
VIX β_7	0,0606	-0,0478	-0,1989	-0,3059	-0,3973	-0,4256
t-statistics	(0,95)	(-0,55)	(-1,95) *	(-2,57) **	(-3,29) ***	(-3,47) ***
Oil VIX β_8	-0,0090	-0,0442	-0,1057	-0,1232	-0,1177	-0,0992
t-statistics	(-0,35)	(-1,10)	(-2,17) **	(-2,44) **	(-2,26) **	(-1,72) *
Ted-spread β_9	0,0194	0,0718	0,1314	0,1641	0,1795	0,1775
t-statistics	(1,46)	(3,71) ***	(5,35) ***	(5,87) ***	(6,28) ***	(6,63) ***
R-squared	**0,0874**	**0,1118**	**0,2010**	**0,2612**	**0,2923**	**0,3189**
Adjusted R-Squared	**0,0846**	**0,1090**	**0,1985**	**0,2589**	**0,2901**	**0,3168**
N	**2869**	**2869**	**2869**	**2869**	**2869**	**2869**

risk premiums in the markets. It also seems to imply that the market participants follow current spot price developments more rigorously than historical prices when trading derivatives.

Finally, Table 13 presents the results of the fifth extended multifactor model used to study the third hypothesis, specified in Formula 22. The model includes the same spot price distribution factors that were used in the final model, Formula 17, in the previous

Table 13. The fifth factor model with rolling mean spot price, rolling variance and rolling skew. Regression is run using daily frequency observations. Model used is 22 in the matter specified in Chapter 5.4. Regression is run for 6 different time series that are distincted from each other by the time they are traded prior to settlement date (full months). All the regressions are run using Newey-West heteroskedasticity and autocorrelation robust estimators (HAC). Statistical significance is indicated with *, **, *** for 10 %, 5 %, and 1 % significance levels respectively.

	Full months prior to the settlement of the futures contract					
	0	**1**	**2**	**3**	**4**	**5**
Constant β_0	-5,8032	-3,1667	-0,8399	-0,7152	-0,8563	-4,5113
t-statistics	(-2,81) ***	(-1,14)	(-0,26)	(-0,21)	(-0,27)	(-1,29)
Rolling mean spot _s_m22 β_1	0,0854	0,1419	0,1578	0,1045	-0,0495	-0,0513
t-statistics	(1,98) **	(2,37) **	(2,13) **	(1,27)	(-0,64)	(-0,71)
Variance σ^2_s_22 β_2	0,0080	0,0050	-0,0053	0,0015	0,0197	0,0124
t-statistics	(0,82)	(0,55)	(-0,58)	(0,14)	(1,65) *	(1,14)
Skewness_s_22 β_3	-0,6577	-1,1218	-0,2763	-0,0443	0,2016	0,1629
t-statistics	(-1,92) *	(-2,30) **	(-0,49)	(-0,07)	(0,29)	(0,25)
Deviation nordics β_4	-0,0671	-0,1155	-0,2383	-0,4193	-0,6592	-0,6903
t-statistics	(-0,99)	(-1,26)	(-2,11) **	(-3,13) ***	(-4,66) ***	(-4,87) ***
Temperature deviation β_5	0,1832	0,1683	0,4029	0,4794	0,4686	0,4435
t-statistics	(1,95) *	(1,48)	(3,45) ***	(3,73) ***	(3,42) ***	(3,30) ***
Coal β_6	-0,0213	-0,0269	-0,0009	0,0203	0,0463	0,0533
t-statistics	(-1,40)	(-1,33)	(-0,04)	(0,73)	(1,70) *	(1,92) *
Oil β_7	0,0074	0,0070	0,0044	0,0058	0,0086	0,0135
t-statistics	(2,16) **	(1,53)	(0,82)	(0,96)	(1,40)	(2,32) **
LNG β_8	0,0065	0,0015	-0,0076	-0,0099	-0,0062	-0,0045
t-statistics	(2,30) **	(0,33)	(-1,22)	(-1,60)	(-1,05)	(-0,80)
VIX β_9	0,04303	-0,08877	-0,2276	-0,31102	-0,37433	-0,40747
t-statistics	(0,67)	(-1,00)	(-2,25) **	(-2,61) ***	(-3,13) ***	(-3,36) ***
Oil VIX β_10	-0,0039	-0,0293	-0,0948	-0,1227	-0,1306	-0,1086
t-statistics	(-0,15)	(-0,75)	(-2,02) **	(-2,42) **	(-2,45) **	(-1,88) *
Ted-spread β_11	0,0210	0,0721	0,1294	0,1646	0,1846	0,1808
t-statistics	(1,57)	(3,69) ***	(5,21) ***	(5,72) ***	(6,23) ***	(6,66) ***
R-squared	**0,0935**	**0,1254**	**0,2062**	**0,2600**	**0,2963**	**0,3207**
Adjusted R-Squared	**0,0900**	**0,1220**	**0,2031**	**0,2571**	**0,2936**	**0,3181**
N	**2869**	**2869**	**2869**	**2869**	**2869**	**2869**

hypothesis. These factors are the following: 22 days rolling mean spot price, 22 days rolling variance, and 22 days rolling skew.

The results of this last model are slightly better than in Model 2 presented in Table 10. However, coefficients for variance and skewness remain insignificant for most times to settlement. The coefficient for the rolling mean price is slightly more significant than the seven days lagged spot price, with 5% significance for three closest to settlement contracts. However, the explanatory power of the coefficient is much lower than the trading day's spot price was in the model 2. The adjusted R-squared however, is slightly higher for the fifth model than it was for the second model for all the times to settlement studied.

6.4. Discussion about the empirical results

The empirical results of the quantile regression show that the most important exogenous factors affecting spot prices in the Nordic markets are the weather and the water reservoir conditions. The model has high explanatory power on all the quantiles of the spot price distribution. Also, the past spot prices and the weekend dummy have strong statistical significance in the regression. The quantile regression studies the prices instead of returns, so it was predicted that these variables would be highly significant. The high significance of past prices suggests that the markets expect the prices to stay at high levels, if the prices have been high in the recent past. It would be interesting to study whether the past returns are able to predict the current returns, but it is not possible due to the design of my models. The high significance of the weekend dummy is not surprising as many authors have reported that the spot prices are usually lower during the weekends, for example Simonsen et al (2004). It seems that this Weekend effect applies across all the quantiles of the spot price distribution.

Both the water level factor and the water deviation factor, obtain highly significant results. The water deviation variable is significant at 1 % level in all quantiles of the distribution. The water deviation factor has a strictly negative relationship with the spot prices, which indicates that unusually low water levels result in unusually high spot prices and vice versa. This is in line with the findings of many authors, for example Vehviläinen & Pyykkönen (2005), Sijm, Neuhoff & Chen (2006), and Botterud et al (2010). Also the temperature variables are highly significant in almost all the quantiles of the spot price distribution. Temperature deviation and level -variables both have strictly negative relationships with the spot prices. This indicates that cold or colder than usual temperatures have a tendency to increase the spot prices and vice versa. Moreover, this effect seems to be highly significant also in the tails of the distribution. This indicates that the weather has a strong effect on spot prices in all the market conditions.

The explanatory power of the fuel and market risk / sentiment variables on the spot market prices are surprisingly weak. Coal and LNG are the most prominent fuel factors affecting the spot prices, whereas oil does not obtain any significant values across the quantiles. Coal prices are highly significant in the right-hand side of the spot price distribution, whereas LNG has mildly significant results on both tails of the distribution. In Table 4, the role of LNG is pronounced especially in the right tail of the distribution. The regressions indicate that coal and LNG prices have pronounced effect during times of high spot market prices. VIX is the most significant of the market uncertainty variables with significant results almost in half of the quantiles, with 10 % confidence level.

The results show that the most important exogenous factors determining the spot market prices are water reservoir conditions and temperatures. Coal, Lng, VIX, and the oil VIX each have some explanatory power on the spot prices. Lagged spot prices, temperature deviations, coal prices and LNG prices are all highly significant at the right tail of the distribution. Therefore, these variables are especially interesting considering the third hypothesis and futures prices. The explanatory power of the model is reasonably high across the quantiles, the pseudo r-squared measures vary between 0.6402 and 0.8237. The model is most accurate around the mean of the distribution. These results show that the model used has ability to explain spot market prices and that by using quantile regression approach the model is able to find variables that have significant ability to explain the extremely low and high spot market prices. Thus, based on the results of quantile regression the 1st hypothesis of the thesis is accepted.

The second hypothesis studies whether the traditional reduced form equilibrium pricing models of Bessembinder et al. (2002) and Longstaff et al. (2004) are able to explain the futures pricing in the markets. The monthly risk premiums are studied in both monthly and daily frequency and with six different times to the start of the delivery period of the monthly contracts. Altogether, four different models are used to test the reduced form models in the Nordic markets.

The first two models study the risk premiums using monthly frequency data and by considering the statistical characteristics of the spot price distribution during the delivery period of the futures contract. The results strengthen the findings of Lucia et al. (2011) who argue that the variance and the skewness of the spot prices have not been able to explain the risk premiums in the markets after 2002. Even though the variance and skewness are of predicted sign, they are not statistically significant. The second model includes the mean of the spot price distribution during the delivery period to the analysis and has much better explanatory power on risk premiums. Mean spot prices are highly significant for all contracts except for the ones closest to maturity.

The constant terms of the both models are significant at the 1 % level. The constant terms obtain positive values and the values are higher for the contracts further from maturity. According to Lucia et al.‘s (2011) paper, this could mean that the market participants overestimate the future spot prices and that the overestimation is higher for contracts further from expiry. Another reason could be that the model is under -specified and omitted variable bias causes the constant term to behave the way it does. This would mean that there are factors that significantly affect the futures premiums in the markets that are not included in these models. This is favorable interpretation considering the third hypothesis of the thesis.

The other two models are structurally similar to previous two models but they study the risk premiums using daily frequency data. This is possible because of the continuous futures timeseries provided by the Thompson Reuters DataStream. Risk premiums are calculated by comparing the daily observations of futures prices with the average spot price of the delivery month. By using the daily frequency data, the sample size is increased from 132 observations to 2869 observations. Whereas the monthly models studied the characteristics of spot price distribution during the delivery period, these two models use 22 days rolling measures of mean, variance, and skewness prior to the trading date of the contract. Thus, the interpretation of the models changes essentially. The daily models study whether or not the market participants consider characteristics of recent past spot prices when they trade futures contracts.

The model omitting the mean of the spot price distribution provides significant coefficients for variance and skewness measures for some of the times to maturity studied. Furthermore, the signs of the coefficients are as predicted by the theory regarding reduced form models. According to the model recent past variance prior to trading date increases the futures premiums whereas the recent past skewness, prior to the trading date, decreases the premiums. The constant remains positive and highly significant for all times from maturity and the explanatory power of the model is really low. This could indicate that some important factors are omitted from the model.

The daily frequency model including the past mean of the spot prices provides somewhat mixing results. The statistical significance of the model is increased and the coefficient for the past average spot prices is significant at the 1 % level for all the times from maturity. The variance has mostly negative coefficients and the significance is much lower than with the other daily model. For two closest from maturity contracts the skewness is significant and negative. In fourth regression the constant term remains highly significant, but it obtains negative values for all the times from maturities studied. This is somewhat puzzling but implies that including the mean term of spot price distribution prior to trading date changes the model drastically.

Based on the empirical results of the models, the second hypothesis cannot be accepted. These results thus strengthen the argument of Lucia et al. (2011), who argue that something changed after the year 2002 in the pricing fundamentals of the Nordic markets and that the reduced form model does not explain the futures premiums anymore. However, the model shows that the mean and the variance of the past spot prices have some explanatory power on the risk premiums. Their effects on risk premiums should thus be further studied. Moreover, the key finding of the second hypothesis is that the models used could suffer from underspesification issue and therefore models using more explanatory factors should be studied. These findings lay the foundation for the third and last hypothesis of the thesis.

The third hypothesis combines the finding of the first and second hypotheses to study the risk premiums in the markets. It uses the whole data set collected for the thesis and tries to identify key factors affecting the pricing. The assumption is that especially the factors that explain the tail behavior of the spot price distribution could have significant explanatory power for the risk premiums. Five slightly different models are used to study the risk premiums. The models differ from each other mainly by the way they include the characteristics of the spot price distribution prior to the trading period into the analysis.

The models of the third hypothesis provide a much better fit than the daily models of the second hypothesis. Also, the significance of the constant term is decreased, which indicates that the models studying the second hypothesis might have been under -specified. Water deviation and temperature deviation factors are found to have the most explanatory power on risk premiums. The water deviation factor obtains strictly negative and significant results with all the different times from settlement studied. So as expected, unexpectedly low water reserves during the trading period of the contracts increase the risk premiums of the derivative contracts. The temperature deviation factor obtains strictly positive and significant values. This is not as expected by the theory or logic, according to the models lower than usual temperatures during the trading period decrease the risk premiums in the markets. Market participants might not consider that for example lower than usual temperatures have any effect on the spot prices of the delivery period. It should be noted that the delivery period can be months from the trading date and because of that, it is probable that market participants do not consider much the current weather when they are trading futures contracts with settlement date months ahead in the future.

The fuel price proxies obtain surprisingly weak results for most of the contracts studied. Almost all results that are significant have positive coefficients, which implies that there could be some positive causality between fuels and risk premiums. LNG and Oil prices seem to have more explanatory power than the coal prices, which is a little surprising as the coal seemed to have the most explanatory power on spot prices in the first regressions.

Also, the risk factors seem to indicate that the risk premiums are, to some degrees, driven by other fundamentals than the spot prices. Overall the risk factors seem to have more explanatory power on risk premiums than the fuels, the opposite was true for the spot prices. The significance of these factors is higher for the contracts furthest from the settlement. The TED -spread seems to have the most explanatory power on risk premiums. Increased spread seems to tighten the risk considerations of the market participants. This finding is line with the findings of Koch (2014) who observe relationship between the TED -spread and energy commodities prices. VIX and oil VIX both obtain some significant results but with positive coefficients. Thus, it seems that the global volatility in equity and oil markets is not spilt over to the Nordic electricity derivative markets. It might even indicate that high volatility in these markets could decrease the risk premiums in the Nordic derivative markets. It might be interesting to study whether electricity derivatives could act as “safe havens” during times of high volatility in the global equity and oil markets.

One of the key findings of the models is that the significance of the constant term is greatly reduced and that the overall performance of the model is greatly improved from the daily models studied in the previous hypothesis. This implies that the high significance of the constant term in the results of the second hypothesis is mainly explained by the underspecified model and omitted variable bias. The fit of the model is slightly improved by including statistical characteristics of the spot prices, prior to the trading date, in the model. Proxies of the level of the spot price are the most important statistical variables explaining the premiums. The spot price of the trading date of the futures contract is the best performing proxy of the spot prices. It obtains positive and significant values for most of the times from settlement studied. However, seven day lagged spot price and 22 days rolling average spot price are still viable proxies and obtain significant values for almost half of the contracts studied. The variance and skewness of the spot price prior to the trading date obtain much less significant values in the models. This finding, together with the findings of the second hypothesis, indicates that market participants do not focus on the recent past variance and skewness of the spot price distribution nearly as much as they consider the current or recent past spot prices. Moreover, all the statistical proxies of the spot price studied are much more significant for contracts closer to maturity. This could strengthen the findings of Fleten et al. (2015) who argue that the futures pricing mechanism is different for close to maturity contracts than it is for further from maturity contracts. They find evidence that close to maturity contracts are clearly more speculative instruments, whereas the pricing for contracts further from the maturity is affected more by factors that can be related to hedging demand literature.

Perhaps the most interesting factors explaining the risk premiums in the markets are the variables for water deviation and the temperature deviation. They are both highly weather related and can thus be argued to be completely exogenous and random variables. It is easy to argue that Nordic weather temperatures or water inflows are not affected by the global stock markets or electricity spot prices. On the other hand, as seen from the first hypothesis, the Nordic spot prices are highly related to weather temperatures and water inflows.

Based on the results, the third hypothesis can only be partly accepted. By including those variables, in the models that were studied in the first hypothesis, the explanatory power of the reduced form models was significantly improved. Some of the variables that had high explanatory power on the spot prices in the markets also had high explanatory power on the risk premiums. Deviations from the average Nordic water reserves and temperature deviations are the most important variables that have high explanatory power on both spot prices and futures premiums. The market risk variables seem to have more explanatory power on the risk premiums than the fuel price proxies. However, fuel price proxies performed much better than the market risk variables on explaining the spot prices in the markets. The statement that those variables that explain the pricing behavior of the spot prices in the tails of the spot price distribution are the most important variables for the risk premium models; cannot be approved based on the results.

The hypothesis seems to apply for the water deviation and the temperature deviation factors but the same relationship is not observed for the other variables used. It seems that the pricing process in the spot and in the futures markets follows different fundamentals to a large extent. This might be related to the findings of Huisman et al. (2012), who noted that Nord Pool markets seem to be much more prediction driven markets than electricity markets that have heavier dependency on fuel prices.

7. CONCLUSIONS

The Nordic markets have many unique features compared with other electricity markets in a global comparison. The most characteristic feature of the Nordic markets is that a significant proportion of the total production in the markets is generated using hydropower. The vast water reserves located in Norway and Sweden enable a cost efficient and flexible way for producers to react to most sudden and unexpected demand shocks. The Nord Pool markets are also a prime example of a well-functioning market that has been recently liberated.

Nord Pool spot prices are determined in auction-based markets where the producers and the consumers of electricity meet and trade for the deliveries of electricity for the following day. Electricity is traded on hourly bases. In addition, derivative contracts, traded in Nasdaq Commodities, for Nord Pool electricity are an essential element of the markets.

This thesis studies spot and futures pricing in the Nordic markets. Electricity is a peculiar commodity, mainly because it cannot be stored. The non -storable nature of electricity makes the spot markets highly volatile and prone to price spikes. Non -storability also means that the Theory of Storage, commonly applied in commodities derivatives pricing models, cannot be used to study futures pricing in electricity markets. Electricity derivatives pricing is commonly modeled by considering the supply and demand conditions of hedges for the deliveries of spot electricity. This field of research is called risk premium literature. However, recent research suggests that electricity markets could have some storage-like features, because of the fact that electricity can be in fact be indirectly stored by storing fuels that can be used to produce electricity.

By using an extensive data set and advanced econometric methods, this thesis aims to provide insights into the complex pricing processes of the Nordic markets. It aims to identify the key factors, that have effect on the spot market pricing, and studies how these factors can be used to explain risk premiums in the futures markets. The literature assumes that extreme volatility and price spikes in the spot markets are the key factors creating the hedging demand in the electricity derivative markets. Studying the spot price distribution in quantile regression framework, enables me to study factors that explain the extreme prices in the markets. Quantile regression methodology enables me to study also the tails of the spot price distribution; something that is not possible with traditional OLS models. By including the tail behavior of the spot prices to the analysis, I can study also the risk premiums in more depth.

The study period is 1.1.2005-2015 and the analysis are mostly conducted on daily frequency observations. Risk premiums are studied using monthly futures contracts, which are the shortest contract available on Thompson Reuters DataStream. Continuous indexes enable me to study the monthly premiums also in daily frequency. This approach might not be the optimal way for studying risk premiums, but I feel that it is necessary for the purpose of the thesis. The small sample size of monthly frequency data would prevent me doing statistically reasonable multifactor analyses of the risk premiums. The best way to increase the sample size would be to study weekly contracts with weekly frequency futures market data, but this is not possible due to the expensive paywall for obtaining such data.

Risk premiums in the futures markets are studied with six different times to settlement. The exogenous variables of the thesis can be divided into three categories; temperature and water reserves data, fuel price data, and market risk / sentiment data. Norwegian, Swedish, and Finnish water reserves, by their relative share, are used to construct an index proxying the Nordic water levels. Deviations from historical averages are also calculated for both temperature and water level data, in order to reduce the highly seasonal nature of weather data. Temperatures are collected from 58 weather stations across Norway, Sweden and Finland and the observations are combined into one Nordic temperature index based on the population living in the area of the weather station. To my knowledge, this is the first study using population weighted temperatures to study Nordic electricity markets. Fuel factors include coal, LNG, and oil prices. Market risk / sentiment factors include VIX, Oil VIX, and the TED-spread. VIX and Oil VIX are used as the proxies of global financial uncertainty, and the TED-spread is used as the proxy of international credit risk. Furthermore, statistical characteristics of the spot price distribution are used to study the risk premiums.

The first hypothesis studies whether the quantile regression model is able to explain spot market pricing in the Nordics. Moreover, the hypothesis studies the significance of the chosen variables in different quantiles of the spot price distribution. The results show that the quantile regression model is a prominent tool for studying the spot market prices. Ability of the model to explain different quantiles of the spot price distribution varies between 62-81 %. Nordic water levels, water reserve deviations, temperatures, and temperature deviations obtain highly significant results throughout the spot price distribution. Coal and LNG also have explanatory power on spot prices. Especially for coal, significance is at the highest at the right tail of the distribution. This could indicate that coal prices have, at least to some degree, ability to explain price spikes in the markets. In addition, VIX and Oil VIX both have some ability to explain the spot market prices. They have pronounced effect on the left tail of the distribution.

In both monthly and daily frequency analyses, risk premiums are found to be on average positive and significant. Risk premiums seem to be higher for contracts with longer times from maturity. In contrast to spot market prices, no clear seasonal trend can be observed in the risk premium data. The second hypothesis of the thesis studies the ability of standard reduced form of Bessembinder et al. (2002) and Longstaff et al. (2004) in explaining the risk premiums. The results comply with Lucia et al. (2011) finding that the reduced form no longer explains the futures pricing in the Nordic markets. It seems that the market fundamentals have changed permanently after the highly volatile period of 2002.

The last hypothesis studies the risk premiums with daily frequency data using the whole data set. The model is found to significantly outperform the simple reduced form model, which seems to be under -specified. Water deviation and temperature deviation factors have the strongest explanatory power on the risk premiums. Unexpectedly, the sign of the temperature deviation variable is positive. Another surprising result is that the market risk / sentiment variables have higher explanatory power on risk premiums than the fuel price proxies, contrary to the models studying spot prices. Statistical measures of the spot price distribution prior to the trading date of the futures contract have higher significance for closer to maturity contracts. Overall it seems that the pricing follows different fundamentals for closer to maturity contracts than for contracts further from settlement.

Despite the prominent results of the regressions, the third hypothesis can only be partly accepted. The assumption that those variables explaining the tails of the spot price distribution would also explain the risk premiums cannot be unambiguously proven. The assumption seems to hold for water and temperature deviation factors but does not hold for the fuel price proxies and the proxies of the market and liquidity risk. The models studying the third hypothesis do provide interesting insights regarding the relationship between the spot prices and risk premiums, but the hypothesis cannot be accepted.

This study contributes to the existing literature by studying how the tail distribution of the spot market prices affects the risk premiums in the Nordic electricity markets. It introduces several factors that have not been previously used to study electricity pricing in the Nordics. Perhaps the most interesting new factor is the population weighted temperature index, that I have constructed particularly for the purposes of this thesis. The population -weighted temperature has high explanatory power for both spot prices and risk premiums.

The Nordic markets are changing rapidly and the change provides interesting venues for future research. The markets are becoming increasingly interconnected with the Central European markets; and as they do this could change the market fundamentals observed in the Nordics. Furthermore, technology is changing the demand and supply conditions in the markets. Smart Electricity Grids, the Internet of Things, and better and more efficient solutions for storing electricity might make the markets behave more like traditional commodities markets. Smart Grids make the demand side more elastic by optimizing the consumption of households and businesses. Smart Grids allow machines to follow spot market prices and time their electricity consuming processes so that they get the needed electricity as cheaply as possible. This kind of automation could increase the demand -side price elasticity and reduce seasonality in the spot prices. Increased demand elasticity, more efficient storability, and more interconnected markets would also probably reduce the risk of price spikes in the markets. These changes would probably change the pricing of both spot and futures markets fundamentally. However, this would not reduce the value of the findings of this thesis; the better we understand the fundamentals of the today's markets, the more informed decisions we are able to make in the future. Thus, there is much more to study in this field. For example, it would be interesting to conduct a similar study with weekly futures contracts. Other interesting venue would be to study the role of speculation in the derivative markets and how interconnected the markets are with other global financial markets. For example, the causality and interconnections between the Nordic risk premiums and interest rates, Credit Default Swap prices, and equity markets could provide fascinating results.

REFERENCES

Amic, E. (2005). *The Oil Market as a World Market.* Published in Commodities and Commodity Deriatives: Modeling and Pricing for Agriculturals, Metals and Energy., Edited by Geman. John Wiley & Sons Ltd. ISBN: 978-0-470-01218-5. Pp. 201-226.

Azcel, A. D., J.Sounderpandian (2008). Complete Business Statistics. Boston McGraw-Hill, 7th edition. ISBN: 13-978-0-39-050192-9.

Bachmeier, L. J., J. M. Griffin (2006). *Testing for market integration crude oil, coal, and natural gas.* The Energy Journal, 55-71.

Bessembinder, H. (1992). *Systematic risk, hedging pressure, and risk premiums in futures markets.* Review of Financial Studies, 5(4), 637-667.

Bessembinder, H., M. Lemmon (2002). *Equliribium Pricing and Optimal Hedging in Electricity Forward Markets.* The Journal of Finance, 57(3), 1347-1382.

Black, F. (1976). *The Pricing of Commodity Contracts.* Journal of Financial Economics, vol 3, 167-179.

Black, F., M. Scholes (1973). *The pricing of options and corporate liabilities.* Journal of political economy, 81(3), 637-654.

Borenstein, S. (2000). *Understanding Competitive Pricing and Market Power in Wholesale Electrity Markets*. The Electricity Journal, 13(6), 49-57.

Borenstein, S., S, Holland (2005). *The Long-run Efficiency of Real-time Electricity Pricing.* The Energy Journal 26, 93-116.

Botterud, A., T. Kristiansen & M. D. Illic (2010). *The Relationship Between Spot and Futures Prices in the Nord Pool Electricity Market.* Energy Economics 32, 967-978.

Brennan, M (1958). *The Supply of Storage.* American Economic Review 48: 50-72.

Broadstock, D. C., G. Filis (2014). *Oil price shocks and stock market returns: New evidence from the United States and China*. Journal of International Financial Markets, Institutions and Money, 33, 417-433.

Brunnenmeier, M. (2009) *Deciphering the Liquidity and Credit Crunch 2007-2008.* Journal of Economic Perspectives 23, 1, 77-100.

Bye, T., P.V. Hansen (2008). *How Do Spot Prices Affect Aggregate Electricity Demand?* Discussion Papers NO. 527, January 2008, Statistics Norway, Research Department. Pp. 82.

Carter, A. C, Rausser & A. Schmitz (1983). *Efficient Asset Portfolios and the Theory of Normal Backwardation.* Journal of Political Economy, 91, 319-331.

Chang, C. (1985). *Returns To Speculators and the Theory of Normal Backwardation.* The Journal of Finance 40 (1), 193-208.

Chicago Board Options Exchange (2016). *CBOE's Home Page* [Online] [Cited 4.10.2016]. Available from Internet: <URL: http://www.cboe.com >.

Cornett, M., J. McNutt, P. Strahan & H. Tehranian (2011). *Liquidity Risk Management and Credit Supply in the Financial Crisis.* Journal of Financial Economics 101, 297-312.

CME group (2016) *CME group's Home Page* [Online] [Cited 6.12.2016]. Available from Internet: <http://www.cmegroup.com/trading/energy/>.

Creti, A., M. Joëts, & V. Mignon (2013). *On the links between stock and commodity markets' volatility.* Energy Economics, 37, 16-28.

De Roon, F., T. Nijman & C. Veld (2000). *Hedging Pressure Effects in Futures Markets.* The Journal of Finance. 55, 1437-1456.

Deakin, S., S.J. Konzelmann (2004). *Learing from Enron.* Corporate Governance: An international Review. Volume 12, Number 2, 134-142.

Douglas, S., J. Popova (2008). *Storage and the Electricity Forward Premium*. Energy Economics 30, 4, 1720-1727.

Dutta, A. (2017). *Modeling and forecasting oil price risk: the role of implied volatility index*. Journal of Economic Studies, 44(6), 1003-1016.

Emery, G. W., Q. Liu (2002). *An analysis of the relationship between electricity and natural-gas futures prices.* Journal of Futures Markets, 22: 95–122.

Escribano, A., Ignacio Peña, J., & Villaplana, P. (2011). *Modelling electricity prices: International evidence*. Oxford bulletin of economics and statistics, 73(5), 622-650.

Eydeland, A., H. Geman (1999). *Fundamentals of electricity derivatives.* Energy Modelling and the Management of Uncertainty, 35-43.

Fama, E., K. French (1987). *Commodity Futures Prices: Some Evidence on Forecast Power, Premiums and the Theory of Storage.* Journal of Business, vol.60, no.1, 55-73.

Fleten, S. E., L. A. Hagen, M. T. Nygård, R. Smith-Sivertsen & J. M. Sollie (2015). *The overnight risk premium in electricity forward contracts.* Energy Economics, 49, 293-300.

Frydenberg, S., J. I. Onochie, S. Westgaard, N. Midtsund & H. Ueland (2014). *Long-term relationships between electricity and oil, gas and coal future prices evidence from Nordic countries, Continental Europe and the United Kingdom.* OPEC Energy Review, 38(2), 216-242.

Geman, H. (2005). *Commodities and Commodity Derivatives: Modeling and Pricing for Agriculturals, Metals and Energy.* John Wiley & Sons Ltd., Pp 393. ISBN: 978-0-470-01218-5.

Geman, H., O. Vasicek (2001). *Forwards and Futures on Non-storable Commodities: The Case of Electricity*. Risk, August, 12-27.

Gjolberg, O., T-L. Brattested (2011). *The Biased Short-Term Futures Price at Nord Pool: Can It Really Be a Risk Premium?* The Journal of Energy Markets. Volume 4, Number 1, 3-19.

Hameed, A., W. Kang & S. Viswanathan (2010). *Stock market declines and liquidity.* The Journal of Finance, 65(1), 257-293

Huisman, R., M. Kilic (2012). *Electricity Futures Prices: Indirect Storability, Expectations and Risk Premiums.* Energy Economics 34, 892-898.

Ilmanen, A. (2012). *Expected Returns on Major Asset Classes.* Research Foundation of Cfa Institute. Pp180. ISBN 978-1-934667-48-4.

Kaldor, N. (1939). *Speculation and Economic Stability.* Review of Economic Studies 7, 1-27.

Kaminski, V. (1997). *The challenge of pricing and risk managing electricity derivatives.* The US Power Market, 3, 149-71.

Kauppalehti (2017a). *Älykkäät sähköverkot ovat välttämättömyys* [Online] [Cited 15.12.2017].

Kauppalehti (2017b). *Asiakkaat pääsevät aktiivisesti mukaan sähkökauppaan.* [Online] [Cited 15.12.2017].

Keynes, J. (1971). *The Collected Writings of John Maynard Keynes: In 2 Volumes. A Treatise on Money. The Applied Theory of Money*. Macmillan for the Royal Economic Society.

Kirschen, D., G. Strbac (2004). *Fundamentals of Power System Economics.* John Wiley & Sons Ltd. 284 pp. ISBN 9780470845721

Koch, N. (2014). *Tail events: A new approach to understanding extreme energy commodity prices.* Energy Economics, 43, 195-205.

Koenker, R., G. Bassett (1978). *Regression Quantiles*. Econometrica. January, 46:1, pp. 33–50.

Koenker, R., K. F. Hallock (2001). *Quantile Regression.* Journal of Economic Perspectives, 15 (4): pp. 143-156.

Lindboe, H. H., Hagman, B. & J. F. Christensen (2016). *Regional Electricity Market Design.* Nordic Council of Ministers. Pp. 123. ISBN: 978-92-893-4669-6. Available from Internet: <URL: http://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1039397&dswid=-9121>.

Liu, M. L., Q. Ji, Q. & Y. Fan (2013). *How does oil market uncertainty interact with other markets? An empirical analysis of implied volatility index.* Energy, 55, 860-868.

Lucia, J., H. Torró (2011). *On the risk premium in Nordic electricity futures prices.* International Review of Economics & Finance, 20(4), 750-763.

Lundby, M., K. Uppheim (2011). *Fundamental Risk Analysis and VaR forecasts of the Nord Pool System Price.* Norwegian University of Science and Technology, Industrial Economics and Technology Management. Master's Thesis.

Longstaff, F.A., A. Wang (2004). *Electricity Forward Prices: a High-Frequency Empirical Analysis.* The Journal of Finance 59 (4), 1877–1900.

Marshall, B. R., N. H. Nguyen & N. Visaltanachoti (2013*). Liquidity measurement in frontier markets.* Journal of International Financial Markets, Institutions and Money, 27, 1-12.

Mjelde, J. W., D. A. Bessler (2009). *Market integration among electricity markets and their major fuel source markets.* Energy Economics, 31(3), 482-491.

Mosquera-López, S., J. M. Uribe & D. F. Manotas-Duque (2017). *Nonlinear empirical pricing in electricity markets using fundamental weather factors.* Energy, 139, 594-605.

Murat, A., E. Tokat (2009). *Forecasting oil price movements with crack spread futures.* Energy Economics 31(1), 85-90.

Nasdaq OMX Commodities. Nasdaq Commodities homepage. [Online] [Cited 22.1.2018]. Available from Internet: <URL http://www.nasdaqomx.com/commodities>.

Nasdaq OMX (2013). *Nasdaq OMX Global Data Products – Nordic Newsletter # 17 June 26.* The Nasdaq OMX Group, INC.

Nasdaq Oslo ASA & Nasdaq Clearing AB (2017). *Trading Appendix 2 / Clearing Appendix 2 - Contract Specifications – Commodity Derivatives.* Nasdaq Oslo ASA & Nasdaq Clearing AB. Effective Date: 20 November 2017, Pp. 252.

Nord Pool AS. Nord Pool AS' homepage. [Online] [Cited 4.10.2017]. Available from Internet: <URL https://www.nordpoolgroup.com>.

Nord Pool Spot (2009). *The nordic electricity exchange and the nordic model for a liberalized electricity market.* Nord Pool Spot, Norway.

Pahkala, T., H. Uimonen & V. Väre (2017). *Matkalla kohti joustavaa ja asiakaskeskeistä sähköjärjestelmää–Älyverkkotyöryhmän väliraportti.* Ministry of Economic Affairs and Employment of Finland, Energy 38/2017, Pp. 65.

Pirrong, C., M. Jermakyan (1999). *Valuing power and weather derivatives on a mesh using finite difference methods.* Energy Modelling and the Management of Uncertainty, 59-69.

Puller, S. (2007). *Pricing and Firm Conduct in California's Deregulated Electricity Market.* The Review of Economics and Statistics, Vol. 89, No. 1: 75-87.

Rothovius, T., J. Nikkinen, J. Sihvonen & A. Klemola (2013). *Johdannaisten hyödyntäminen energiayhtiön liiketoiminnassa – Loppuraportti.* Vaasan Yliopiston julkaisuja, selvityksiä ja raportteja 193. Vaasan Yliopisto. Pp. 97. ISBN 978-952-476-509-1. Available from Internet:
<URL:http://www.uva.fi/materiaali/pdf/isbn_978-952-476-509-1.pdf>

Routledge, S., D. J. Seppi & C. S. Spatt (2000). *Equilibrium forward curves for commodities*. Journal of Finance 55, 1297–1338.

Routledge, S., D. J. Seppi & C. S. Spatt (2001). *The Spark Spread: An Equilibrium Model of Cross-Commodity Price Relationship in Electricity.* Carnegie Mellon University. Working paper.

Sari, R., U Soytas & E. Hacihasanoglu (2011). *Do global risk perceptions influence world oil prices?* Energy Economics, 33(3), 515-524.

Savolainen, M. K., R. Svento (2012). *Real-Time Pricing in the Nordic Power Markets.* Energy Economics 34, 4, 1131-1142.

Sengupta, C. (2004). *Financial Modeling Using Excel and VBA.* Wiley Finance, ISBN 9780471651093, Pp. 464.

Shawky, H. A., A. Marathe & C. L. Barrett (2003). *A first look at the empirical relation between spot and futures electricity prices in the United States*. Journal of Futures markets, 23(10), 931-955.

Siegmund, D. O. (1967). *Some problems in the theory of optimal stopping rules.* The Annals of Mathematical Statistics, 1627-1640.

Sijm, J., K. Neuhoff & Y. Chen (2006). *CO2 cost pass-through and windfall profits in the power sector.* Climate policy, 6(1), 49-72.

Simonsen, I., R. Weron & B. Mo (2004). *Structure and stylized facts of a deregulated power market.* Working Paper presented at the 1st Bonzenfreies Colloqium on Market Dynamics and Quantitative Economics, Alessandria.

Statistics Finland. [Obtained December 2016]. Creative Commons Attribution 4.0 International License.

Statistics Norway. [Obtained December 2016]. Norwegian License for Open Government Data.

Statistics Sweden. [Obtained December 2016]. Creative Commons Attribution 4.0 International License.

Stoft, S. (2002). *Power System Economics.* John Wiley & Sons Ltd.

Tarjanne, R., A. Kivistö (2008). *Comparison of Electricity Generation Costs.* Lappeenranta University of Technology, Faculty of Technology, Department of Environmental Technology, Research report EN A-56, 24.

Telser, L. (1958). *Futures Trading and the Storage of Cotton and Wheat.* Journal of Political Economy 66, 233-255.

The Finnish Meteorological Institute. Open Data Service [Obtained January 2017]. Creative Commons Attribution 4.0 International License.

The Norwegian Meteorological Institute. Official Data [Obtained January 2017]. Norwegian License for Public Data and Creative Commons Attribution 4.0 International License.

The Swedish Meteorological and Hydrological Institute. Open Data Service [Obtained January 2017]. Creative Commons Attribution 4.0 International License.

U.S Energy Information Administration (2016). *Energy Today: Crude Oil Prices Started 2015 Relatively Low, Ended the Year Lower.* [Online] [Cited 7.9.2017]. Available from Internet: <URL :https://www.eia.gov/todayinenergy/detail.php?id=24432>

United States Oil Fund, LP. *USO's Home Page* [Online] [Cited 4.10.2016]. Available from Internet: <URL :http://www.unitedstatescommodityfunds.com>.

Van Treslong, A. B., R. Huisman (2010). *A comment on: Storage and the electricity forward premium.* Energy Economics, 32(2), 321-324.

Vehviläinen, I., T. Pyykkönen (2005). *Stochastic factor model for electricity spot price -the case of the Nordic market.* Energy Economics, 27(2), 351-367.

Weron, R., & Zator, M. (2014). *Revisiting the relationship between spot and futures prices in the Nord Pool electricity market.* Energy Economics, 44, 178-190.

Wooldridge, J. M. (2013). *Introductory econometrics: A modern approach* (5th int. ed.). Australia: South-Western/Cengage Learning. 878 pp. ISBN: 9781111534394.

Working, H. (1948). *The Theory of the Price of Storage.* American Economic Review 39, 1254-62.

Wårell, L. (2006). *Market integration in the international coal industry: A cointegration approach.* The Energy Journal, 99-118.

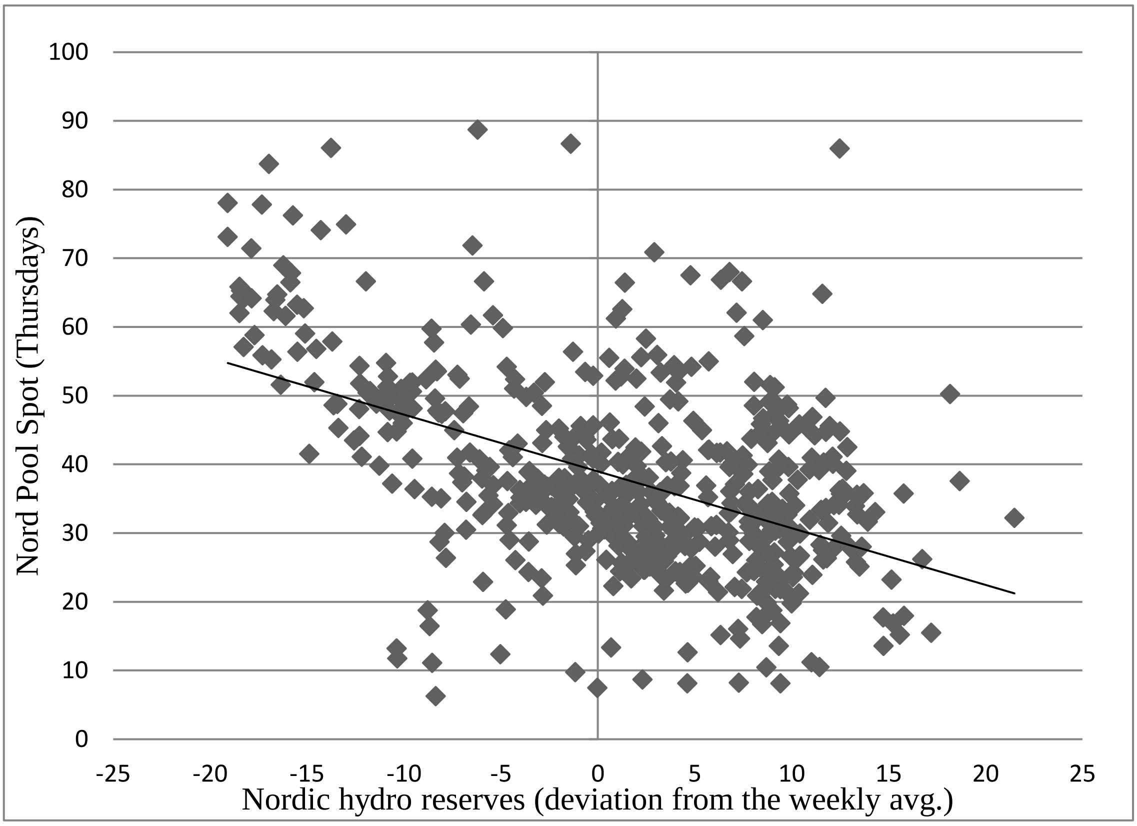
Yang, J., D. Bessler & D. Leatham (2001). *Asset Storability and Price Discovery in Commodity Futures Markets: A New Look.* The Journal of Futures Markets, Vol. 21, No. 3, 279-300.

Zhang, Y. J., J. Chevallier & K. Guesmi (2017). "*De-financialization" of commodities? Evidence from stock, crude oil and natural gas markets.* Energy Economics, 68, 228-239.

APPENDIX 1. Statistical characteristics of relative risk premiums in monthly contracts. Daily frequency.

		Full months prior to the settlement date of the futures contract					
		0	1	2	3	4	5
Whole Period							
	Average Premium	0,0271	0,0444	0,0528	0,0605	0,0636	0,0637
	Standard Deviation	0,1625	0,2125	0,2512	0,2757	0,2904	0,3051
	T-test	8,9288 ***	11,1892 ***	11,2712 ***	11,7542 ***	11,7393 ***	11,1796 ***
	Skewness	-0,4703	-0,6525	-0,6915	-0,5907	-0,5516	-0,5068
	Kurtosis	1,2897	1,4137	1,0270	0,6616	0,5638	0,0986
	Smallest Value	-0,6800	-0,8478	-0,9608	-1,0574	-1,0124	-1,0175
	Largest Value	0,4659	0,5812	0,6287	0,6606	0,6812	0,6780
	N	2869	2869	2869	2869	2869	2869
Winter							
	Average Premium	0,0094	0,0179	0,0273	0,0415	0,0493	0,0265
	Standard Deviation	0,1834	0,2420	0,2455	0,2306	0,2697	0,3387
	T-test	1,3627	1,9746 **	2,9596 ***	4,7944 ***	4,8691 ***	2,0818 **
	Skewness	-0,8884	-1,1980	-0,8351	-0,6518	-0,1561	-0,4411
	Kurtosis	0,5850	1,5035	0,0538	0,2349	0,1899	-0,1249
	Smallest Value	-0,5919	-0,8478	-0,6602	-0,7004	-0,7267	-1,0175
	Largest Value	1,3627	1,9746	2,9596	4,7944	4,8691	2,0818
	N	709	709	709	709	709	709
Spring							
	Average Premium	0,0136	0,0521	0,0492	0,0436	0,0299	0,0377
	Standard Deviation	0,1210	0,1738	0,2443	0,2800	0,2566	0,2206
	T-test	3,0267 ***	8,2966 ***	4,8046 ***	3,5330 ***	3,0937 ***	5,0270 ***
	Skewness	0,0990	0,3612	-0,2348	-0,0162	-0,0020	-0,2912
	Kurtosis	1,1158	0,2531	0,0862	-0,7379	-0,4121	1,1875
	Smallest Value	-0,4326	-0,3951	-0,7505	-0,7037	-0,6401	-0,7189
	Largest Value	0,4048	0,5812	0,5660	0,5827	0,5388	0,5323
	N	722	722	722	722	722	722
Summer							
	Average Premium	0,0349	0,0374	0,0561	0,0771	0,0965	0,1103
	Standard Deviation	0,1656	0,1856	0,1832	0,2215	0,2527	0,2953
	T-test	5,6613 ***	5,4167 ***	8,2285 ***	9,3602 ***	10,2639 ***	10,0439 ***
	Skewness	0,2934	0,1411	0,0958	-0,8698	-0,9241	-0,8869
	Kurtosis	0,0271	0,0852	-0,3380	3,0820	2,1253	0,8593
	Smallest Value	-0,4507	-0,4643	-0,3868	-0,7758	-0,8287	-0,8316
	Largest Value	0,4659	0,4834	0,4860	0,6065	0,6812	0,6780
	N	723	723	723	723	723	723
Autumn							
	Average Premium	0,0503	0,0699	0,0787	0,0796	0,0788	0,0797
	Standard Deviation	0,1704	0,2378	0,3131	0,3501	0,3645	0,3441
	T-test	7,8978 ***	7,8605 ***	6,7173 ***	6,0772 ***	5,7788 ***	6,1946 ***
	Skewness	-0,9135	-0,8092	-1,0311	-0,8035	-0,8008	-0,3990
	Kurtosis	2,5156	1,0921	1,2418	0,2890	0,1695	-0,7875
	Smallest Value	-0,6800	-0,7064	-0,9608	-1,0574	-1,0124	-0,8423
	Largest Value	0,4458	0,5606	0,6287	0,6606	0,6498	0,6598
	N	715	715	715	715	715	715

APPENDIX 2. Scatter plot diagram of Nordic Hydropower reserves and spot prices of all Thursdays in the dataset



APPENDIX 3. Counties, population, and weather observation stations

	County	Population	Admin. center	Weather station	Elevation	Lat.	Lon.
Finland							
1	Uusimaa	1 628 358	Helsinki	Helsinki Kaisaniemi	4	60,18	24,94
2	Varsinais-suomi	474 208	Turku	Turku Artukainen	8	60,45	22,18
3	Satakunta	222 629	Pori	Pori Tahkoluoto satama	3	61,63	21,38
4	Kantahäme	174 516	Hämeenlinna	Hämeenlinna Lammi Pappila	125	61,05	25,04
5	Pirkanmaa	506 735	Tampere	Tampere Härmälä	85	61,47	23,75
6	Päijät-Häme	201 748	Lahti	Lahti Laune	78	60,96	25,63
7	Kymenlaakso	178 497	Kouvola	Kouvola Anjala	33	60,70	26,81
8	Etelä-Karjala	130 626	Lappeenranta	Lappeenranta lentoasema	105	61,04	28,15
9	Etelä-Savo	149 674	Mikkeli	Mikkeli lentoasema	101	61,69	27,21
10	Pohjois-Savo	247 666	Kuopio	Kuopio Maaninka	90	63,14	27,31
11	Pohjois-Karjala	164 443	Joensuu	Lieksa Lampela	98	63,32	30,05
12	Keski-Suomi	275 134	Jyväskylä	Jyväskylä lentoasema	138	62,40	25,68
13	Etelä-Pohjanmaa	192 516	Seinäjoki	Seinäjoki Pelmaa	26	62,94	22,49
14	Pohjanmaa	181 232	Vaasa	*	6	63,06	21,75
15	Keski-Pohjanmaa	69 057	Kokkola	Kokkola Tankar	5	63,95	22,84
16	Pohjois-Pohjanmaa	410 324	Oulu	Oulu Vihreäsaari satama	3	65,01	25,39
17	Kainuu	75 085	Kajaani	Kajaani lentoasema	132	64,28	27,67
18	Lappi	180 276	Rovaniemi	Rovaniemi rautatieasema	85	66,50	25,71
	Population total	**5 462 724**					

*****Due to missing observations: The weather station for Vaasa is Vaasa airport for the period 1.1.2005-31.12.2010 and Vaasa Klemettilä for the period 1.1.2011-31.12.2015.

	County	Population	Admin. center	Weather station	Elevation	Lat.	Lon.
Sweden							
1	Stockholm	2 231 439	Stockholm	Stockholm	44	59,34	18,06
2	Uppsala	354 164	Uppsala	Uppsala Aut	0	58,68	17,12
3	Södermanland	283 712	Nyköping	Oxelösund	13	59,86	17,63
4	Östergötland	445 661	Linköping	Malmslätt	16	58,40	15,53
5	Jönköping	347 837	Jönköping	Jönköpings Flygplats	223	57,75	14,07
6	Kronoberg	191 369	Växjö	Växjö A	199	56,85	14,83
7	Kalmar	237 679	Kalmar	Kalmar Flygplats	16	56,68	16,29
8	Gotland	57 391	Visby	Visby Flygplats	51	57,66	18,34
9	Blekinge	156 253	Karlskrona	Ronneby-Bredåkra	58	56,26	15,27
10	Skåne	1 303 627	Malmö	Malmö A	13	55,57	13,07
11	Halland	314 784	Halmstad	Varberg	15	57,11	12,27
12	Västra Götaland	1 648 682	Gothenburg	Göteborg A	23	57,72	11,99
13	Värmland	275 904	Karlstad	Karlstad Flygplats	107	59,44	13,34
14	Örebro**	291 012	Örebro	Karlstad Flygplats	107	59,44	13,34
15	Västmanland	264 276	Västerås	Västerås	15	59,60	16,60
16	Dalarna	281 028	Falun	Borlänge Flygplats	152	60,43	15,51
17	Gävleborg	281 815	Gävle	Gävle A	16	60,72	17,16
18	Västernorrland	243 897	Härnösand	Härnösand	8	62,63	17,95
19	Jämtland	127 376	Östersund	Frösön	376	63,20	14,49
20	Västerbotten	263 378	Umeå	Umeå Flygplats	7	63,79	20,29
21	Norrbotten	249 733	Luleå	Luleå Flygplats	17	65,54	22,12
	Population total	**9 851 017**					

****** No reliable data in Örebro’s county. Karlstad’s airport (Karlstad Flygplats) is the nearest weather station with reliable observations.

	County	Population	Admin. center	Weather station	Elevation	Lat.	Lon.
Norway							
1	Østfold	289 867	Sarpsborg	SARPSBORG	57	59,29	11,11
2	Akershus	594 533	Oslo***	OSLO - BLINDERN	94	59,94	10,72
3	Oslo	658 390	Oslo	OSLO - BLINDERN	94	59,94	10,72
4	Hedmark	195 356	Hamar	DREVSJØ	672	61,89	12,05
5	Oppland	188 953	Lillehammer	LILLEHAMMER - SÆTH-ERENGEN	240	61,09	10,48
6	Buskerud	277 684	Drammen	DRAMMEN - BERSKOG	8	59,75	10,12
7	Vestfold	244 967	Tønsberg	MELSOM	26	59,23	10,35
8	Telemark	172 494	Skien	GVARV - NES	93	59,38	9,21
9	Aust-Agder	115 785	Arendal	GVARV - NES	93	59,38	9,21
10	Vest-Adger	182 701	Kristiansand	OKSØY FYR	9	58,07	8,05
11	Rogaland	470 175	Stavanger	SOLA	7	58,88	5,64
12	Hordaland	516 497	Bergen	BERGEN - FLORIDA	12	60,38	5,33
13	Sogn og Fjordane	109 530	Leikanger	FURENESET	7	61,29	5,04
14	Møre og Rømsdal	265 290	Molde	MOLDE LUFTHAVN	3	62,74	7,26
15	Sør-Trøndelag	313 370	Trondheim	TRONDHEIM - VOLL	127	63,41	10,45
16	Nord-Trøndelag	136 399	Steinkjer	STEINKJER - SØNDRE EGGE	6	64,02	11,45
17	Nordland	241 906	Bodø	BODØ VI	11	67,27	14,36
18	Troms Romsa	164 330	Tromsø	TROMSØ	100	69,65	18,94
19	Finnmark	75 758	Vadsø	VADSØ LUFTHAVN	39	70,07	29,84
	Population total	**5 213 985**					

APPENDIX 4. Robustness analysis of quantile regression analysis of the spot price. Temperature deviation factor omitted.

Quantile	0,01	0,05	0,1	0,15	0,2	0,25	0,3	0,35	0,4	0,45	0,5	0,55	0,6	0,65	0,7	0,75	0,8	0,85	0,9	0,95	0,99
c	-0,0092	0,6339	-0,7163	-0,8321	-0,7047	-0,3477	-0,0047	0,2310	0,2557	0,3391	0,6363	0,7947	0,8280	1,2169	1,2284	1,5497	1,9241	2,3300	3,3017	4,7468	3,0948
t-statistics	(-0,01)	(1,26)	(-1,45)	(-2,79) ***	(-2,44) **	(-1,16)	(-0,02)	(0,88)	(0,94)	(1,24)	(2,29) **	(2,65) ***	(2,59) ***	(3,84) ***	(3,76) ***	(4,28) ***	(3,96) ***	(2,94) ***	(4,03) ***	(4,02) ***	(1,20)
Lagged spot_t-1	0,6244	0,7491	0,8033	0,8316	0,8324	0,8460	0,8522	0,8507	0,8487	0,8363	0,8282	0,8255	0,8180	0,8073	0,8052	0,7902	0,7870	0,7657	0,7521	0,7652	0,7775
t-statistics	(24,94) ***	(44,81) ***	(56,37) ***	(67,89) ***	(52,95) ***	(46,83) ***	(48,67) ***	(60,42) ***	(61,85) ***	(51,32) ***	(55,55) ***	(60,68) ***	(59,68) ***	(68,31) ***	(79,28) ***	(72,50) ***	(66,40) ***	(60,77) ***	(31,95) ***	(27,47) ***	(13,72) ***
Lagged spot_t-7	0,1901	0,1509	0,1288	0,1146	0,1143	0,1052	0,1056	0,1118	0,1126	0,1238	0,1287	8,3742	0,1329	0,1389	0,1380	0,1483	0,1489	0,1639	0,1720	0,1530	0,2158
t-statistics	(7,42) ***	(17,93) ***	(14,86) ***	(13,29) ***	(8,48) ***	(6,82) ***	(6,55) ***	(8,59) ***	(8,41) ***	(7,59) ***	(8,25) ***	(0,13)	(8,76) ***	(11,10) ***	(12,95) ***	(11,72) ***	(9,54) ***	(14,43) ***	(8,77) ***	(7,77) ***	(2,65) ***
Water Deviation Nordics	-0,2049	-0,0667	-0,0538	-0,0434	-0,0507	-0,0425	-0,0377	-0,0326	-0,0332	-0,0389	-0,0385	-4,1104	-0,0470	-0,0473	-0,0481	-0,0525	-0,0605	-0,0773	-0,0879	-0,1182	-0,0766
t-statistics	(-3,70) ***	(-3,24) ***	(-3,35) ***	(-3,55) ***	(-5,32) ***	(-4,33) ***	(-3,69) ***	(-3,21) ***	(-3,29) ***	(-3,79) ***	(-3,76) ***	(-0,04)	(-4,33) ***	(-4,44) ***	(-4,64) ***	(-4,80) ***	(-4,57) ***	(-4,40) ***	(-4,43) ***	(-3,88) ***	(-0,71)
Nordic temperature	-0,0735	-0,0320	-0,0264	-0,0287	-0,0364	-0,0339	-0,0344	-0,0315	-0,0339	-0,0403	-0,0429	-8,5991	-0,0528	-0,0601	-0,0641	-0,0673	-0,0677	-0,0716	-0,0918	-0,1133	-0,2669
t-statistics	(-0,87)	(-1,25)	(-1,63)	(-2,27) **	(-3,82) ***	(-4,25) ***	(-4,81) ***	(-4,93) ***	(-5,55) ***	(-6,92) ***	(-7,96) ***	(-0,05)	(-8,90) ***	(-9,60) ***	(-10,31) ***	(-10,01) ***	(-7,56) ***	(-6,31) ***	(-6,39) ***	(-5,34) ***	(-2,91) ***
Oil	0,0031	0,0010	0,0003	0,0008	0,0010	0,0010	0,0007	0,0002	0,0004	0,0005	0,0004	1,0212	0,0008	0,0005	0,0008	0,0008	0,0005	0,0001	-0,0007	-0,0011	-0,0006
t-statistics	(0,47)	(0,61)	(0,25)	(1,29)	(1,97) **	(2,22) **	(1,57)	(0,57)	(1,02)	(1,11)	(0,91)	(0,00)	(1,66) *	(1,18)	(1,76) *	(1,54)	(0,78)	(0,11)	(-0,49)	(-0,68)	(-0,07)
Coal	-0,0229	-0,0106	0,0021	0,0012	0,0030	0,0026	0,0023	0,0033	0,0045	0,0053	0,0066	4,0344	0,0079	0,0102	0,0111	0,0121	0,0149	0,0194	0,0233	0,0276	0,0437
t-statistics	(-0,90)	(-1,66) *	(0,43)	(0,45)	(1,30)	(1,13)	(1,05)	(1,69) *	(2,29) **	(2,78) ***	(3,69) ***	(0,01)	(4,24) ***	(5,27) ***	(5,88) ***	(5,77) ***	(5,65) ***	(5,32) ***	(3,49) ***	(4,10) ***	(1,28)
LNG	0,0091	0,0028	0,0022	0,0022	0,0019	0,0016	0,0012	0,0011	0,0009	0,0012	0,0009	1,8614	0,0012	0,0009	0,0012	0,0012	0,0010	0,0015	0,0021	0,0021	0,0076
t-statistics	(1,99) **	(2,20) **	(2,38) **	(5,25) ***	(4,81) ***	(3,92) ***	(3,00) ***	(2,77) ***	(2,20) **	(2,79) ***	(2,06) **	(0,00)	(2,08) **	(1,69) *	(2,30) **	(2,24) **	(1,48)	(1,35)	(1,99) **	(1,74) *	(0,70)
Vix	-0,0702	0,0322	0,0226	0,0221	0,0251	0,0177	0,0107	0,0052	0,0082	0,0067	0,0084	1,2977	0,0127	0,0160	0,0191	0,0217	0,0191	0,0127	0,0015	0,0164	-0,0047
t-statistics	(-2,00) **	(1,48)	(1,25)	(1,76) *	(2,56) **	(1,98) **	(1,31)	(0,69)	(1,03)	(0,80)	(0,93)	(0,01)	(1,46)	(1,93) *	(2,26) **	(2,44) **	(1,83) *	(0,74)	(0,05)	(0,80)	(-0,05)
Oil Vix	-0,0012	-0,0285	-0,0165	-0,0109	-0,0085	-0,0055	-0,0041	-0,0028	-0,0032	-0,0010	-0,0029	-0,7363	-0,0025	-0,0070	-0,0051	-0,0071	-0,0079	-0,0046	0,0015	0,0025	0,0684
t-statistics	(-0,03)	(-2,57) **	(-2,22) **	(-2,31) **	(-1,95) *	(-1,39)	(-1,07)	(-0,78)	(-0,89)	(-0,26)	(-0,74)	(-0,00)	(-0,60)	(-1,61)	(-1,14)	(-1,46)	(-1,31)	(-0,51)	(0,10)	(0,13)	(1,21)
Ted-spread	0,0336	0,0052	0,0002	-0,0014	-0,0036	-0,0030	-0,0018	-0,0013	-0,0015	-0,0016	-0,0013	-0,0009	-0,0019	-0,0010	-0,0021	-0,0013	-0,0008	-0,0010	0,0000	-0,0041	-0,0300
t-statistics	(3,08) ***	(0,68)	(0,04)	(-0,50)	(-1,68) *	(-1,37)	(-0,91)	(-0,78)	(-0,98)	(-1,06)	(-0,87)	(-0,60)	(-1,29)	(-0,69)	(-1,38)	(-0,62)	(-0,38)	(-0,34)	(0,01)	(-0,84)	(-2,12) **
Weekend dummy	-4,9258	-2,2355	-1,8722	-1,6782	-1,5431	-1,4673	-1,4239	-1,4026	-1,4094	-1,4518	-1,4051	-1,4404	-1,4821	-1,6289	-1,7972	-1,9139	-2,0919	-2,4504	-2,9555	-3,9811	-5,3995
t-statistics	(-4,23) ***	(-5,97) ***	(-9,42) ***	(-11,67) ***	(-12,45) ***	(-14,19) ***	(-15,63) ***	(-16,85) ***	(-16,98) ***	(-17,02) ***	(-17,03) ***	(-17,90) ***	(-18,46) ***	(-20,42) ***	(-22,35) ***	(-21,90) ***	(-19,73) ***	(-17,14) ***	(-13,35) ***	(-12,19) ***	(-3,89) ***
Pseudo R-squared	**0,6385**	**0,7286**	**0,7539**	**0,7689**	**0,7800**	**0,7883**	**0,7946**	**0,7999**	**0,8041**	**0,8076**	**0,8107**	**0,8134**	**0,8158**	**0,8171**	**0,8177**	**0,8166**	**0,8133**	**0,8088**	**0,8027**	**0,7844**	**0,7323**
Adjusted R-squared	**0,6375**	**0,7278**	**0,7532**	**0,7683**	**0,7794**	**0,7877**	**0,7940**	**0,7993**	**0,8035**	**0,8070**	**0,8101**	**0,8129**	**0,8153**	**0,8166**	**0,8172**	**0,8161**	**0,8128**	**0,8082**	**0,8022**	**0,7838**	**0,7316**