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Empirical Studies of Spot- and Futures Prices in the Nordic Energy Market

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Abstract

The Nordic Energy Market is introduced and its characterizations discussed. Descriptive analysis of spot- and futures prices has been performed and the results have further been used in order to uncover forecast errors, basis risk and seasonal trends. Additionally the N02 area price has been compared to the unconstrained system price, aiming to explore the potential of cross hedging through short-term futures contracts.

The relationship between spot prices and short-term futures contracts showed forecast errors of 2,1%, 9,2% and 11,6%, respectively for weekly contracts in one-, four-, and six-week holding periods throughout the period 2007-2012. Nevertheless, the futures price is found to be the best estimate for the future spot price in a one-week horizon, but the six-week prediction was improved by including additional historical price information.

It is found likely that the forecast errors are a result of a net-long demand from consumers, creating negative risk premiums. Unique market- and commodity characterizations provide asymmetric flexibility between producers and consumers. Further, we find the electricity price to be extremely volatile with annualized weekly changes of 110% and with frequent values far beyond this. Combined with positive skewness, these price properties could

contribute to amplify the imbalance in the market. A pitfall was uncovered when the forecast errors were interpreted as risk premiums. There was an unexpected deviation between the results from the forecast error equation and results from the equation of the Theory of Risk Premium. This must be taken into account when comparing different studies on this topic.

Due to hydro dominance in the market, the Theory of Storage was successfully interpreted to the empirical results. We found the market to exhibit Contango, showing negative net-convenience yield, throughout most of the year. However, the size of the risk premium was not found to be dependent of the futures curve, nevertheless increasing with rising price level.

At last, we found the N02 area price to be almost exclusively below the system price. This could give producers in such areas incentives to take short-positions in futures contracts. Simple cross hedging methods gave variance reduction of around 50%, but the basis risk was still substantial. However, both the skewness and the extreme values indicate that the upside of spot exposure is minimal. Hence, the risk of lost upside through hedging is negligible.

Preface

This thesis completes my Master of Science in Industrial Economics, with specialization in Risk- and Contract management, at the University of Stavanger.

In that occasion, I wanted to expand my knowledge of energy-economics and especially the Nordic energy market. Energy-economics and energy in general, is an important issue worldwide, and an important industry for Norway.

The topic has opened me to a market and its financial products, which I personally had minimal knowledge of in advance. I have found theory and tools from our syllabus useful and stimulating to use in a more virtual and realistic setting. These are in particular the Statistical and econometric techniques. Additionally have my spreadsheet skills been developed, and I have been introduced to the software EViews and XLSTAT.

The process has been challenging and engaging from start to end. I hope my work is found to be contributive in order to understand the mechanisms of the Nordic power market, and form a basis for further studies.

I would like to thank my supervisor Roy Endrè Dahl, first of all for guiding me towards this topic, which has proven to be very educational, and further for being helpful and supporting throughout the writing period. Thanks also to Lyse AS, with Odd-Bjarte Nilsen for providing me price data.

Further I want to thank Simen Kleven Rasmussen and Andreas Fiskerstrand for giving honest feedback and performing correction with great passion. Christian Osnes is always supportive and helping me out with illustrations. And a special thanks to my beloved Synnøve Ekremsæter for being supportive and simply for being the one she is.

Stavanger, 17.06.2013

Joakim Svoren Årvik

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1 Introduction

Few other prices are subject to more attention in the media than the electricity prices. That said, few other commodities have characteristics that complicate the conditions for a well-functioning, balanced market with symmetrical flexibility between the producers and the consumers in such a way as electricity. The environment-friendly hydro-dominance in the Nordic energy market brings lots of benefits, but there are also aspects to the price formation that are unique, even for an energy market. Not only is the Nordic energy market one of the most complicated, it is also considered one of the most successful through the introduction of Nord Pool Spot for organizing trade of electricity. Nevertheless, previous studies like Gjølberg & Brattestad (2011) and Botterud, Kristiansen, & Ilic (2010), have found the short-term futures contracts prices to be biased predictors of the future spot prices.

Throughout this thesis, the characterizations and mechanisms of the Nordic energy market will be presented, discussed and analyzed with focus on the relationship between the spot- and futures prices. In that case, the following important questions will be tried answered:

- What makes the Nordic energy market so challenging regarding the matter of price-formation and -expectations, and how are these challenges solved?
- How are Nordic spot- and futures prices of electricity reflecting the market they are a result of?
- Are the short-term futures prices really biased predictors of the future spot price, and if so, can the forecast errors and basis risk be interpreted through the Theory of Risk Premium and the Theory of Storage, respectively?
- Does the characterizations of the relationship between the area prices and the system price give incentives for hedging, and if so, how can this be performed and with what effect?

1.1 Overview of the Thesis

Based on these questions, the Nordic energy market will be introduced and discussed through background theory. Historical prices will further be used to analyze the properties of the spot- and futures prices. Then, the relationship between these prices will be investigated, mainly through regression analysis. Potential seasonal trends and deviations between the different spot prices will be analyzed and we look at the effects of hedging. At last we will present and discuss the findings and compare them to our expectations based on the background theory.

In order to understand the mechanisms of the Nordic energy market, a quite thorough introduction of the market is included. The underlying main theory is presented in Chapter 2, 3 and 4.

Chapter 2 defines the Nordic Energy Market, what is special about this market and how it is structured. In Chapter 3 the general theory of derivatives is presented, ending the Chapter with describing the characteristics of the specific financial market at Nord Pool.

The presentation of theoretical background ends with Chapter 4, where general theory of price determination and two different theories for calculating the future spot price are discussed. Most studies of the relationship between spot and futures prices in the electricity market are based on the Theory of Risk Premium. But as the Nord pool market is characterized by a high share of hydro power with large reservoirs, arguments for use of the Theory of Storage are also presented. In Chapter 5, the background theory is discussed with respect to the characteristics of the Nordic Energy Market.

In Chapter 6, the methods which will be used in the empirical part of the thesis will be introduced. These include parametric tests, OLS regression and special time series analysis.

In addition to laying the foundation for further analysis, Chapter 7 describes both the historical spot prices and the historical futures contracts prices.

Chapter 8 builds on the general theory presented in Chapter 4, in order to derive models for further empirical analysis. These results are then presented in the following Chapter. In Chapter 10 the results so far are subject to seasonal analysis and comparison between the system price and the area prices.

Chapter 11 highlights the potential of hedging based on the results from previous sections, and introduces some theory behind hedging. Hedging analysis and results are presented and discussed in chapter 12.

At last Chapter 13 includes a discussion of the results and compares them to the theory that has been presented. The conclusion in Chapter 14 will then summarize and evaluate the thesis and present suggestions for further work.

1.2 Scope of the Thesis

This thesis is focused on the Nordic energy market, which includes Norway, Sweden, Finland and Denmark. Especially the Norwegian part of the market will be studied, due to availability of data. Even though the markets of Nord Pool Spot keep expanding to different areas, like the Baltic area, this is not the focus in this thesis.

We define the energy market as the electrical market. Although oil and gas are mentioned as fossil fuels used to produce electrical power, these are outside the scope of what is meant by the energy market.

2 The Nordic Energy Market

Compared to other parts of Europe, and the rest of the world, the Nordic energy market[1] stands out, in terms of both production and consumption.

Nordic consumers are some of the most energy consuming in the World, as Figure 2.1 displays, with all of the four Nordic countries among the top six per capita, worldwide. Furthermore, the share of energy consumption coming from electricity is high, especially in Norway and Sweden. This can be explained through a relatively low electricity price per kw/h[2] compared to other countries, along with a more developed infrastructure for transmission of electricity (SSB, 2011).

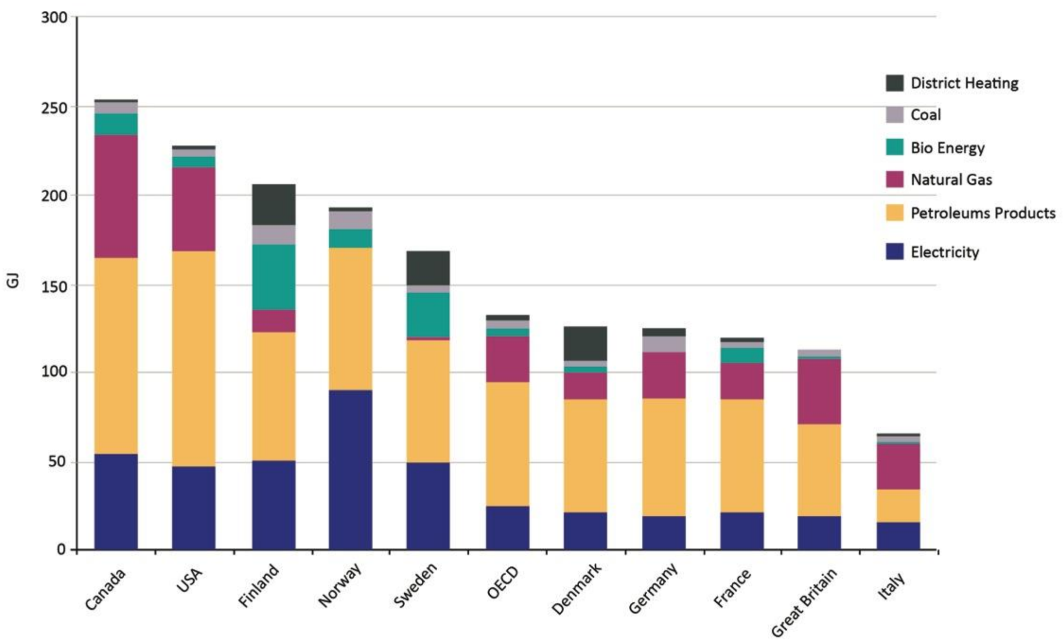


Figure 2.1 ENERGY CONSUMPTION PER CAPITA IN OECD-COUNTRIES 2002: Translated from source: (Regjeringen, 2006)

While Nord Pool Spot is responsible for organizing the Nordic market, and the trade[3] of electricity, *Statnett* is the owner, operator and regulator of the Norwegian main grid[4]. Ownership implies responsibility of transmitting and distributing electricity in Norway. From

[1] The Nordic energy market consists of Norway, Sweden, Finland and Denmark.
[2] Income adjusted.
[3] Restricted to physical trade since the trade of derivatives was sold to NASDAQ OMX Commodities in 2010.
[4] The Norwegian electricity grid is divided into three levels; main grid, regional grid and distribution grid (Statnett.no)

the countrywide production to the consumers, so that production meets the demand for electricity at any time. Similar, Sweden have *Svenska Kraftnät*, Finland have *Fingrid Oyj* and Denmark have *Energinet.dk*, as their respective system operators (Nordpoolspot, 2013a).

Like many other commodities, the Nordic electricity price is characterized by its high volatility. However, few, if any, commodities experience such extreme volatility values as the electrical prices from hydro dominated energy markets. Figure 2.2 displays the weekly price change of the three commodities Gold, Crude Oil and the Nordic system price. The annualized weekly volatility is respectively 20%, 40% and 110%. Gold and electricity can be considered two extremities of commodities, where physical trade of gold is mainly for insurance reasons while physical trade of electricity is exclusively for consumption. A following section about energy sources will further highlight the reason for the high volatility in the electricity prices, from a supply point of view.

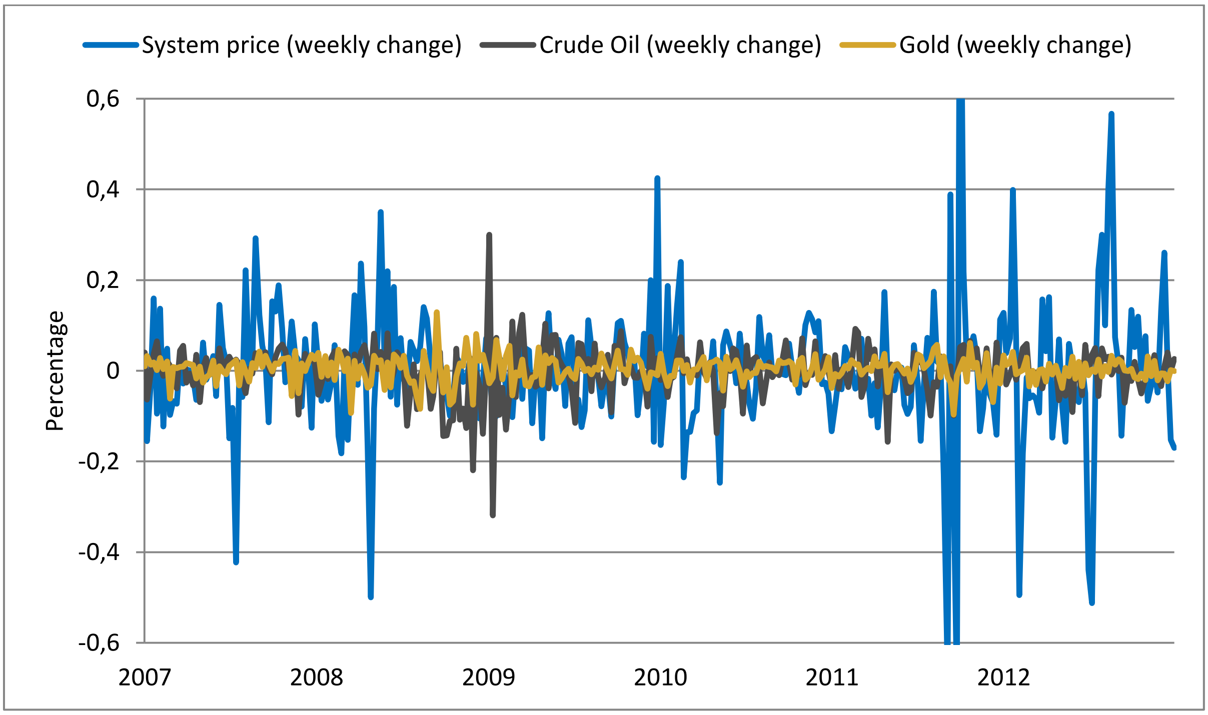


Figure 2.2 COMPARISION OF COMMODITY VOLATILITY: Weekly volatility of Gold, Crude Oil and the Nordic system price 2007-2012. Sources: Lyse AS for system prices. SPDR (GLD) ETF NYSEArca (Yahoo Finance, 2013a), Ipath S&P GSCI Crude Oil TR Index ETN (OIL) NYSEArca (Yahoo Finance, 2013b).

2.1 Regulations

The Nordic electricity market has been subject to significant regulatory developments the last decades. Regulatory challenges arises from the organization of a social rational energy market that safeguards the interests of the environment and the security of supply, in a national-, Nordic- and European perspective (UIO, 2012).

In 1991 Norway regulated their energy market and created Nord Pool Spot. Since then, the other Nordic countries have regulated their markets and have been included in the regulated market of Nord Pool.

Until the 1st of January 1991, local energy producers in Norway had a monopoly on serving the consumers within their area with electricity, resulting in highly fluctuating prices across the country. The introduction of regulations in the energy market has led to price equalization through competition and market transparency, and made the Norwegian, and furthermore the Nordic market, an integrated market with a high degree of price influence between areas. A thorough national juristic framework was developed, concerning planning, development and operation of production plants, transmission infrastructure and management of the water resources, aiming to secure public interests, like biodiversity, tourism, hunting and fishing (OED, 2013a). The result was the Energy Act of June 1990 that covers production, transformation, transmission, turnover, distribution and use of energy in Norway, serving to secure that this takes place in a social and rational way, considering public and private interest affected (enl.§1-1, 1990). The other Nordic countries have their own similar juristic framework, but the common factor is that they are all based on the frameworks of The Single European Act which was implemented in the Nordic countries at the time, through the EES agreement.

Figure 2.3 illustrates the Norwegian organization of the energy and water resource activities. The Norwegian Water Resources and Energy Directorate (NVE), is responsible for regulating Nord Pool Spot.

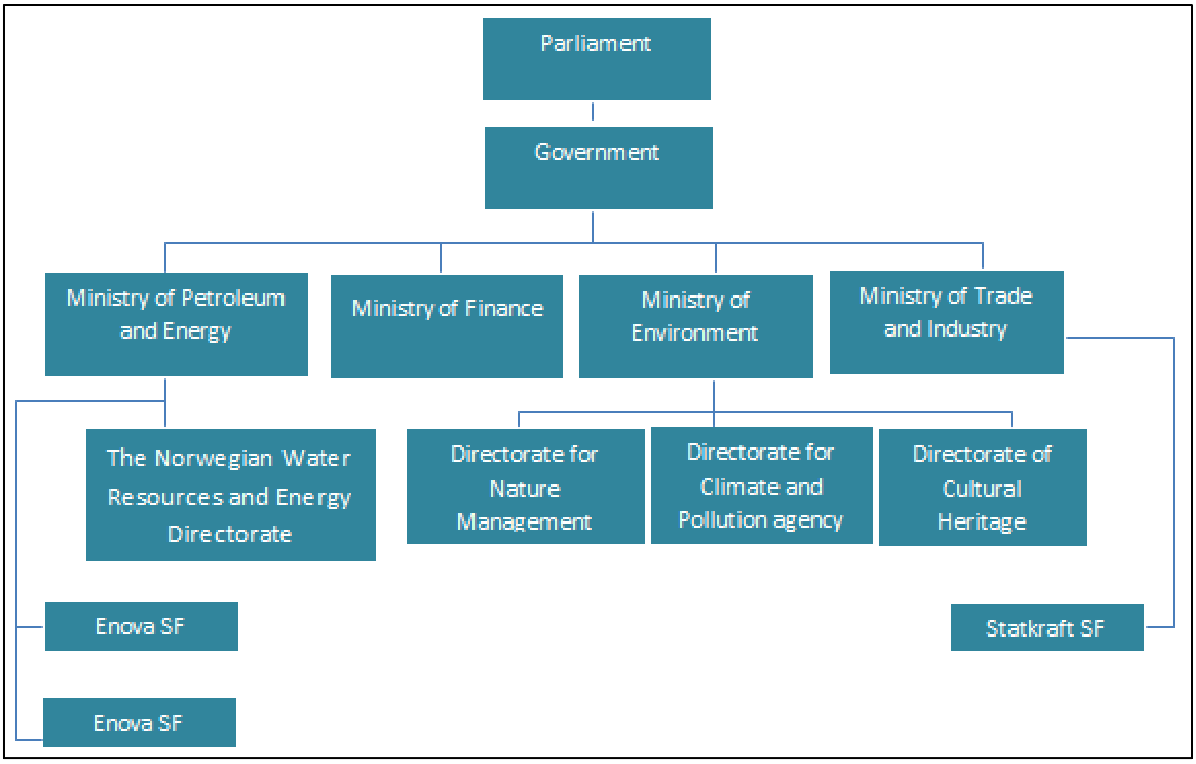


Figure 2.3 ORGANIZATION OF THE NORWEGIAN ENERGY AND WATER RESOURCE ACTIVITIES; translated from source: (NVE, Annual Report, 2011).

At present Nord Pool Spot is the only entity that has been granted license, to operate and organize a marketplace for trading physical electricity, by the NVE. In addition, Nord Pool Spot is also licensed for cross border power exchange issued by the Ministry of Petroleum and Energy (NVE, 2011). NVE splits the players in the Norwegian power sector into five main groups:

- Generation; generator
- Transmission; transmission system operator (TSO), e.g. Statnett SF
- Distribution; distribution system operator (DSO)
- Supply; supplier
- Power exchange; Nord Pool Spot

The different groups of players are given different obligations by NVE, both economic- and direct- obligations. This thesis will focus on the Suppliers, but since many suppliers also are DSO's, their main obligations will also be included. Most importantly, a power producer must be licensed to start production, and it is these licenses that carry the obligations.

The overall objective of economic regulation is to ensure a socioeconomic efficient power system through enabling an effective power market and effective management, utilizing and developing the electricity network. An important economic regulation is revenue caps (NVE, 2011), which limits the capitalist behavior. Of direct obligations, licensed producers are obligated to produce energy within the geographical area for which the license covers, and make unused transmission capacity available to others (NVE, 2009)[5].

2.2 Energy Sources

Electricity is different from most other commodities as it cannot be stored[6], furthermore is electricity, as a commodity, a result of a regeneration of fossil fuels, renewables like wind and solar, hydro production or nuclear production.

The Nordic power is generated from *hydro*, *wind*, *nuclear* and *thermal* power based on coal, oil, gas and biofuels. Total generation in the Nordic countries was 373 TWH in 2010, while the total consumption was 390 TWH (NordReg, 2011). Figure 2.4 displays the total Nordic production capacity per country and per production source for 2010. More than half of the installed capacity for power production in the Nordic market comes from renewable power sources, and hydropower alone stands for 50% of the total capacity. Virtually all of the Norwegian production and half of the Swedish production come from hydropower. Landscape and climate, especially in Norway with large rivers and high mountain-drops to sea level, combined with relative high precipitation, makes such a high share of hydropower production possible.

[5] The obligations following the licenses could be basis for further work proposed at the end of this thesis.
[6] Storing is only possible for small amounts of energy (batteries), but not effectively for larger amounts.

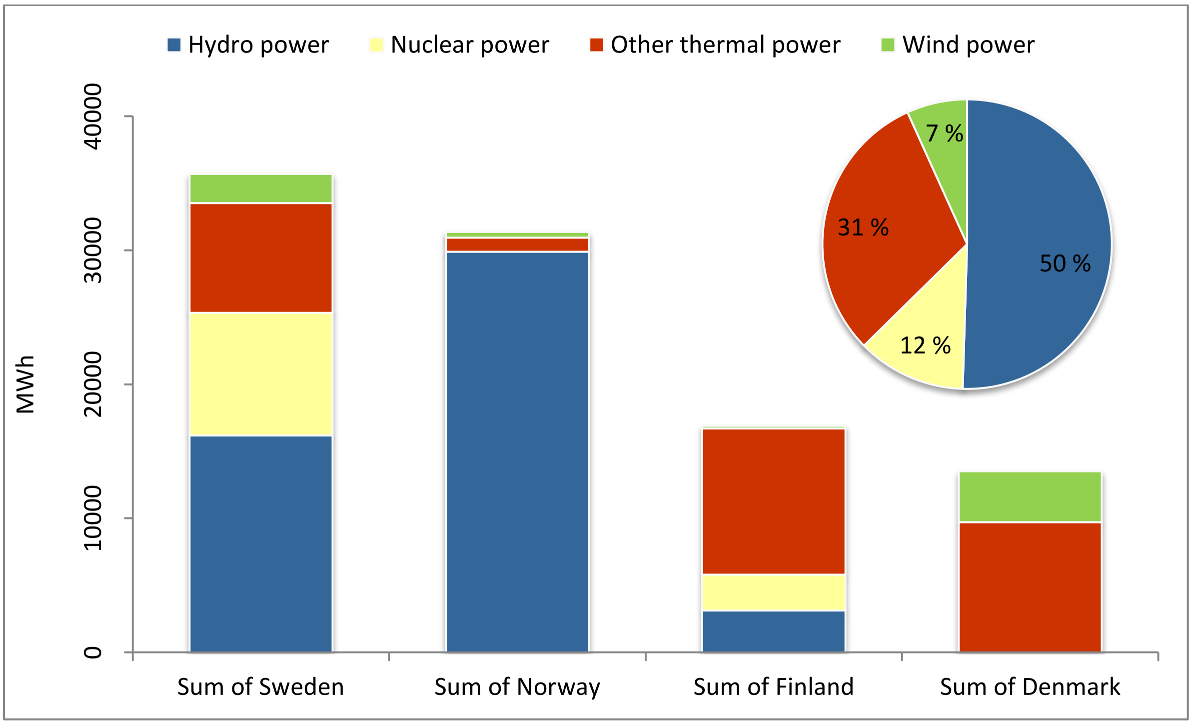


Figure 2.4 NORDIC POWER GENERATION CAPACITY: per country in bars (MW/h) and per production type in pie diagram (2010). Source: data from (NordReg, 2011).

The total of other thermal power sources stands for 31% of total generation capacity and is thereby the second largest power source in the Nordic market. Nuclear power production, located in Sweden and Finland, then follows with a share of 12%, while wind power accounts for about 7%. Note that wind power production has had a considerable increase the recent years. This development is visualized in Figure 2.6.

Figure 2.5 compares the Nordic production sources in terms of cost and profit. Note that there is a spread in production cost and that the graph illustrates a typical situation (Nordpoolspot, 2012a). By clear margin, hydropower has got the lowest marginal cost. When the reservoirs decrease the electricity will increase and more of the production sources will become profitable.

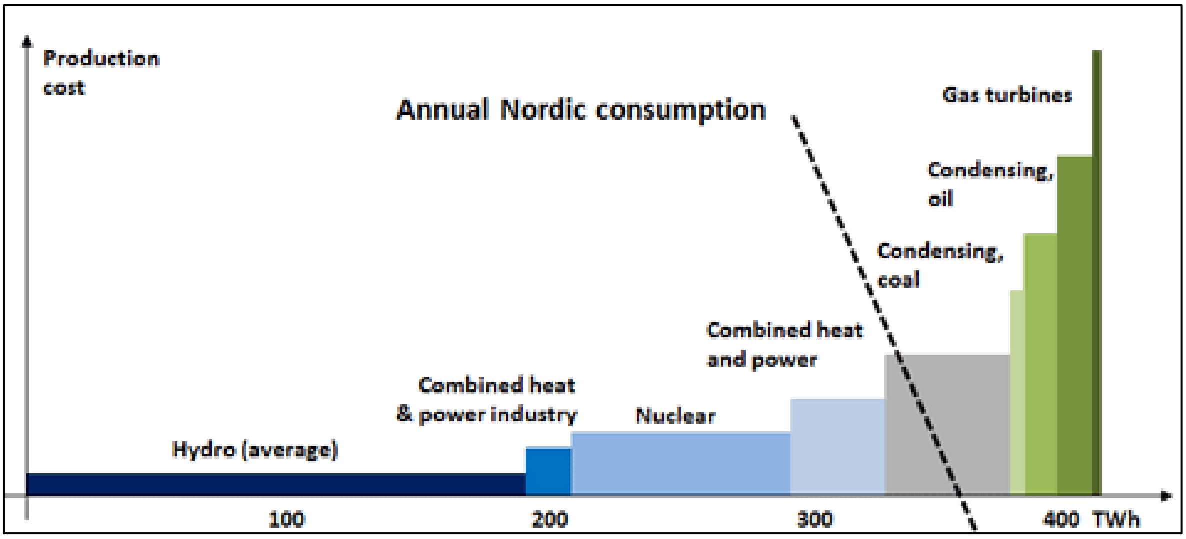


Figure 2.5 NORDIC CONSUMPTION AND PRODUCTION COST PER PRODUCTION SOURCE. Source: (Nordpoolspot, 2013b)

By combining the Nordic countries into one transmission grid through cables, it is easier to adjust production to both meet demand, and unexpected problems with the supply. It facilitates better utilization of the properties in each production source.

Hydropower is unique, as water can be stored in reservoirs until used for production of electricity. Compared to nuclear power production and other thermal power, hydropower production does not require long and expensive start-up time, since water valves can be opened and closed immediately, and thereby adjust the production almost free of charge.

However, hydropower production is highly dependent on precipitation. This results in high season variations in production capacity, since reservoir levels are higher during spring and summer, than during the winter. Other production sources (except wind power) have the advantage that they through long-term planning give predictable production over time and thereby can cover up for a decline in production from water power, when the reservoirs are low. Figure 2.6 displays how the production from the different sources has varied through the recent years. The total production exhibits a clear seasonal trend with a peak during mid-winter (Jan-Mar) and bottom during summer (Jul-Aug).

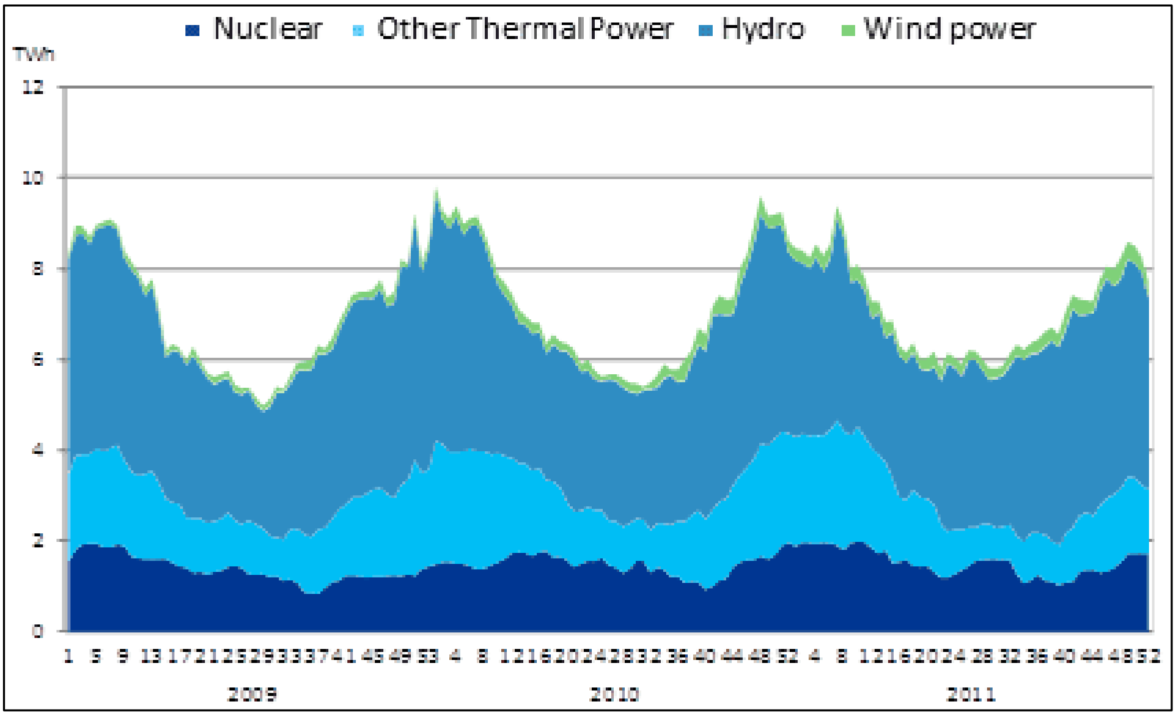


Figure 2.6 NORDIC PRODUCTION PER TYPE 2009-2011. Source: (Nordpoolspot, 2013b)

Although a combination of different sources both reduce price volatility and provide backup if critical situations occur, the effect of this is not fully utilized because of the congestions in transmission capacity between different geographical areas. This issue will be discussed later in the thesis.

2.3 Nord Pool Spot

Nord Pool Spot's function is to provide liquid, secure power markets, provide accurate information to the whole market, ensure transparency, and provide equal access to the market for everyone wanting to trade power and to be the counterparty for all trades, guaranteeing settlement and delivery (Nordpoolspot, 2012b). **Error! Reference source not found.** place Nord Pool Spot in the physical Nordic power market.

Nord Pool Spot was actually the world's first market for trading power, and is today the largest market of its kind (Nordpoolspot, 2013c). Since its start up in 1993 and further development, Nord Pool Spot has established itself as the only liquid spot- and financial-market for electricity in the Nordic countries. Today, the physical trade of electricity in the

Nordic market is organized through Nord Pool Spot, while the trade of derivatives was sold in 2010 and is done through NASDAQ OMX Commodities[7].

Norway was as mentioned the first member of Nord Pool Spot, and was followed by Sweden, Finland and at last Denmark at the turn of the millennium. It is owned by the Nordic and Baltic system operators, with shares as illustrated in Figure 2.7, and is regulated by the Norwegian Water Resources and Energy Directorate (NVE).

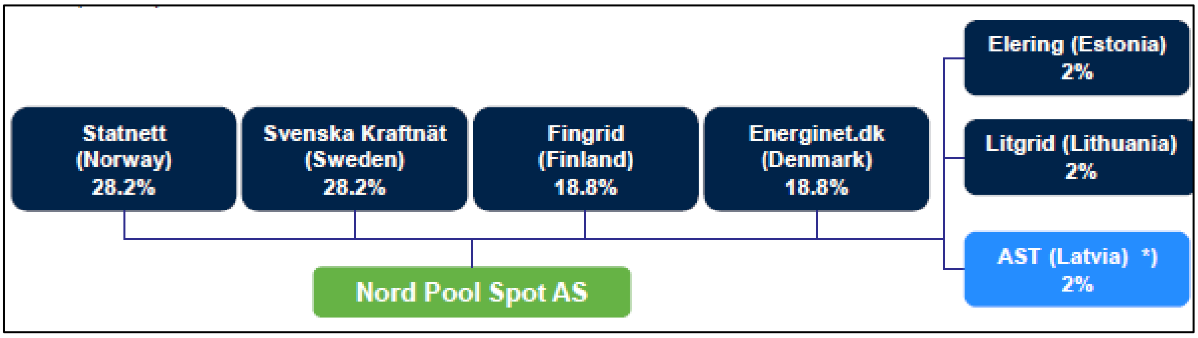


Figure 2.7 NORD POOL SPOT STAKEHOLDERS. Source: (Nordpoolspot, 2012b)

370 companies from 20 countries trade on Nord Pool Spot, and in 2012 the turnover was 432 TWH (Nordpoolspot, 2013a). Figure 2.8 displays the development of the Elspot volume since 1996. Per 2010, *Vattenfall* was the largest energy generator in the Nordic region with 18,4% of the total generation, followed by *Statkraft* (13%), *Fortum* (12,7%) and *E.ON* (7,3%) (NordReg, 2011).

[7] Note that the financial markets also are called Nord Pool. www.nordpool.com directs you to the NASDAQ OMX websites.

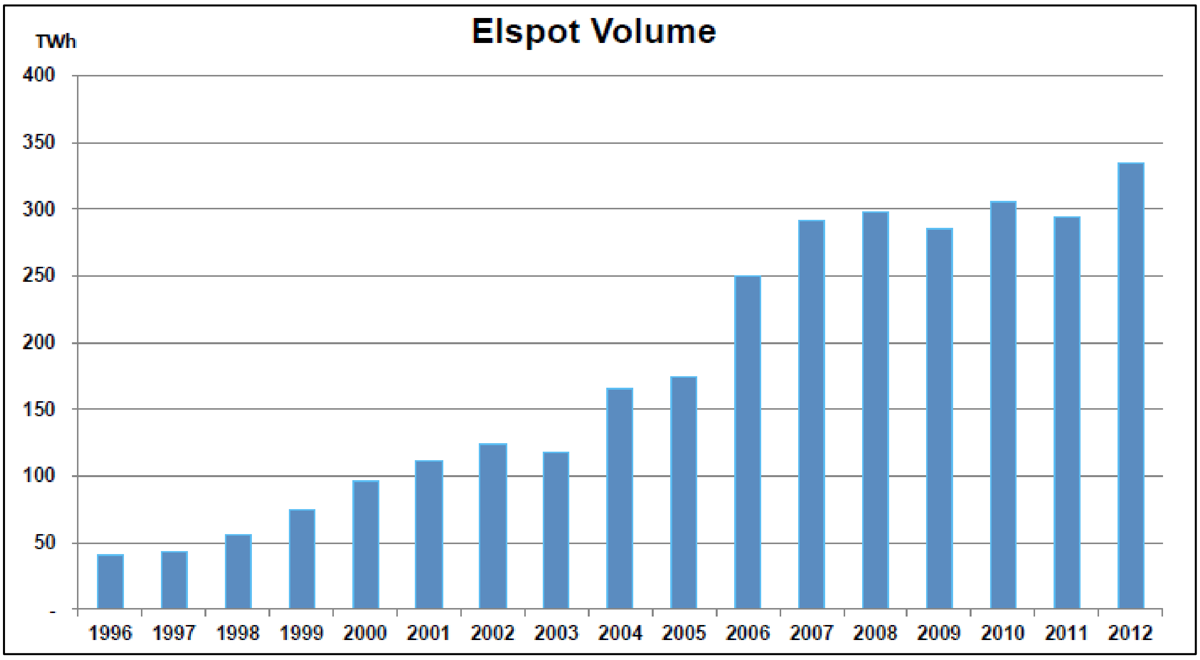


Figure 2.8 ELSPOT VOLUME: 1996-2012 (TWh). Source: (Nordpoolspot, 2012b)

Nord Pool Spot is responsible for organizing the Nordic energy market, but it is the TSO's that divide the market into separate bidding areas. These are illustrated in Figure 2.9. Norway is divided into the geographical price areas N01-N05, Sweden into SE1-SE4, Denmark into DK1-DK2, while Finland has no in-country domestic borders.

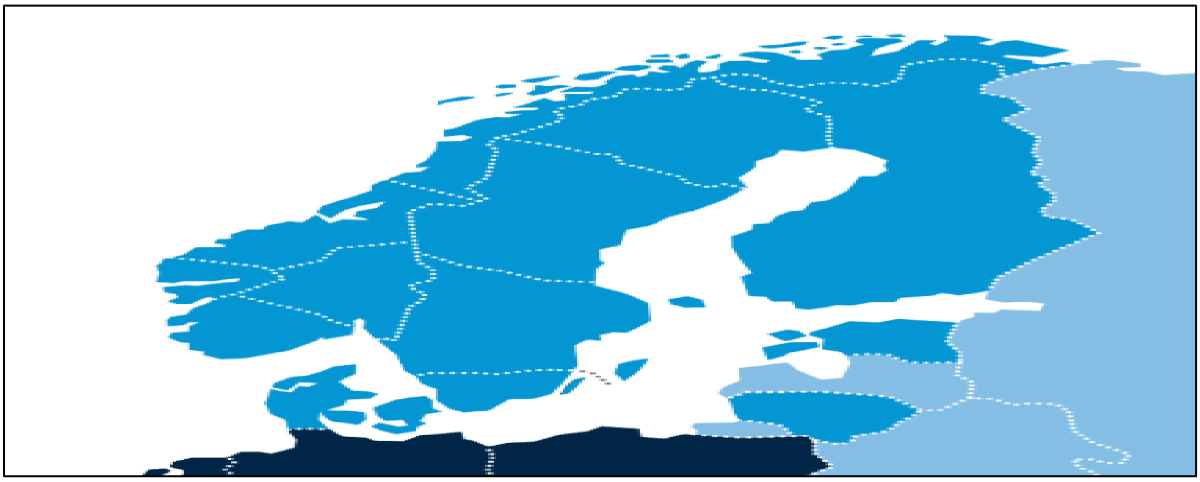


Figure 2.9 ELSPOT BIDDING AREA MARKET OVERVIEW 2013. Source: (Nordpoolspot, 2013d)

The price of electricity in these areas will differ from the system price, which is a common unconstrained price for the entire Nordic market set by Nord Pool Spot through supply and demand. The Nordic Energy market is balanced, combining the financial markets, the day-ahead market, the intraday market and the system operator's final adjustments, to ensure a supply and frequency in the power grid that secures supply and meet the demand. The areas are made to equalize differences in supply and demand due to constraints between geographical areas, for instance capacity and cost of transmission since electricity is dependent of a power grid to exhibit physical consumption. For a characterization of technical electricity networks, see Kirchhoff's law (Hogan, 1992). Each area has unique prices that deviate from the system price if the planned power flow exceeds the transmission capacity between two areas. These are the so-called area prices. A more detailed discussion of the price determination and the factors involved will follow. Since this thesis will investigate the relationship between the system price and specific area prices, one must keep in mind that the area definition is not final. Figure 2.10 illustrates the former changes of the Norwegian area definition.

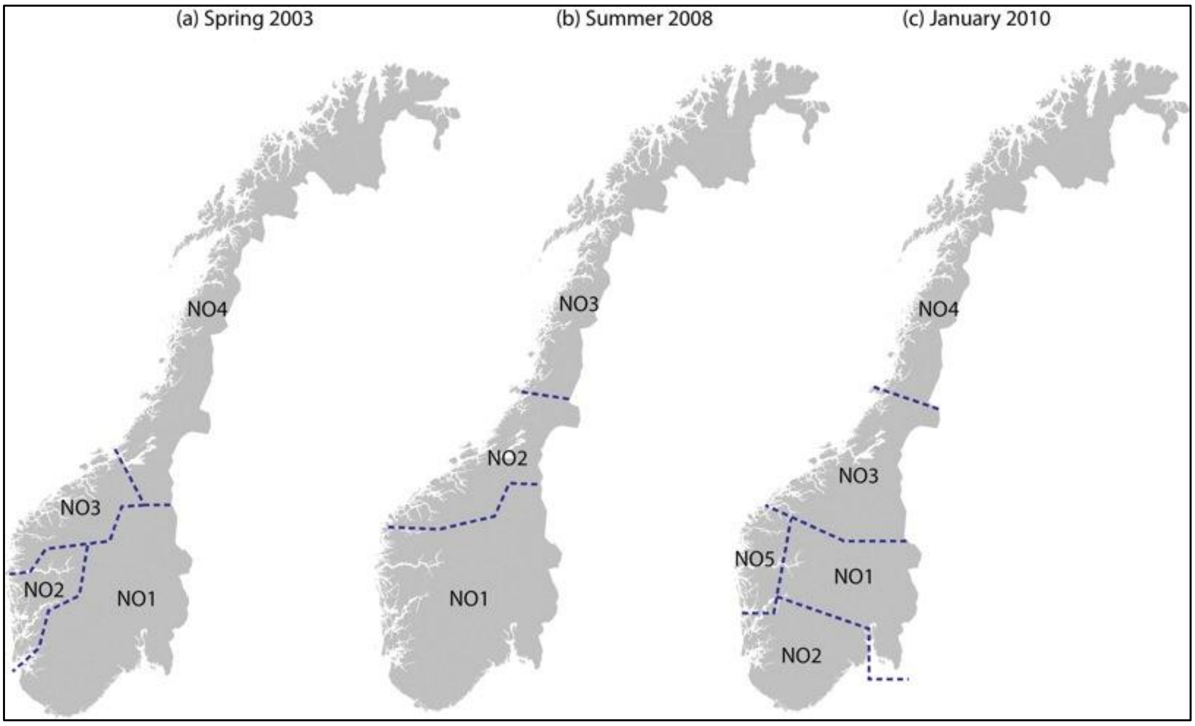


Figure 2.10 ELSPOT BIDDING AREAS IN NORWAY. Source: information from (Nordpoolspot, 2013) and (OED, 2003).

3 Derivatives

In addition to physical trade of commodities, derivatives play an important role, meeting the demand for risk management and hedging against the uncertainty of future prices. "*A derivative can be defined as a financial instrument whose value depends on the values of other, more basic, underlying variables*" (Hull, 2009, p. 1). The variables underlying derivatives are often the prices of traded assets.

Hedgers use derivatives as insurance for future price fluctuations, while speculators buy derivative contracts in order to make money on them. If they get lucky (unlucky), speculators can buy (sell) assets or financial positions at a lower (higher) price than the current market price, making it a gamble on future prices on the underlying asset.

The most common derivatives are futures, forwards, options and cfd's. In this thesis we will focus on futures contracts. These are standardized at an exchange where aspects regarding the quantity, place of-, method of- and time of delivery are specified. Price of the contract is left out blank, and is to be determined by the two parties. In contrast, contracts dealt over-the-counter (OTC) are less standardized and is open for negotiation on all parts of the contract. These contracts are called forward contracts, and the prices of these contracts are normally kept undisclosed between the two parts (Hull, 2009).

3.1 Forward- and Futures Contracts

A forward contract is the simplest of the derivatives. Defined as an agreement to buy or sell an asset at a certain future time for a certain price (Hull, 2009). In contrast to a spot contract, which is an agreement to buy or sell an asset today. There are two positions in a forward contract, one party assumes a long position and the other party assumes a short position.

When assuming a long position, you have agreed upon buying the underlying asset on a certain specified future date for a certain specified price. Following that the party assuming a short position has agreed to sell the asset at the same date for the same price. Notice that there is no transaction or payment between the two parties until delivery. The contract is settled at the agreed date, and payoff on one unit, in a long position will then be current spot price minus agreed forward price. In other words, having a long position you will have a positive payoff as long as the spot price at maturity is lower than the agreed forward price. The party having the short position is then obligated to pay you a higher price than the current market price.

The risk of the price of a futures contract not equal to the price of the underlying asset is called the basis. The basis risk and the determination of forward prices will be discussed later when we look into the relationship between spot and forward prices.

Futures contracts can be extinguished through the offset, in addition to at the actual delivery. Since a futures contract normally is a financial instrument for managing risk, a physical delivery seldom takes place, and the contract is settled in cash.

Standardizations of the futures contract are made to attract liquidity in trading. The futures contract is settled daily through the mark-to-market[8] mechanism, thus removing the potential counterparty risk.

3.1.1 Forward Contracts = Futures Contracts

Before we investigate the relationship between spot and futures price, we will state a common assumption for the forward and futures prices. Margrabe (1976) demonstrates that if interest rates are constant and the same for all maturities, the forward price will equal the futures price[9] (Hull, 2009).

As the holder of a future contract realizes the gains or losses at the end of each day, he gets the opportunity to reinvest the proceeds, in contrast to a holder of a forward contract, who has to wait until the end of the contract. It can be demonstrated[10] that the forward- and futures- price would be similar, if delivery occurs at a single point of time. This leads us to why the forward price deviates from the futures price; randomly varying interest rates and the mark-to-market mechanism.

---

[8] A clearing house acts as an intermediary for all traders. Each trader deposits security in an account. Today's future price is quoted in the market, the contract for yesterday's futures price is replaced by a contract with today's futures price, and the gain or loss for each position following from this price change is settled against each traders accounts. Insufficient funds require additional deposits or the positions will be closed." (Hull, 2009)

[9] See Hull (2009) for proof

[10] Given some assumptions; taxes, transaction costs and the treatment of margins (Hull, 2009)

This thesis will adopt the assumption of a constant riskless interest rate, for simplicity. This is supported by Hull (2009) who concludes that the theoretical differences between forward and futures prices for contracts that last only a few months are in most cases sufficiently small enough to ignore.[11]

3.2 Contango and Normal Backwardation

The shape of the futures curve is important to commodity hedgers and speculators. When the futures price is below the expected future spot price, the situation is known as normal backwardation, and when the futures price is above the expected futures spot price, the situation is known as Contango (Hull, 2009). Figure 3.1 illustrates these situations. The reasons for normal backwardation and Contango to occur will be discussed when the risk premium is introduced in section 4.2.2.

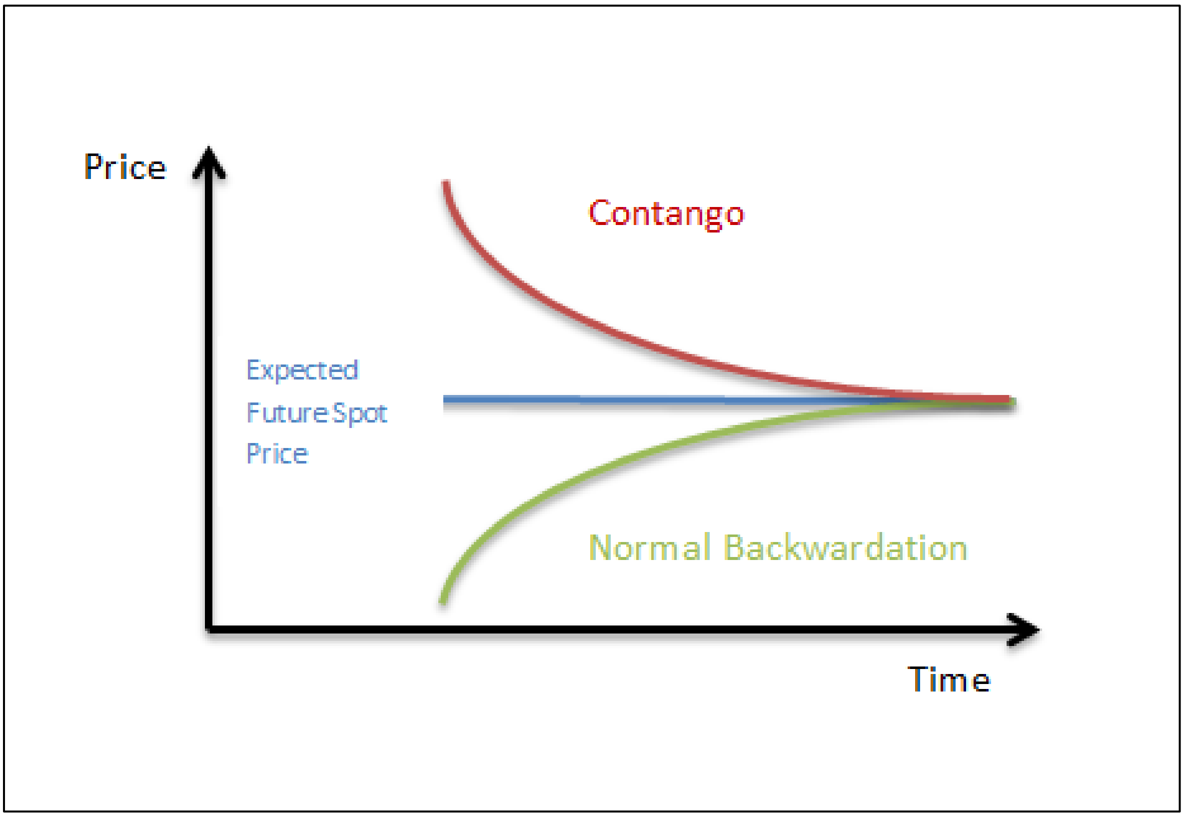


Figure 3.1 THE FUTURE PRICE OF A CONTRACT, CONTANGO AND NORMAL BACKWARDATION.

Even though the terms normal backwardation and Contango should be used considering the relationship between the futures price and the expected future spot price, the term is here used considering the current spot price.

[11] Factors that are not reflected in the theoretical models may cause the prices to be different. (Hull, 2009)

3.3 Energy Derivatives on NASDAQ OMX Commodities

This chapter will elucidate the main characteristics of the derivatives traded with the Nordic system price as the underlying asset, and what distinguishes this market from theoretical background. As mentioned, all trade of Nordic energy derivatives as of 2010 has found place on NASDAQ OMX Commodities.

There have been many adjustments of the structure of futures and forward contracts traded on Nord Pool over the years. For a complete description of the structure of the financial contracts, see nasdaqomx.com[12]. Note again that the system price set by Nord Pool Spot is the common underlying price for all Nordic exchange traded derivatives.

The futures contracts that are listed consist of daily contracts, and weekly contracts up to six weeks ahead. The weekly contracts are cascaded (split) into daily contracts as maturity is approached. Settlement of the futures contracts involves both the daily mark-to-market in addition to a final spot reference cash settlement, after the contract reaches its expiry date. Final settlement, which begins at delivery, covers the difference between the final closing price of the futures contract and the system price in the delivery period. Throughout the final settlement period, which starts on the expiry date, the member is credited/debited an amount equal to the difference between the spot market price and the futures contracts closing price (Nasdaqomx, 2013a).

Similar as for the general theory, the forward contracts traded on Nord Pool (NASDAQ) have no settlement during the trading period prior to the expiry date. The forward contracts include rolling monthly contracts for the next six months, rolling quarters for this year and the next two years in quarters. And at last, annual forward contracts for the subsequent ten years. As maturity is approached, the yearly contracts are cascaded (split) into quarters, and quarter contracts are cascaded into months. Monthly contracts are not further cascaded. This is illustrated by Figure 3.2. The mark-to-market amount is accumulated, but not realized, throughout the trading period as a daily loss/profit, and realized in the delivery period. Settlement throughout the delivery period is made out as for futures contracts (Nasdaqomx, 2013b).

[12] http://www.nasdaqomx.com/commodities/markets/products/power/

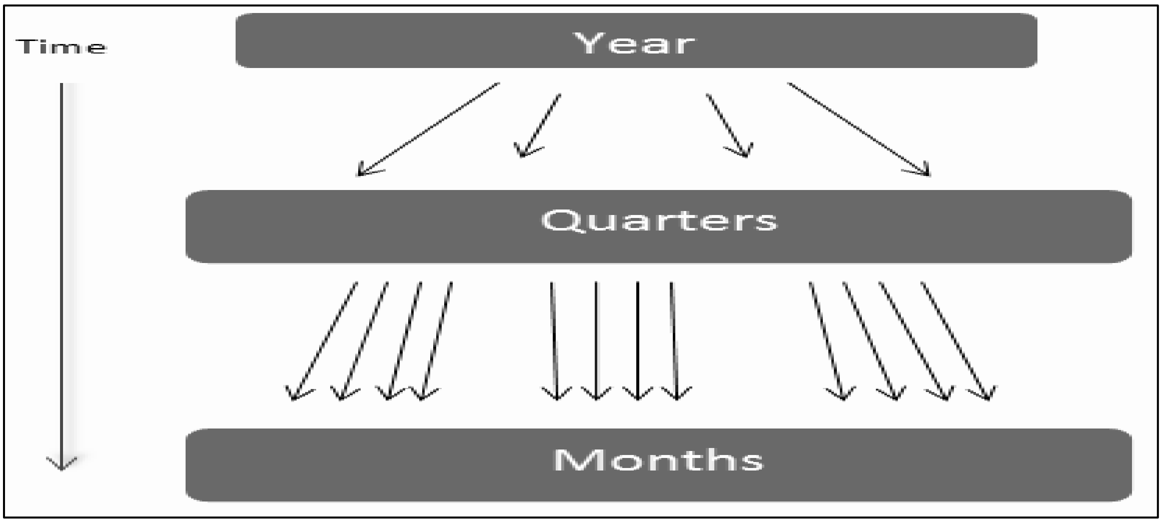


Figure 3.2 CASCADING OF FORWARD CONTRACTS.

4 Price Determination and Expectation

In this section we introduce the theory behind price determination in spot- and futures-markets for commodities.

4.1 Supply and Demand Equilibrium

All other things equal, the law of demand says that as price falls, quantity demanded rises, and as price rises, the quantity demanded decays. This gives an inverse relationship between price and quantity demanded. Increased demand can be showed as a shift of the demand curve to the right, while a decreased demand can be showed as a shift of the demand curve to the left. Shifts in demand can occur following changes in taste, number of buyers, income, price of related goods, substitutes, complements, unrelated goods and consumer expectations. This is not to be confused with changes in quantity demanded, which is a movement from one point to another on the demand curve, because of an increase or decrease in the price of the product (McConnell, Brue, & Flynn, 2009).

In contrast, the law of supply says that as the price level rises; the quantity supplied rises, as price falls; the quantity supplied falls. Increased supply can be showed as a shift of the supply curve to the right, while a decrease in supply can be showed as a shift of the supply curve to the left. Shifts in supply can occur following changes in technology, taxes and subsides, price of other goods, producer expectations or the number of sellers, and is not to be confused with a change in quantity supplied (McConnell et al., 2009).

In a free-market, suppliers and consumers interact and form equilibrium for price and demand. Surplus or shortage of a good is adjusted by the market forces into a new equilibrium price, making a rationing function of prices and efficient allocation. Adam Smith (1976) was the first to introduce “the invisible hand” that operates in a market system, where both public and social interests are promoted. To make full advantage of these forces, the market must be in the state called pure competition, characterized by a large number of competitors, a standardized product, no government interference with price[13], and with no barrier to enter into the market (McConnell et al., 2009). Figure 4.1 illustrates the effect of changes in supply or demand, in a market with pure competition.

[13] Price floors/roof etc.

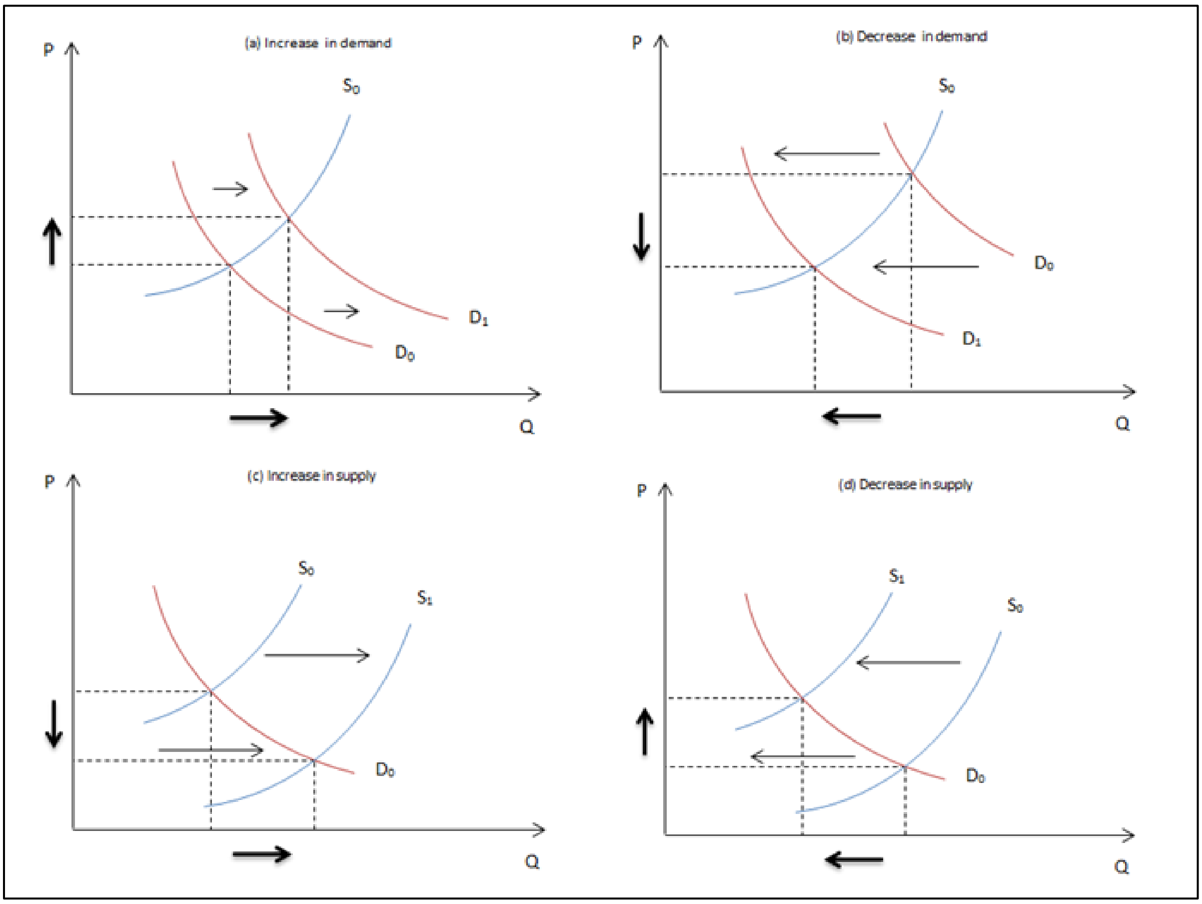


Figure 4.1 CHANGES IN DEMAND AND SUPPLY AND THE EFFECT ON PRICE AND QUANTITY.

The slope of the lines can be explained by diminishing marginal utility and price elasticity. In markets without diminishing marginal utility, the demand slope will form a straight line. Further, the slope of this straight line will be determined by how sensitive the demand is for changes in underlying price level. For some goods, demand will rise substantially when the price decline, while for other goods, demand is only slightly changed by a change in price. When the price does not affect demand in short term, we call the demand inelastic, which can be illustrated with a vertical demand slope.

4.2 Commodity Spot and Futures Price Relationship

Figure 4.2 shows how the futures contract price will converge to the spot price of the underlying asset as the delivery period for a futures contract is approached, resulting in a spot price equaling the futures contract price at maturity.

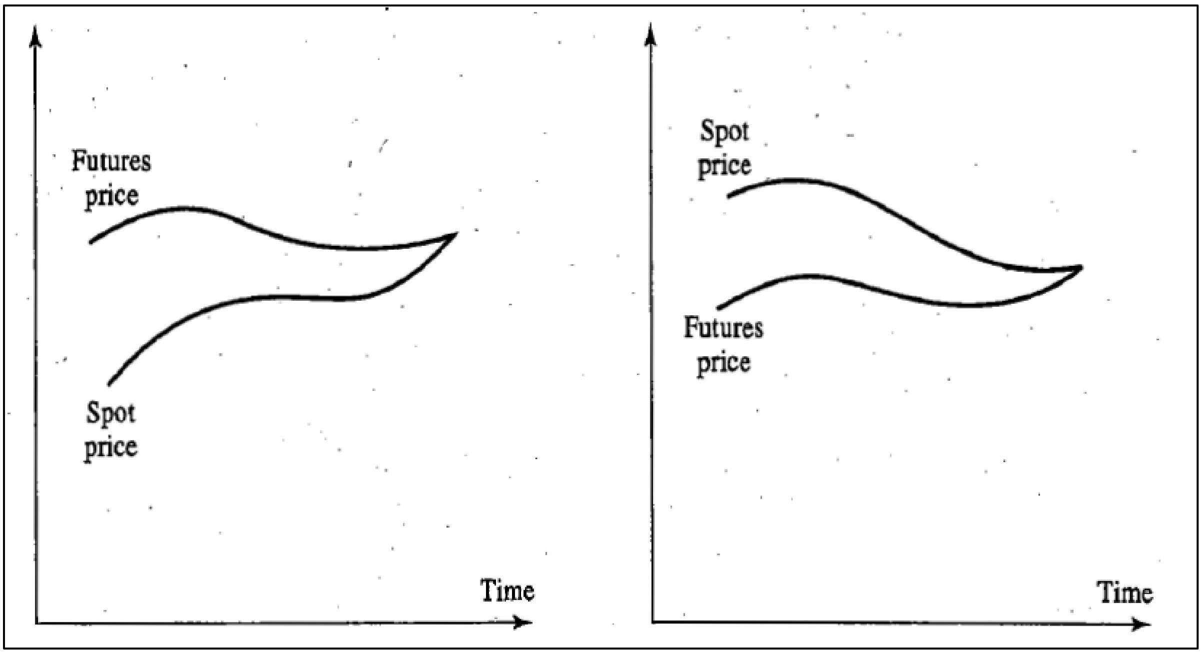


Figure 4.2 FUTURES PRICE CURVE. Source: (Hull, 2009)

The relationship can be explained by the arbitrage opportunity occurring if the futures price is respectively above or beneath the spot price at delivery. Arbitrageurs take advantage of markets out of balance, hence they are actually correcting the market back into balance as prices will be adjusted and finally reach equilibrium where arbitrage is nonexistent. Arbitrage will for instance increase the demand for an under-priced contract and thus push the price up towards its non-arbitrage equilibrium. The difference between the spot price and the futures price at any time is called *the basis.*

Further, we will briefly discuss the two main theories of the relationship between spot- and futures prices. Both theories build on the markets expectations for future price, where the storage theory is based on the gains or losses of holding inventories, the risk premium theory is based on the holder of the position to be compensated for the risk involved taking a position. For a more detailed discussion see Hull (2009).

4.2.1 Theory of Storage

Working (1933) was the first to introduce the theory of storage, since then it has been one of the most popular theories to describe the relationship between spot and futures prices for commodities. The storage theory can be developed from the simplest equation showing the relationship between the spot- and futures price. If we consider a forward contract on an investment asset with price S_t that provides no income, we get the following equation stating that that the current price of a futures contract, equals to the present value of the future spot price[14].

$$F_{t,T} = S_t e^{r_t} \qquad \textbf{Equation 4.1}$$

Where $F_{t,T}$ and S_t are the futures and spot prices today, r being the risk free interest rate at time t. The arbitrage argument explains the equation. If $F_{t,T} > S_t e^{r_t}$, arbitrageurs can buy the asset and short forward contracts on the asset. If $F_{t,T} < S_t e^{r_t}$ they can short the asset and enter into long forward contracts on it. The forward price is higher than the spot price because of the cost of financing the spot purchase of the asset during the life of the forward contract (Hull, 2009). If shorting is not possible, this can be explained simply by selling the asset if the forward price is too low, and entering into a long position with a forward contract.

Following the theory of storage the term convenience yield was introduced, which cover the *gains* and *losses* from holding an inventory. *Convenience yield* is the benefit (gains) of holding the inventory, while the term "*storage costs"* (including terms of interest forgone in storing the commodity, storage space costs, insurance, physical deterioration or wastage) will reflect the losses experienced by holding an inventory. The convenience yield is defined as the benefit from owning the physical commodity that is not obtained by holding a futures contract. In contrast to a non-storable commodity, the convenience-yield of a storable commodity must be zero to avoid arbitrage opportunities.

We develop the equation with the introduced terms and get the Theory of Storage in Equation 4.2, expressing storage costs and convenience yield as fractions of the spot price. One can derive the following formula for the futures price, $F_{t,T}$, at a time t with delivery at time T:

$$F_{t,T} = S_t e^{(r_T + u_T - y_T)} \qquad \textbf{Equation 4.2}$$

[14] As mentioned, futures and forward prices with a certain date of delivery, is only the same as long as the risk free rate is constant for all dates of maturity. For proof see Hull (2009), where it is also shown that the argument can be extended to situations where the interest rate is a known function of time.

where S_t is the spot price of the commodity at time t, $r_T$is the risk-free interest rate for the holding period T, u_T is the cost of physical storage, and y_T is the convenience yield over T[15]. The theory explains the difference between current spot prices and futures prices for future delivery in terms of interest forgone in storing the commodity, warehousing costs, and a convenience yield on the inventory.

When net convenience yield (i.e. convenience yield minus cost of storage $(y_T - u_T)$ is positive and higher than the risk-free interest rate the futures market will exhibit a Normal Backwardation, while it will be in Contango when the net convenience yield is lower than the risk free interest rate.

4.2.2 Theory of Risk Premium

We start this section off by once again looking at Figure 4.2 showing the futures price converging against the spot price. Economist John Maynard Keynes and John Hicks, argued why the futures price in some situations tend to lay above the spot price, while it is below in other situations.

When hedgers tend to hold short positions, and speculators tend to hold long positions, the futures price of an asset will be below the expected spot price. This because speculators require compensation for the risk they are holding. Speculators will invest only if they can expect to make money on average, while hedgers are prepared to lose money on average as a compensation of reduced risk. For similar reasons, the futures price will be above the spot price when hedgers tend to hold long positions while speculators hold short positions (Hull, 2009).

This leads us to the Theory of Risk Premium, which argues that the price of a futures contract is the expected future spot price, $E_t(S_{t+T})$, in addition to a risk premium for the underlying commodity. If we define i_t as the appropriate risk-adjusted discount rate for the commodity, the futures price can be expressed as:

$$F_{t,T} = E_t(S_{t+T})\, e^{(r_t - i_t)} = E_t(S_{t+T})\, e^{-P_T} \quad \textbf{Equation 4.3}$$

[15] *"We do not consider margin requirements here, and assume that the futures contract is fully settled at delivery, similar to a forward contract. This is a common assumption in analyses of commodity futures contracts. It can be proven that with a deterministic interest rate the futures price equals the forward price "* (Hull 2006)

where $P_t = i_T - r_t$ is the commodity's risk premium. According to the risk premium theory presented in Equation 4.3 we see that without a risk premium, the futures price will equal the expected future spot price. In other words when the risk adjusted discount rate for the commodity is equal to the risk-free interest rate.

5 Price Determination, Expectation and Risk in the Nordic Energy Market

Having already established the underlying theories, we will furthermore investigate the price factors that are special for the Nordic energy market, including both short- and long-term considerations.

5.1 System- vs. Area Prices

The system price is a result of Nord Pool Spot balancing supply and demand hour to hour over the entire area. Market participants can submit offers to sell or bids to buy physical electricity for the following day[16]. The around 360 members of Nord Pool place a total of around 2000 orders for contracts on power on a daily basis (Nordpoolspot, 2013e).

The buyers on Nord Pool Spot are mainly power distributors, but also major power consumers in addition to power producers with an obligation to deliver energy to their customers, buying the excess of what they don't produce themself. The distributors are often also power producers, while companies like *Norsk Hydro* and *Elkem*, are examples of major power consumers. The distributors may be confused with the consumers throughout this thesis, but when we talk about the power demand these are virtually the same since the consumers channel their demand through the distributors. The sellers in the Nordic market are the licensed power producers. *Statkraft*, *Vattenfall*, *Dong Energy* and *Fortum Oyj* are the main producers in respectively Norway, Sweden, Denmark and Finland. Figure 5.1 illustrates how this is organized through Nord Pool Spot. Note that the volume of bilateral contracts (OTC), which are agreed outside of Nord Pool Spot (and NASDAQ OMX Commodities) between large consumers and the power producers directly, is steadily decreasing.

[16] Note that the Elspot market is a daily spot market concluded at the day-ahead stage.

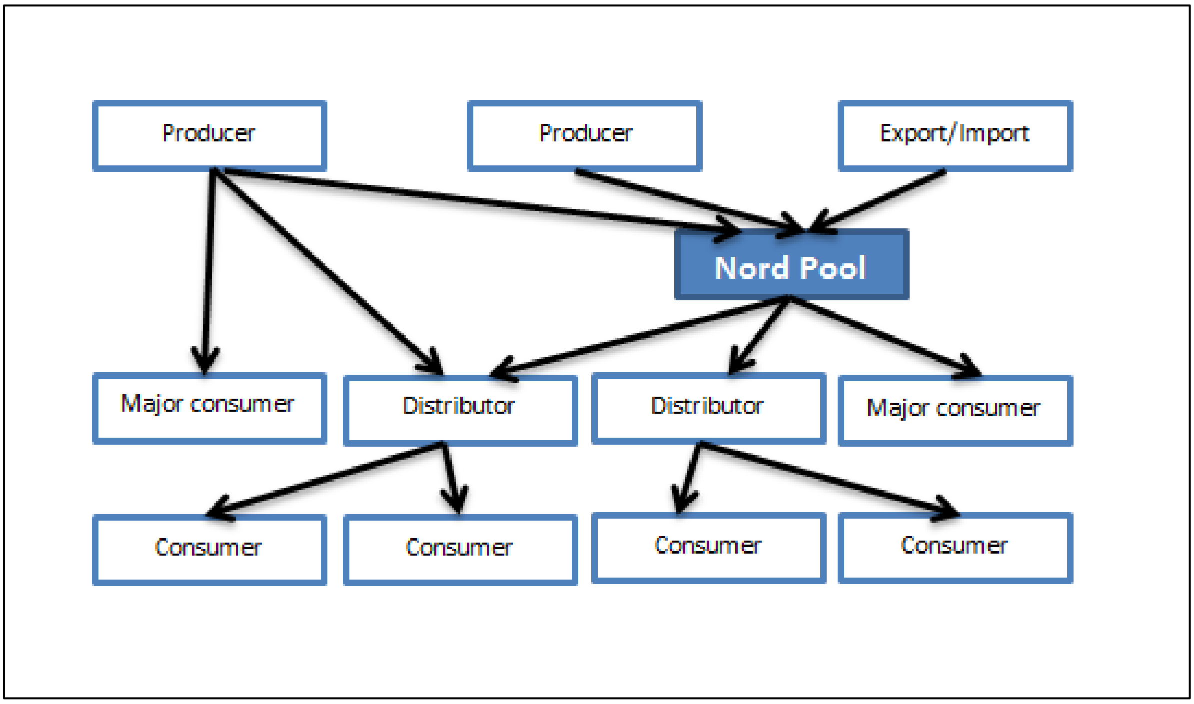


Figure 5.1 ORGANIZATION OF THE NORDIC POWER MARKET. Translated from Source: (Nome, 2010)

Physical trade at Nord Pool Spot is based on planning and expected consumption. Buyers need to assess how much energy they need in order to meet demand the following day, and how much they are willing to pay for this volume. In contrast, sellers need to decide how much energy they are willing, or able, to deliver and at what price, each hour. The deadline for submitting bids for delivery[17] the next day is 12.00 CET every day, and within the next hour the equilibrium price for all hours the next day is published, after being calculated at Nord Pool Spot (Nordpoolspot, 2013e). Figure 5.2 illustrates the equilibrium system price.

[17] Note that this is contracts with physical delivery, not to be mixed with financial positions.

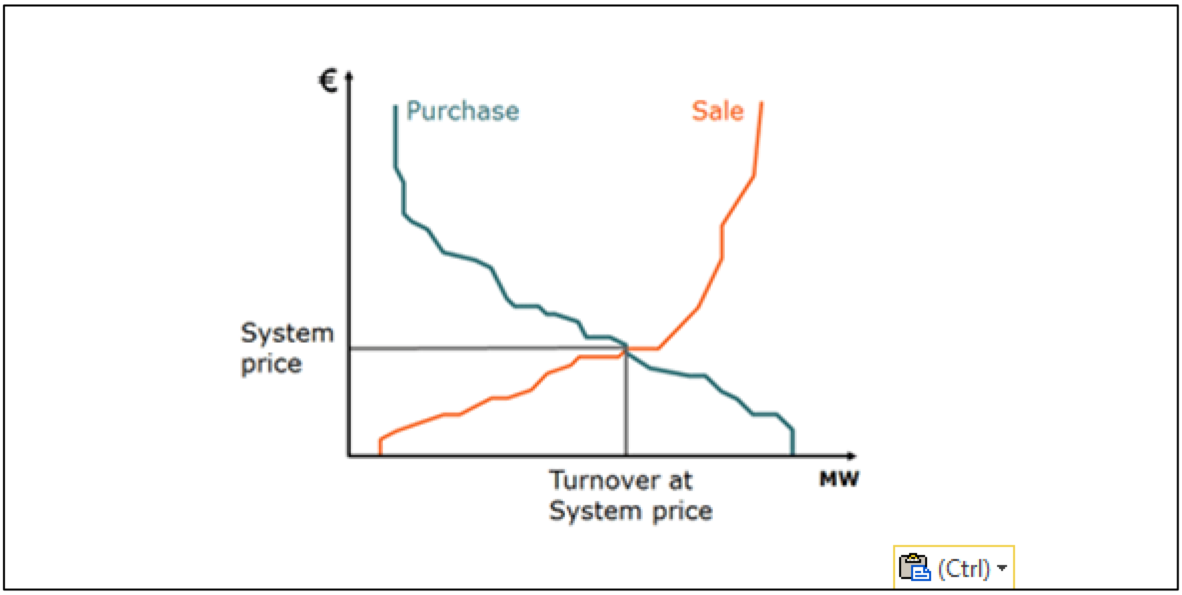


Figure 5.2 EQUILIBRIUM PRICE IN THE ELSPOT MARKET. Source: (Nordpoolspot, 2013f)

Although prices and volumes are determined the one day ahead, the market have risk for the trades not carried out as agreed upon. For instance can, more wind than expected in Denmark, or producers with technical problems, bring the market out of balance. The *Elbas* market is created to balance the spot market. These trades on the *Elbas* market can be made until one hour prior to delivery in order to balance the market (Nordpoolspot, 2013g).

The generator- and supplier companies operate under free competitive conditions in the spot market (NVE, 2010). Following that the determination of the system price is, by far, a result of pure competition between the licensed power producers[18]. In contrast, the determination of the area prices exhibits more obstacles, partly since electricity is dependent on a complex infrastructure to be delivered. Hence, the area prices are a result of a more regulated pricing process and cannot be considered to be a result of a pure competition market.

Background theory states that higher demand will be met with higher production. However, in areas with limitations in the transmission capacity, higher demand cannot be met by higher production or import, as the capacity is already reached. Consequently, these areas should experience higher prices given a market with pure competition. Figure 5.3 illustrates how the area prices are introduced to counter this effect. The area prices will balance these

[18] Licenses are however a barrier in order to enter the market.

prices with the system price to counter that the surplus area will have the lowest price and the deficit area will have the highest price.

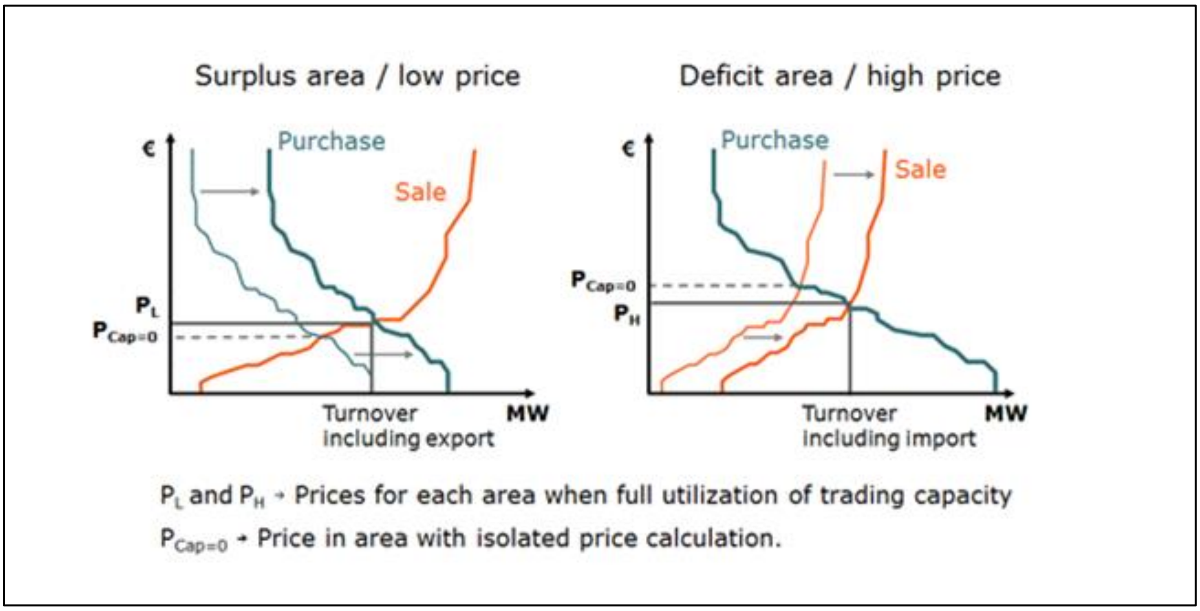


Figure 5.3 EQUILIBRIUM PRICE WITH AREA CONGESTIONS SOURCE: (Nordpoolspot, 2013f)

Although general theory will argue that the higher prices will be adjusted by *the invisible hand* causing the demand to decrease, the characteristics of the electricity market prevents this. Because of inelastic demand the reduction in demand will be low, compared to the increase in price. PÖYRY (2010) argue that demand for electricity is inelastic in the short-term, and significant less elastic than the supply. He is supported by Fiorenzani (2006). The reason is that electricity is a necessary normal good with no or few substitutes. This situation is illustrated in Figure 5.4.

Congestions in the transmission capacity must be considered the main reason why pure competition is not possible in the electricity market. This prevents that higher demand are met with higher production[19] and lower prices, since the producers cannot freely underbid each other. In contrast, the characterizations of the demand prevent that lower prices, due to higher supply, will be met with higher demand, hence higher prices. Nor will higher prices be met with substantial lower demand, that would have reduces the prices, because of the inelastic demand.

[19] Further analysis of these processes could be subject for further work.

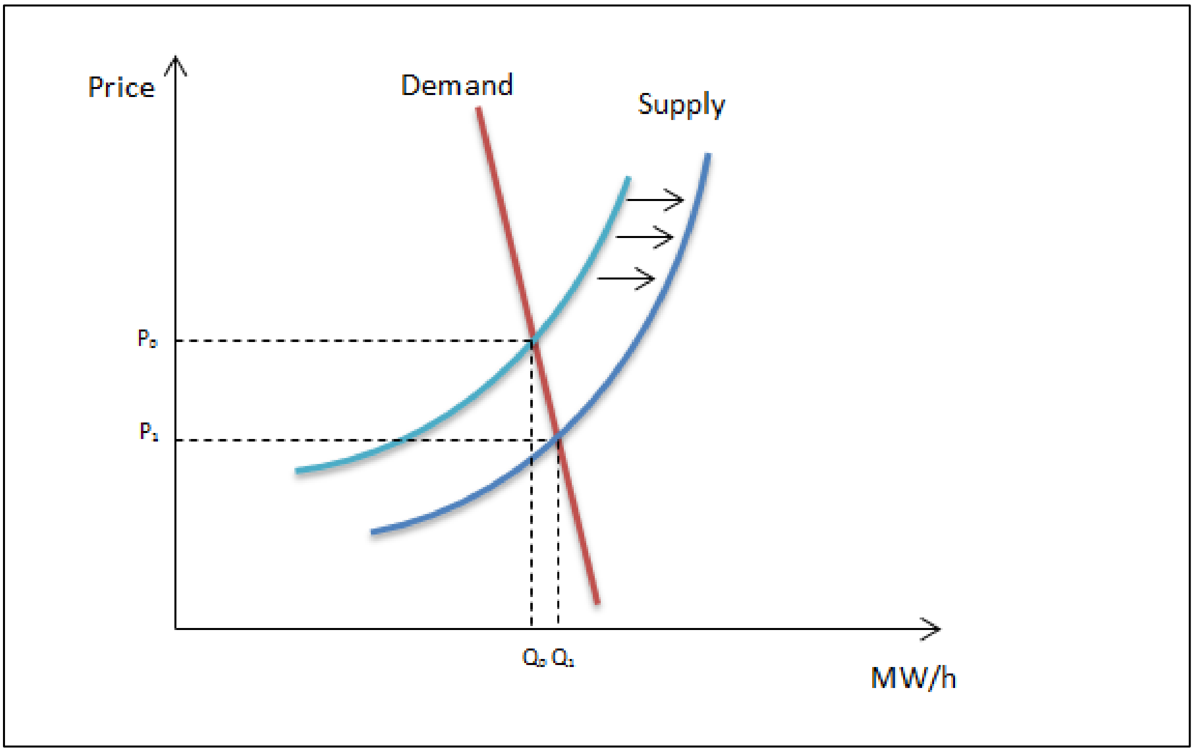


Figure 5.4 INELASTIC DEMAND FOR ELECTRICITY

In addition to the bottlenecks that can occur between different price areas, local bottlenecks can occur within a price area. There are different methods to determine the zonal price for the entire transmission network, like nodal pricing and zonal transmission pricing (Eydeland & Wolyniec, 2003). These methods are also used when dividing the area into the different bidding areas[20]. Local bottlenecks are temporary, and can occur everywhere, with different duration. They are solved as the system operator pays for the producers to produce more or less, or for the consumers to reduce their demand, and thereby reduce the transmission over the bottlenecks.

5.2 Hydro Dominated Market

The Theory of Storage presupposes that the commodity can be stored[21]. For the energy market in general this is not the case, but the unique situation of the Nordic energy market with its high share of hydropower, Botterud et al. (2010) nevertheless argue to apply the storage theory in this market, since water can be stored in reservoirs. On the other hand, the Theory of Risk Premium can be applied to both storable and non-storable commodities.

[20] Price areas are also called bidding areas

[21] It is not possible to obtain a risk-free position from buying the commodity in the spot market for a non-storable commodity.

We will now look further into what is special for price formation, convenience yield and risk premium in a hydro dominated market.

5.2.1 Price Formation

In a short-term, price formation is a result of the expectations to the market regarding precipitation, temperature, reservoir filling, and marginal cost of other complementary products such as oil and gas. In a long-term, an expected rise in in demand and expected development of production size and infrastructures, along with general framework, influences the price (Bye, 2006).

Compared to other energy markets, the high share of hydropower in the Nordic market makes weather forecasts very important for the expected future supply of electricity. The market price is heavily dependent of the current reservoir levels, and the expected future hydro conditions. Vehvilainen & Pyykkonen (2005) argue that the value is not based on the filling level, but the filling level compared to the normal. Norway and Sweden experienced relatively high volatility in prices during 2010 while Finland and Denmark experienced more steady developments throughout the year (NordReg, 2011). This could indicate that hydropower production gives higher fluctuations in price, compared to the more long-term stable production from nuclear- and other thermal- power production.

Botterud et al. (2010) argue that an equilibrium consideration based on marginal cost is difficult to apply because hydropower has no or very low marginal cost. Instead, calculations of the water stored in reservoirs are given a "water value", which is the opportunity cost of using water immediately as opposed to storing it for future use. Water values are calculated through complex stochastic dynamic optimization tools, in order to forecast prices and optimize power generation. Uncertainties of future inflow to the reservoirs will reduce the predictability of these models. The dilemma is whether higher production and revenue today is beneficial compared to a lower production today, but higher water values at the end of the planning period and a possibility of higher prices in the future. Having calculated the generation schedules and marginal water value for a period ahead (usually three years with weekly time resolution) for each reservoir, future market prices can be calculated for different inflow scenarios. Hydropower is scheduled when the water value is lower than the current market price. For a detailed discussion of generation scheduling in hydro-dominated markets it is referred to Fosso, Gjelsvik, Haugstad, Moe, & Wangensteen (1999).

Many important factors for the electricity price formation are seasonal. This results in seasonal trend for the electricity price. Normal Nordic winter climate will for instance result in higher demand during winter than summer due to electrical heating of buildings, while it on the other hand results in lower supply as the precipitation decays because of frost. Consequently, demand will be higher during winter than during summer, while the supply from hydropower will normally be lower. In addition, shorter spikes can occur since electricity can't be stored. Extreme weather, loss of producers or power line failures will result in heavy load fluctuations and thereby price peaks. When the situation is stabilized, prices will fall to its normal. A jump in prices will often be followed by a drop (or the other way around) as spikes are a part of a price premium (Eydeland & Wolyniec, 2003). The probability for spikes is higher when demand is close to maximum supply. Furthermore, they argue that areas with high congestion in the transmission network are more likely to suffer from spikes. It is likely that the short-term fluctuations will be reduced as connection between countries with different production technologies is increasing through cables. Take for instance Germany, who suffer from lower flexibility in supply because of technology that cannot be effectively shut down during night, which keeps production going during night and resulting in an exceed in supply. Cables then make it possible for the Nordic countries to buy cheap electricity during nighttime since they can effectively shut down hydro production.

Both short- and long-term arguments are used to claim that the electricity price is mean-reverting. A high electricity price opens the market for producers with high marginal costs, resulting in higher supply and lower prices. In contrast, lower prices will prevent the same producers to enter the market, and thereby reduce the supply which results in higher prices (Hjelset & Monsbakken, 2005). Temperature is mean reverting and since the weather is a main determinant of electricity prices, Escribano, Pena, & Villaplanta (2002) argue for also the electricity prices to be mean reverting. Since demand is the cost driver for electricity, this gives long-term incentives to expand production, and thereby stabilize the price. Bye (2006) argues that the electricity prices will rise until they reach the cost for developing new capacity. If considering forecasts that estimate the cost of new production to 25-30 cents/kwh, this will give us a maximum average price level over time. For the same reasons, high price difference between an area price, and the system price, will give incentives to expand production in that specific area, given the congestions in the transmission network. Obviously the production must meet the rise in demand, and consequently will plans for new production have impact on the long-run price. General economic fluctuations will influence price formation as higher economic activity results in more trade and more power consuming production. During the recent economic crises, this has been noted. In addition, the trend is that we use more electricity per capita, along with a growth in population, resulting in higher electricity consumption and demand over time (Bye, 2006).

The market structure has also got an influence on the price formation. The trend is that more financial players enter into the market, in addition to the producers and the load serving entities. This has increased competition in the market. Liquidity has also changed from higher liquidity in the short term part of the market (day-ahead and weeks) to higher liquidity in the month ahead, quarter ahead and year ahead products. The reason for this is probably caused by the entrance of more financial players who don't want to take any physical positions in the market. Regulations will also affect the market structure, for instance was the cost structure of the thermal producers changed when the European Emission Trading Scheme (ETS) was introduced in 2005, which in turn also influenced the water values and the scheduling of hydro resources (Botterud et al. 2010).

Market players structure this complexity of factors into models for future price scenarios. Even though market information is quite transparent, the price forecasts may still differ. This reveals the complexity and importance of modeling approaches, data preparation and interpretation of results. Burger, Graeber, & Schindlmayr (2007) claim that the futures prices in the electricity market is decided by the expectations of future availability and production cost, not by todays spot price, especially for the long contracts.

5.2.2 Convenience Yield

The following discussion on convenience yield is largely based on Botterud et al. (2010). The lack of direct storage solutions for electricity, and the fact that a constant match between supply and demand is required, makes the electricity market different compared to most other markets. Bessembinder & Lemmon (2002) argue that these factors make the Theory of Storage unsuitable for the electricity market.

Nevertheless, Botterud et al. (2010) argue that even though electricity cannot be bought today and stored for futures sales, the arbitrage argument can still be used in the Nordic market; as hydropower generators can store water in reservoirs. In other words having the opportunity to sell in the spot market or wait and sell electricity in the futures market.

Further, by assuming that the spot and futures prices are known, and that the producers do not face risk of overflow from reservoir by storing water, the two options are both risk free and must yield the same risk-free return. Following that the relationship given in Equation 4.2 should exist in an electricity market with a substantial share of hydropower.

Storage costs can be defined as the total cost of storing the inventory. The marginal cost of storing water in reservoirs is negligible, as long as there is available capacity in an existing reservoir. However, Botterud et al. (2010) argue that we can consider the storage cost as the risk of overflows. This means that the storage cost will increase with the increasing reservoir level, as the risk of overflows and economic loss are higher with a filled reservoir than with an emptied reservoir.

In contrast, the convenience yield will fall as the reservoirs are filled. For commodities in general, spikes in spot price tend to occur when storage levels are low. Adopting this into the equation, the convenience yield is $(y_T - u_T)$, which is a decreasing function of the overall hydro reservoir level in the system.

Even if there are several other factors that also are likely to influence the convenience yield, they are not as significant as the reservoir level. Higher demand will for instance lead to increased demand for futures contracts from customers wanting to hedge the price for future purchases. A higher increase in futures price than in spot price would imply a negative relationship between load level and convenience yield.

Inflow would have an opposite effect. Increased supply gives reduced prices, following an increased supply and reduced demand for futures contracts. This results in a positive relationship between inflow and convenience yield.

Because the market is quite transparent, the prices for futures contracts already reflect the markets anticipation for load and inflow. According to Botterud et al. (2010), the variables are to some extent driven by seasonality, so that the market participants are typically concerned with deviations from the normal values. Current price level, variance and skewness, will also influence the convenience yield through the trading decisions being made. Consider for instance a situation with prolonged drought, having water in the reservoirs is crucial to keep the production running or to meet an unexpected demand. In contrast, a position in a futures contract will not help you to keep production running. This example also shows that the convenience yield is a decreasing function of the stocks being held. The less water available for production, the more valuable it is to have the physical commodity stored. Convenience yield will also reflect the expectations in the market concerning the future availability of the commodity.

5.2.3 Risk Premium

The Nordic energy market is exposed to three main sources of risk; Market risk, Strategic risk and Technical risk (Bernseter, 2003). In this thesis it is reasonable to focus on the market risk. However, note that the physical market suffer from technical risk since the transmission grid is critical for delivery of electricity and thereby exposing both producers and distributors to risk.

Market risk includes price-, volume- counterpart- and liquidity- risks. The Nordic energy market is mainly concerned with volume risk and price risk. Liquidity has increased and the counterpart risk is removed from market with the clearing service that is offered. The volume risk is closely linked to the price risk, since there is strong evidence from previous studies that decreasing reservoirs increase the electricity price.

In the electricity market, we have a situation where the risk aversion varies considerably between the producers and the consumers. There is a substantial difference in the flexibility of adjusting quantities on the supply and demand side (Botterud et al. 2010).

According to Keynes (1936) a risk premium would arise if the degree of risk aversion varies considerably between the producers and the consumers. This is confirmed by Botterud et al. (2010) in their assessment of a hydropower dominated market.

Because of their reservoirs, hydropower producers can control their supply on short notice, and thereby adjust their production in the short-term market. Hedging future price uncertainty is therefore not as important for the producers, as they can profit on price peaks, or store water for future production during collapses[22]. In contrast, the consumers have very limited flexibility. They have limited capability in order to adjust demand to the price, and are therefore interested in hedging future price risk by locking the future price through futures contracts. This unbalanced relationship of risk aversion and flexibility is reinforced by the fact that electricity cannot be stored.

Consumers in other commodity markets normally have the opportunity to build a stock as a hedge against spot price peaks, giving them some flexibility. Hence, the reservoirs give extensive asymmetry to the Nordic energy market. Bernseter (2003) argues that the distributors are interested in a short hedging horizon since their customers can switch distributor in short notice. This exposes the distributors to substantial risk if they lose customers when tied up in long-term long positions.

Marckhoff & Wimschulte (2009) argue for a more balanced situation as they claim that also producers could have interests in hedging. In periods with heavy rain fall, producers in such areas will hedge the price, as the area price will be lower than the system price, making them net exporters. The limited transmission capacity prevents the cheap hydropower to spread across to all areas. This is confirmed in studies by (Kristiansen, 2004).

Highly volatile markets will normally attract speculators. The situation described should be alluring for them, and provide opportunities for profit. Speculators will try to take advantage of the difference in flexibility and thereby the difference in risk aversion by taking opposite positions in the market. Hence, they help to balance the market. The extent to which this is enough in order to balance the market will be further analyzed in the empirical part of this thesis. Earlier studies like Botterud et al. (2010) and Gjølberg & Brattestad (2011) has found that the futures prices tend to exceed the expected future spot prices. In the long term, it is then expected a negative return from holding futures contracts.

Botterud et al. (2010) argue that the risk premium is likely to be driven by the same variables influencing price formation and convenience yield, in addition to the mentioned differences in flexibility between the supply- and demand- side. Low reservoirs leads to high demand for futures contracts, and vice versa, resulting in a negative relationship between risk premium

[22] Investigation whether the regulations prevent this form of speculation is as suggested topic for further work at the end of this thesis.

and reservoir levels. In contrast, higher than expected inflows will result in lower risk premium since the likelihood for high spot prices will fall.

6 Methods and Techniques

The econometric test and techniques used in the empirical analysis will be presented throughout this chapter.

6.1 Parametric Tests

Parametric tests require that the test material (data series) is normally distributed, while non-parametric tests should be used if the data is not normally distributed (Walpole, Myers, Myers, & Ye, 2012). They claim that one of the biggest misuses of statistics is to assume an underlying normal distribution when carrying out a statistical inference, when it is not normal. Most of the tests are nevertheless reliable despite slight departures from normality, particularly when the sample size is large. In this thesis, the same normality test will be used both when to test time series and when to test the residuals from a regression analysis. See chapter 6.3.1 for more details of the Jarque-Bera test which is used in this thesis.

6.1.1 T-test

The test is based on the Student's distribution and is used when the standard deviation is unknown, and estimated with the estimator S, based on the normal distribution. The test can be performed on both one- and two samples. For a one-sample test, the test size is given by:

$$t = \frac{\bar{x} - \mu_0}{S/\sqrt{n}} \qquad \textbf{Equation 6.1}$$

When n>30, many textbooks suggest that one can safely replace σ by s and still use the Z-tables for the appropriate critical region. When we imply that $s \approx \sigma$, the Central Limit Theorem is invoked, but we must view the result as an approximation. The confidence to the results will rise with the sample size (Walpole et al. 2012).

Spreadsheet software has been used to perform the t-tests in this thesis. Generally, the test is performed by establishing a null hypothesis and an alternative hypothesis. We say that H0 is tested against H1, for example:

H0: The expected value is equal to zero

H1: It is not equal to zero.

When performing a one-sided test, we have an indication that the expected value is either greater than or less than zero, and we therefore test H0: the expected value equals zero, against H1: the expected value is above (below) zero.

The critical value, α, is often chosen to be 0,05 or 0,01. P-values are calculated by the software used for performing the test. They are defined as the lowest level of significance at which the observed value of the test is statistic significant (Walpole et al. 2012). We can reject the null hypothesis and conclude that there are statistical difference (two-sided test) if the p-value is less than the critical value.

6.1.2 Wald-test

The Wald-test can be used to test the significance of the coefficients from the regression model. In contrast to the original estimated t-value, the Wald-test can be used in order to test whether if; $\beta_1 \beta_2 = 1$, or simply if; $\beta_1 = 1$. The Wald-test is based on an estimate for the covariance matrix of confidents (Davidson & MacKinnon, 2004).

6.2 OLS Regression Model

This section is largely based on Walpole et al. (2012). Ordinary Least Square (OLS) is a technique for estimating the unknown parameters in a linear regression model. Generalized, a regression model can be expressed as:

$$y_t = a_0 + \beta_1 x_{t1} + \beta_2 x_{t2} + \cdots + \beta_k x_{tk} + \varepsilon_t$$

Equation 6.2

Following the equation, a one-unit increase in x_{t1} changes the expected value of y_t by β_1 and equally for the other variables. To describe the randomness in data, we include the error term ε_t in the equation. The error term, or the random component, takes into account considerations that are not being measured or, in fact, are not understood by scientists or engineers.

By minimizing the sum of squared distances between the observed responses and the estimated regression line, we find the parameters. Hence, we shall find b_0 and b_1 so as to minimize:

$$SSE = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} (y_i - \hat{y_i})^2 = \sum_{i=1}^{n} (y_i - b_0 - b_1 x_1)^2 \qquad \text{Equation 6.3}$$

The calculated coefficients provide us the best fit, but we also want to know how good fit this line has got with the dataset. The regression results display some key information in terms of evaluating the quality of the regression, in addition to information regarding the reliability of the regression.

The R-values of a regression is important as it measures how much variation the model captures, and is said to measure the quality of fit. R-squared[23] is called the coefficient of determination and is a measure of the proportion of variability explained by the fitted model. The R-squared values are limited of 0 and 1. If the model's fit is perfect, all residuals would be zero, and thus R^2=1. There is no standard rule for what is an acceptable value, except for that it must be large enough for the situation in question. Since the R-squared has the pitfall that it rises unconditionally when including additional variables to the model, it is normal to use the adjusted R-squared, which accounts for the number of variables included in the model.

It is important that the regression analysis does not exclude explanatory variables. On the other side, it is important that the included variables actually are explanatory. The p-values are important in order to test this. Where the R-values evaluate the model as a whole, the p-values evaluate the effect of each explanatory variable. To test if proper variables are included into the regression model, we test whether the coefficient is significantly different from zero.

6.3 OLS Assumptions

Whether or not a regression is reliable has fulfilled its underlying properties. Primarily the relationship between the dependent variables (x and y) must be linear with the choice of a linear model. Secondly the independent variables (x1, x2) must not be linearly dependent or perfect collinear. Perfectly collinear makes it hard to calculate the beta coefficients and identifying the explanatory power of the individual betas. The OLS regression is consistent if this is fulfilled in addition to the residual assumption of zero conditional mean.

---

[23] R^2=1-(SSE/SST),

6.3.1 Residual Assumptions

In order to be BLUE (best linear unbiased estimator) the OLS regression must also fulfill the following residual assumptions:

- **Zero conditional mean,** $E(\boldsymbol{\varepsilon})$=0
- **Homoskedasticity,** $Var(\varepsilon) = constant$
- **No autocorrelation,** $Cov(\varepsilon_i, \varepsilon_j) = 0$
- **Normal distributed,** $\varepsilon \sim N$

When the error terms are conditional, then they are said to be heteroskedastic. This means that they do not have the same variance for all values of X, hence violating the assumption. A violation of the assumption of homoscedasticity can simply be seen from a residual plot if the residuals tend to be larger at larger values of the independent values. In this thesis a Breusch-Pagan test will be performed to test the null hypothesis of homoskedasticity. The test uses a regression model that tests squared estimated residuals for dependence of the independent variables. Furthermore, an F-test is used to determine if the null hypothesis of significant coefficients can be rejected. If rejected, so is the assumption of homoscedasticity. For more details see Kennedy (2003).

If the residual vector is auto-correlated, the residuals will have inherent memory of previous residuals, making them correlated (Biørn, 2008). In this thesis I have used the Breusch-Godfrey test which tests the null hypothesis of no autocorrelation. The test is calculated by re-running the regression using p-lagged OLS residuals as the dependent variable. The coefficients are then tested against the OLS residual as the dependent variable. For more details see Kennedy (2003).

The OLS BLUE assumptions are violated if the residuals have autocorrelation and heteroskedasticity. However, these violations do not affect the estimated slope coefficients, only the estimated standard errors. The Newey-West Standard Errors are similar to the Heteroskedastic-Corrected Standard errors. They have in common that they approach the violations by adjusting the problem itself, thus, the estimation of the standard errors. This correction is important in order to use the standard errors in t-tests. The Newey-West standard errors of the coefficients (beta) are typically larger than the ordinary least square estimated standard errors, which results in lower t-values and hence decreasing the probability that a given estimated coefficient will be significantly different from zero (Studenmund, 2006). For calculation of these standard errors software has been used. This thesis will not describe the calculation further in detail.

The assumption of normally distributed residuals are optional, but is usually invoked (Studenmund, 2006). As mentioned, the Jarque-Bera test will used to test for normality. It tests the null hypothesis of normality, and has a critical value of 5,99 at a 5% significance level. The Jarque-Bera test is an adaption of the chi-square procedure and relies on the skewness and the kurtosis. Since the kurtosis is 3 for a normal distribution, the test relies on that the kurtosis is equal to 3, while the skewness is close to 0 (Newbold, Carlson, & Thorne, 2010).

6.4 Special Assumptions for Time Series

6.4.1 Stationarity

A stationary time series will have constant basic properties (mean and variation) over time. In contrast, non-stationary time series has one or more basic properties that do change over time (Studenmund, 2006). To get an indication of whether a time series is stationary, the mean can be plotted against the data series. If the variable tends to cross the mean, it indicates a stationary process. A stationary time series tend to return to its mean; peaks will be followed by a collapse. In contrast non-stationary data series will not return to a normal.

However, one should note that the time series can be non-stationary even though the mean is constant. Non-stationarity can also be caused by a change in the variance, or if the correlation coefficient between X_t and X_{t-k} depends on other variables than the length of the lag k. Non-stationary data series affect the regression as they inflate the R-squared and the t-values, which may lead to incorrect model specifications (Studenmund, 2006).

In order to test for non-stationarity, we can test if the time series has a unit root. If so, the variable follows a random walk and is thereby non-stationary. Note that both trends and unit roots can cause non-stationarity. The Augmented Dickey-Fuller test is used in this thesis to test for unit root. It tests the null hypothesis of a unit root, hence, the null hypothesis of non-stationarity. Before this test is used, it is important to remove any trends[24]. Time trends (such as increasing mean) in the time series can be removed by differentiating the values. If the time series is still non-stationary, it is stochastic and shows the form of a random walk. Since the ADF test is derived on the assumption of no autocorrelation in the error term, lag must be included if autocorrelation is found. There are a number of different ways to choose the number of lags to add. In this thesis the Bayesian Information Criteria (BIC) has been used. Hence, a data sample is stationary if the mean, variance and covariance are constant for each given lag. The following equation is one of many forms the ADF test can have:

$$\Delta Y_t = \beta_0 + \beta_1 Y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta Y_{t-j} + \varepsilon_t \qquad \textbf{Equation 6.4}$$

The values are obtained by running an OLS regression, where β_0 is a constant, p is the number of lags and ε_t is the error term. It is the t-value of β_1 that is compared to the critical value, in order to reject the null hypothesis of non-stationarity.

6.4.2 Cointegration

If non-stationarity is uncovered, one alternative is to first differentiate the data series. For economic data this is usually enough to make the time series stationary. However, this is not unproblematic as we don't take full advantage of the information in the sample. Another alternative is to test if the two non-stationary data series are cointegrated. This is done by matching the degree of non-stationarity of the variables in an equation that makes the error term stationary. It also rids it for spurious regression results.

So, linear combinations of non-stationary variables can still be stationary, through being cointegrated. There exists a long-run equilibrium between cointegrated variables (Studenmund, 2006).

In this thesis we have used the Johansens test for cointegration, which is a vector auto-regression error correction model (VECM). The Johansens cointegration test has been performed using computer software for this thesis.

[24] The ADF test can still be used if the time series include a trend or if it includes a constant. Then these must be included in the regression as variables with a coefficient. Note also that the standard t-value tables do not apply to the ADF test and that different tables must be used whether or not a trend or a constant (or both) is included.

6.5 Bayesian Information Criterion (BIC)

Bayesian information criterion is used in this thesis in order to choose the appropriate number of lags to include in the models. BIC is closely related to the Akaike Information criterion (AIC) but BIC is chosen since it gives a heavier penalty for adding more parameters (Studenmund, 2006). The model with the lowest BIC value is preferable. The Bayesian information criterion can be expressed as:

$$BIC = \ln(\tilde{\sigma}^2) + \frac{k}{T}\ln T$$

Equation 6.5

$\tilde{\sigma}$ is the error variance, k is the number of parameters to be estimated and T is the size of the sample.

7 Data and Descriptive Statistics

This chapter is the first in the empirical part of this thesis, where descriptive analysis of the data material will be presented before regression analysis and model testing will be done in the following Chapters. Table 7.1 summarizes the time series that are used in this thesis. Lyse AS has provided the data and it will not be reproduced in tables as agreed.

Recall that the system price is important as it is the unconstrained market price for the entire Nord Pool area, and the underlying asset in all of the traded derivative products. The N02 price is used in the area price analyses, but since N02 was a part of N01 until 2009, this price is also added for comparison. Weekly futures are used in this thesis because they have the best prerequisites of being unbiased predictors of the future spot price, in addition to being one of the most traded contracts in the derivatives market of Nordic power[25].

Data	Period	Source
Daily and Weekly Spot Price SYS	2000 – 2012	Lyse AS
Daily and Weekly Spot Price N01	2007 – 2012	Lyse AS
Daily and Weekly Spot Price N02	2010 – 2012	Lyse AS
Daily Prices of Weekly Futures contracts (ENOW)	2007 – 2012	Lyse AS

Table 7.1 DATA OVERVIEW

In order to perform the empirical analyzes, quite comprehensive restructuring of the data material has been necessary, especially for the futures contract prices. NOK has been chosen as currency in this thesis, making it necessary to convert some of the data from Euro. Daily exchange rates have been collected at Oanda.com[26]. The daily spot prices are the arithmetic averages of all trading hours for each trading day. Further, weekly spot prices are the arithmetic mean of all trading hours for each trading week[27].

It is possible to trade the weekly futures contracts as of six weeks prior to delivery, and the last trading day is at end of the week before delivery starts. For the futures contracts, the price of the contracts one-, four- and six- week(s) prior to maturity have been used. We

[25] Quarter contracts are the most traded derivatives on NASDAQ OMX.
[26] Oanda.com was recommended by *Norges Bank* (Norges Bank, 2011)
[27] For simplicity reasons, I have removed week 53 in year 2009.

define this price as the last daily trading price of a specific contract, in that respective week. Typically this price will be the Friday price of a contract, one-, four or six weeks prior to maturity, but holidays interrupt this pattern. The future contracts are settled against the average of the 60 hours in the delivery week[28], since these are peak load contracts.

Due to some extreme values in the samples, it was considered to additionally include trimmed data samples. This was still not done since extreme values should be considered an important characterization of the electricity prices and trimming the data in order to make the statistical fit better was considered to be wrong. In addition to the full sample period from 01.01.2007 to 31.12.2012, two sub-samples have been made. The first period stretches from 01.01.2007 to 31.12.2009, while the second period stretches from 01.01.2010 to 31.12.2012. The equal length sub-periods are introduced in order to capture potential changes coming from the restructure of the bidding areas and the introduction of Kristiansand N02 on the first of January 2010. Tables with excerpts of the descriptive statistics are found in each section. For the complete tables with descriptive statistics, see Table 0.1 and Table 0.2 in the appendix which can be found in the end of the thesis.

7.1 Spot- and Futures Price Description

The general price formation was discussed and described in Chapter 5. In this chapter, data series will be quantitatively analyzed in order to compare it to this theory and in order to test whether the data series violate the assumptions introduced in Chapters 6.3 and 6.4. But first of all, the price development for electricity as of the millennium will be given a short qualitative description by comparing important findings with potential causative reasons. Seasonal analysis is found first in Chapter 10 in order to make use of the results from the empirical analysis. Figure 7.1 displays the system price development from year 2000 to the end of 2012.

The high peaks are normally a result of reservoir level below the mean during the winter. The dramatic price increase during winter 2002 was claimed to be a result of high export despite low reservoir levels due to a cold and dry fall (Dn, 2002). This peak was followed by almost three years with a quite stable, but high electricity price which could be explained by

[28] These are Peak load futures contracts with delivery Monday to Friday 08.00-20.00. In contrast Base load contracts have delivery based on all of the 168 hours during a week.

a fear of new peaks (Dn, 2003). Botterud et al.(2010) claim that the introduction of the ETS scheme in 2005 would affect the cost of hydropower. It could seem like the price increased from then, although we do not have basis to claim that the incidents are further connected. A new peak occurred at the end of 2009 and winter 2010.

Dry and cold weather are still pointed out as the price drivers, but in addition the political influence of higher export of electricity should be considered to be contributing for the record high prices (Tn, 2009). Despite the peaks and generally high volatility, the electricity prices seem to have had a slow increase throughout the period, which could be explained by a greater increase in demand than in supply (Bye, 2006).

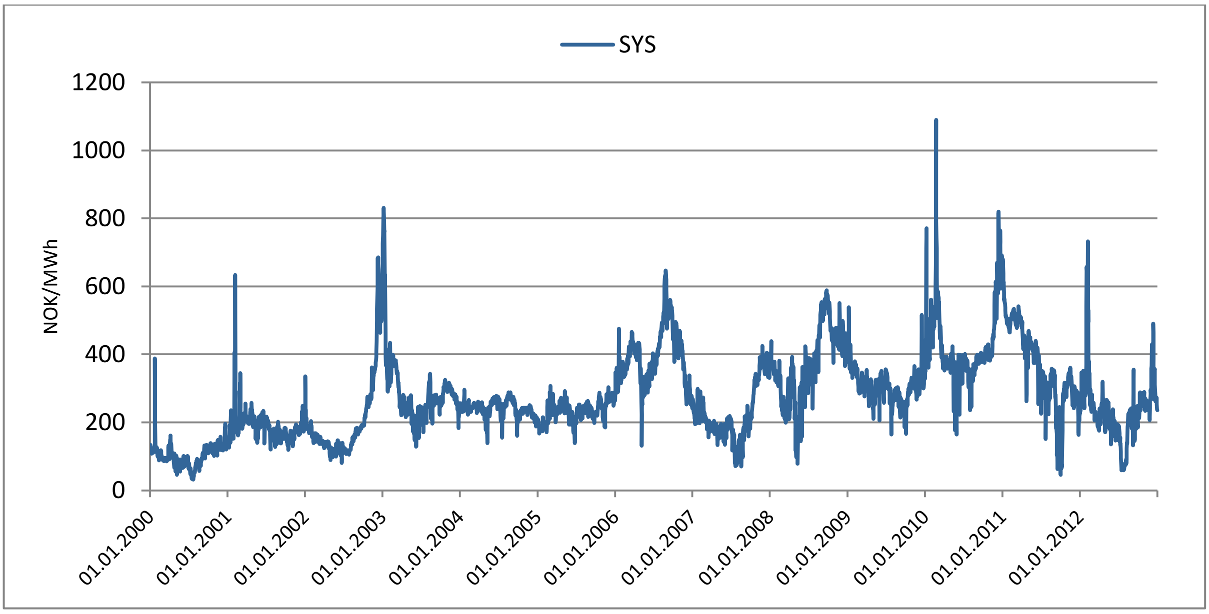


Figure 7.1 DAILY AVERAGE OF SYSTEM PRICE: (NOK/MWh) Jan.2000-Dec.2012.

The system price and the area prices N01 and N02 are displayed in Figure 7.2. Except from a few extreme short-term deviations, the spot prices are similar in level and highly correlated. The different spot prices will therefore exhibit much of the same properties and price patterns in our following discussion. If no explicit comments of differences are made, it is assumed that the different spot prices have the same properties.

The most obvious differences in spot prices are found during summer 2008 and at the beginning of 2010, and partly during the summer of 2007. It is interesting to see that these deviations occur when the bidding areas are restructured. In 2008 the N01 area includes a hydro dominated area (Bergen) and end up with a lower area price than the system, while in

2010 the N01 area excludes a hydro dominated area (Kristiansand/Stavanger) and ends up with an area price much higher than the system price.

Figure 7.3 displays the weekly futures prices of contracts with delivery in the same period as above. Note that it is the futures contracts that are the reference for each observation, not the dates. This can be explained as each value of X refer to three values of Y, which are the prices for that specific contract respectively one-, four- and six- week(s) prior to maturity.

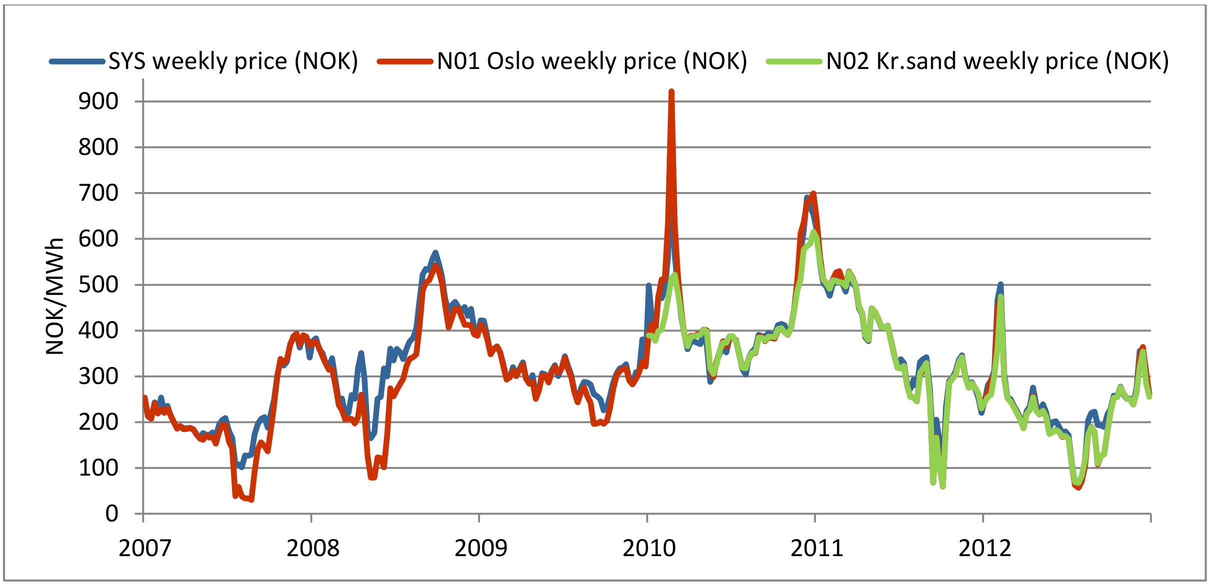


Figure 7.2 WEEKLY AVERAGE SPOT PRICES: SYS, N01 and N02 (NOK/MWh) 01.01.2007-31.12.2012.

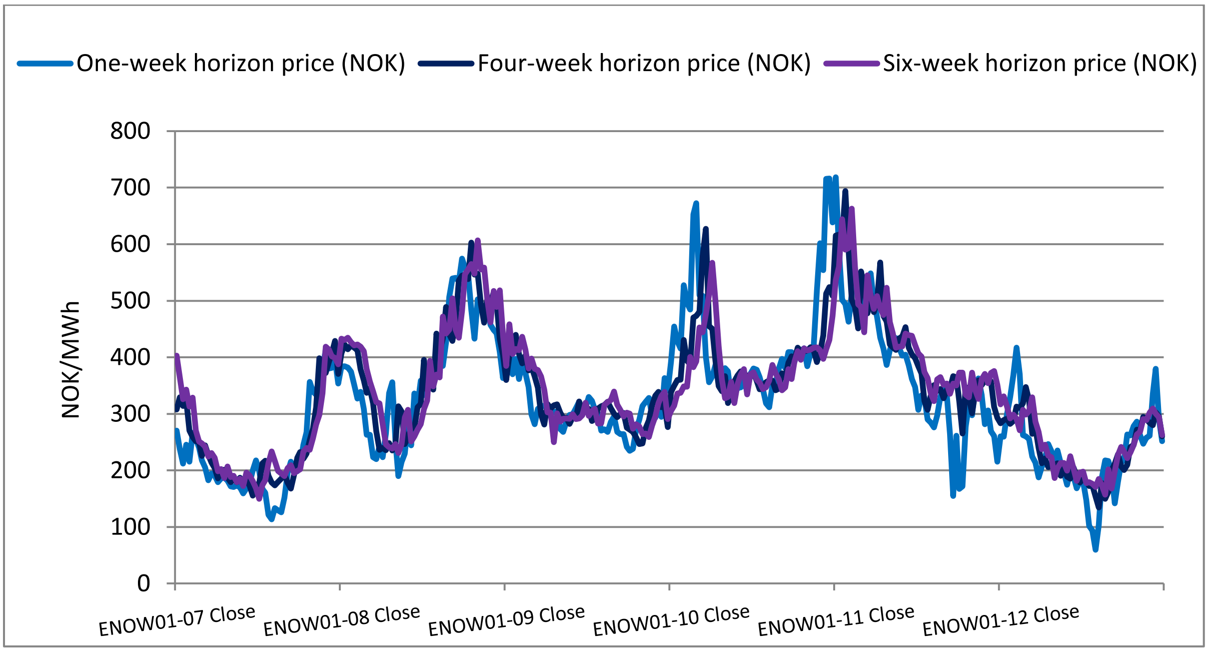


Figure 7.3 FUTURES PRICES OF WEEKLY CONTRACTS (ENOW01.07- ENOW52.12): one-, four- and six weeks prior to maturity.

Table 7.2 provides the price level statistics for the spot- and the futures- prices. Recall that the futures prices only relate to the system price, and not the area prices. Not surprisingly, the spot and the futures prices seem to follow similar price patterns. This is due to the short time horizon for the futures contracts where the futures price is adjusted to new information as maturity approaches. Falling futures prices as maturity approaches indicates that the market exhibits Contango, which will be further investigated later when we analyze the basis risk.

Furthermore, we find the average prices to be higher in the latest period, combined with a higher variation. The price ranges are extremely high for both periods, and is also highest for the second period.

Sample 2007-2012	Mean	St.dev.	Min.	Max.	n
SYS weekly price (NOK)	321,02	116,07	62,14	714,01	312
F1 price (NOK)	324,70	116,83	59,84	718,33	312
F4 price (NOK)	334,17	106,49	134,56	694,01	312
F6 price (NOK)	337,89	103,10	149,99	663,12	312
Sub-sample 2007-2010					
SYS weekly price (NOK)	299,69	98,64	101,80	570,48	156
N01 weekly price (NOK)	275,04	108,65	30,05	542,18	156
F1 price (NOK)	303,62	99,51	113,33	574,62	156
F4 price (NOK)	317,23	99,24	155,26	602,59	156
F6 price (NOK)	322,75	100,76	149,99	606,58	156
Sub-sample 2010-2012					
SYS weekly price (NOK)	342,35	128,00	62,14	714,01	156
N01 weekly price (NOK)	339,88	144,27	56,97	922,17	156
N02 weekly price (NOK)	328,46	123,73	59,90	615,52	156
F1 price (NOK)	345,78	128,79	59,84	718,33	156
F4 price (NOK)	351,11	111,02	134,56	694,01	156
F6 price (NOK)	353,03	103,50	157,21	663,12	156

Table 7.2 DESCRIPTIVE STATISTICS, PRICE LEVEL: Spot- and Futures Prices. 2007-2012. (NOK)

7.1.1 Volatility

Figure 7.4 displays the weekly volatility of the spot prices[29] while Figure 7.5 displays the volatility of the weekly futures contracts at the different horizons to maturity. The futures contracts volatility will be a measure of how much the contract price changes a given week prior to delivery from one traded contract to the following traded contract. Some extreme

[29] The weekly price changes is given by the logarithmic change; $r_t = \ln x_t - \ln x_{t-1}$.

observations in both figures complicate the illustrations[30]. Consequently, the y-axis has been compressed in order to get a better visual of the major part of the fluctuations, instead of trimming the data series.

The high volatility makes it challenging to forecast the price in the electricity market (Gjølberg & Brattestad, 2011). For the whole sample, the system price has a weekly volatility of 15%, which is equivalent to an annualized volatility of 107%. Nevertheless, it is not unlikely to see changes far greater than this. Compared to other commodity and stock markets, these numbers are extremely high. Eydeland & Wolyniec (2003) describe it as truly unusual and extraordinarily high compared to other prices like for instance the dollar/yen exchange rates (10%-20%), SP500 index (20%-30%), NASDAQ (30%-50%), natural gas prices (50%-100%). They find that the electricity prices have values of 100%-500%. The high volatility is confirmed by Gjølberg & Brattestad (2011) that find weekly changes of 25 % and more to be likely. Some of the volatility can be explained by the seasonal price movements; nevertheless, it is likely that the market suffers from substantial price risk (Berg, 2010). Table 7.3 summarizes the descriptive statistics of the weekly changes.

Botterud et al. (2010) argue that more financial activity combined with better connections through cables and thereby better production mix, will decrease volatility over time. When a linear trend line[31] is added onto the system price change in Figure 7.4, we get a slight indication of a decrease as it fell with 0,01% per week, which corresponds to an annualized decrease in volatility of 0,07%. Whether this is to be considered a trend or not will be analyzed when we test for stationarity later in this Chapter.

[30] Information about the extreme values can be found in the data tables as maximum values.
[31] The trend line was further removed again.

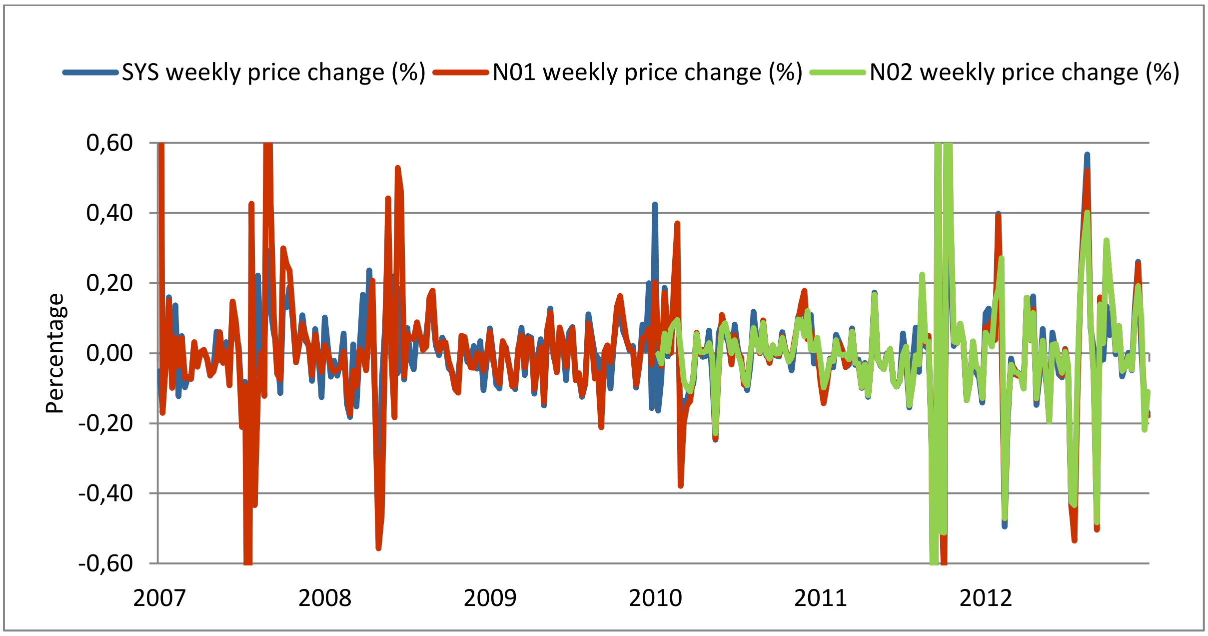


Figure 7.4 WEEKLY SPOT PRICE CHANGE: SYS, N01 and N02 ($r_t = \ln x_t - \ln x_{t-1}$). 01.01.2007.31.12.2012

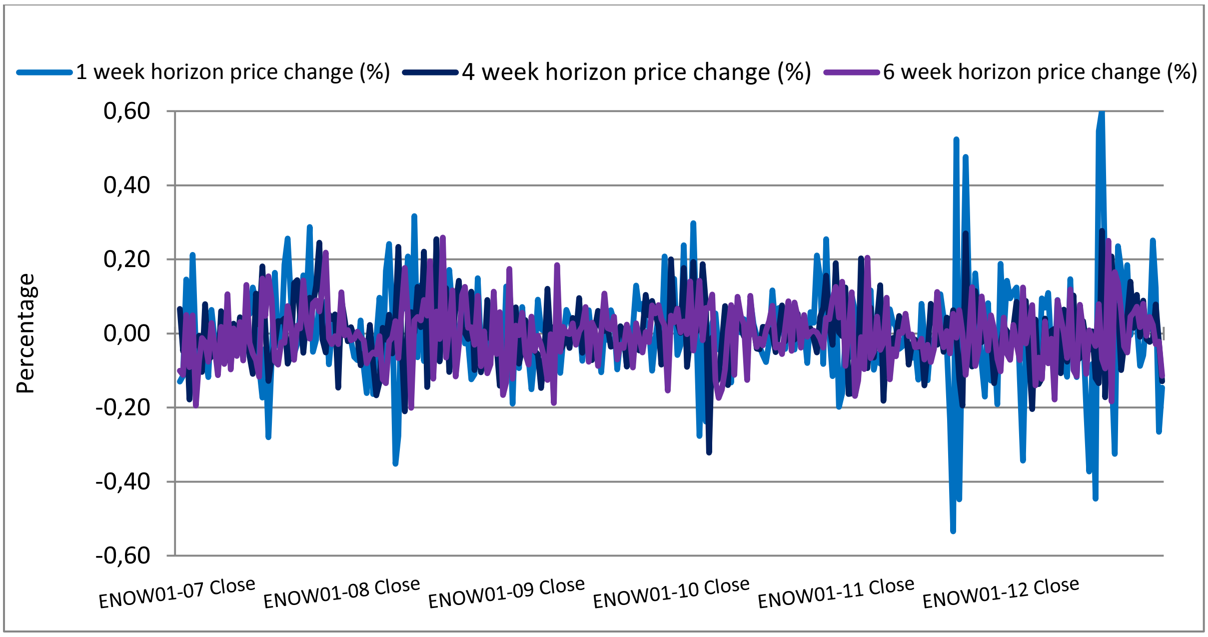


Figure 7.5 FUTURES CONTRACT PRICE CHANGE: ENOW 01.07-52.12, one-, four- and six- week prior to delivery (%)

The data indicates that the area prices suffer from higher volatility than the system price. In the first period the N01 area price has a weekly volatility of 25% while the system price has a volatility of only 10%. In the second period, the system price volatility is still lower than the area price volatilities, but the spread is lower with 18% compared to 22% in N01 and 21 % in N02. This could be explained by the fact that the bidding areas suffer from price risk over space in addition to over time.

Note that volatility in the spot market is higher than in the futures market. This is expected since the spot market is more sensitive to new information. Burger et al. (2007) argue that the volatility in the spot market is significantly higher than in the derivatives market, as we cannot predict the weather at maturity. This is supported by the trend in our data that volatility increases when maturity approaches and the weather forecasts get more precise. Volatility in the one week horizon is 13%, while it is 9% in the four week horizon and 8% in the six week horizon. This is equivalent to an annualized volatility of respectively 96%, 62% and 58%.

If the volatility changes over time, it is a sign of heteroskedasticity. Despite some heavy peaks, the figures indicate that both the spot- and the futures price volatility seem to be quite constant. This will be further analyzed when we perform residual diagnostics in Chapter 1. The volatility will also be subject for further analysis later in the thesis when the variations through the calendar weeks are investigated.

Sample 2007-2012	**Mean**	**St.dev.**	**Min.**	**Max.**	**n**
SYS weekly price change	0,0000	0,149	-0,703	1,092	312
F1 weekly price change	0,0002	0,134	-0,534	0,603	311
F4 weekly price change	-0,0005	0,086	-0,321	0,278	311
F6 weekly price change	-0,0014	0,081	-0,201	0,259	311
Sub-sample 2007-2010					
SYS weekly price change	0,0014	0,107	-0,500	0,350	156
N01 weekly price change	0,0146	0,253	-1,319	2,043	156
F1 weekly price change	0,0015	0,104	-0,352	0,317	155
F4 weekly price change	-0,0007	0,082	-0,210	0,255	155
F6 weekly price change	-0,0021	0,083	-0,201	0,259	155
Sub-sample 2010-2012					
SYS weekly price change	-0,001	0,183	-0,703	1,092	156
N01 weekly price change	-0,001	0,224	-1,317	1,172	156
N02 weekly price change	-0,003	0,211	-1,319	1,172	155
F1 weekly price change	-0,002	0,158	-0,534	0,603	156
F4 weekly price change	0,000	0,091	-0,321	0,278	156
F6 weekly price change	-0,001	0,079	-0,183	0,250	156

Table 7.3 DESCRIPTIVE STATISTICS, VOLATILITY: Spot- and futures weekly price change 01.01.2007-31.12.2012.

7.1.2 Spikes and Normality fit

An excerpt from the test results is found in Table 7.4. The full sample system price is not normally distributed. However, in the first period both the nominal value of the system price, and the nominal and the logarithmical values of the N01 area price are normally distributed. In the second period, the nominal values of both the system price and the N02 area are normally distributed. Furthermore, the result shows that the logarithms of the futures prices are closer to being normally distributed than the nominal values. For the full sample, only the log of F4 and F6 are close to being normally distributed. All of the log values are normally distributed in the first period, while F4 and F6 are normally distributed in both nominal and log values in the second period.

Figure 7.6 illustrates how the different time series are fitted to the normal distribution[32]. We find that both the system price and the six week futures price have best match with the Weibull distribution. The one week futures have a best match with the gamma distribution while the four week futures have best match with the log logistic distribution. All of the spot prices and futures prices have positive skewness. This indicates that the tail of the distribution is larger to the right than to the left, as a result of a predominance of extreme high values. Hence, the electricity prices tend to have greater probability for extreme high prices than for extreme low prices. The histograms indicate that the tails are fatter to the right and in line with the skewness results. In addition they indicate that the frequency of observations that is lower than the mean is higher than the frequency of observations that is higher than the mean. However, skewness is positive because the observations that are higher than the mean seem to be more extreme.

[32] Note that because the educational version of @Risk software had a restriction of 250 input data, every fourth observation was left out. This gave 235 observations.

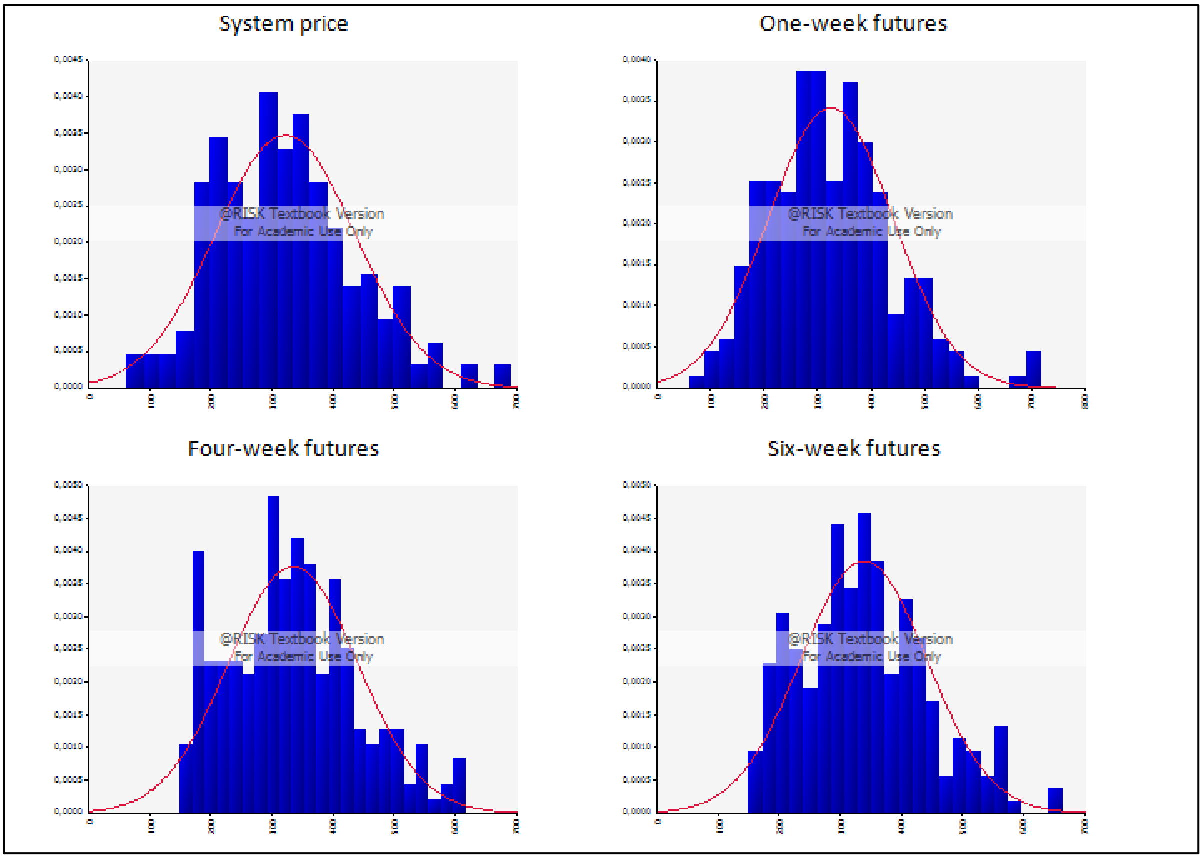


Figure 7.6 NORMAL DISTRIBUTION FIT: SYS, F1, F4 and F6, weekly prices 2007-2012.

Sample 2007-2012	Min	Max	Skewness	Kurtosis	Jarque-Bera	n
SYS weekly price (NOK)	62,14	714,01	0,525	0,379	15,8**	312
SYS weekly price (Ln)	4,13	6,57	-0,789	1,467	58,0*	312
F1 price (NOK)	59,83	718,32	0,649	0,637	26,0*	312
F1 price (Ln)	4,09	6,58	-0,559	0,874	25,0*	312
F4 price (NOK)	134,56	694,00	0,511	0,045	13,0**	312
F4 price (Ln)	4,90	6,54	-0,241	-0,484	6,2**	312
F6 price (NOK)	149,99	663,12	0,456	-0,110	10,9**	312
F6 price (Ln)	5,01	6,50	-0,234	-0,542	6,78**	312

*p=0,0000, **p<0,05, ***p>0,05

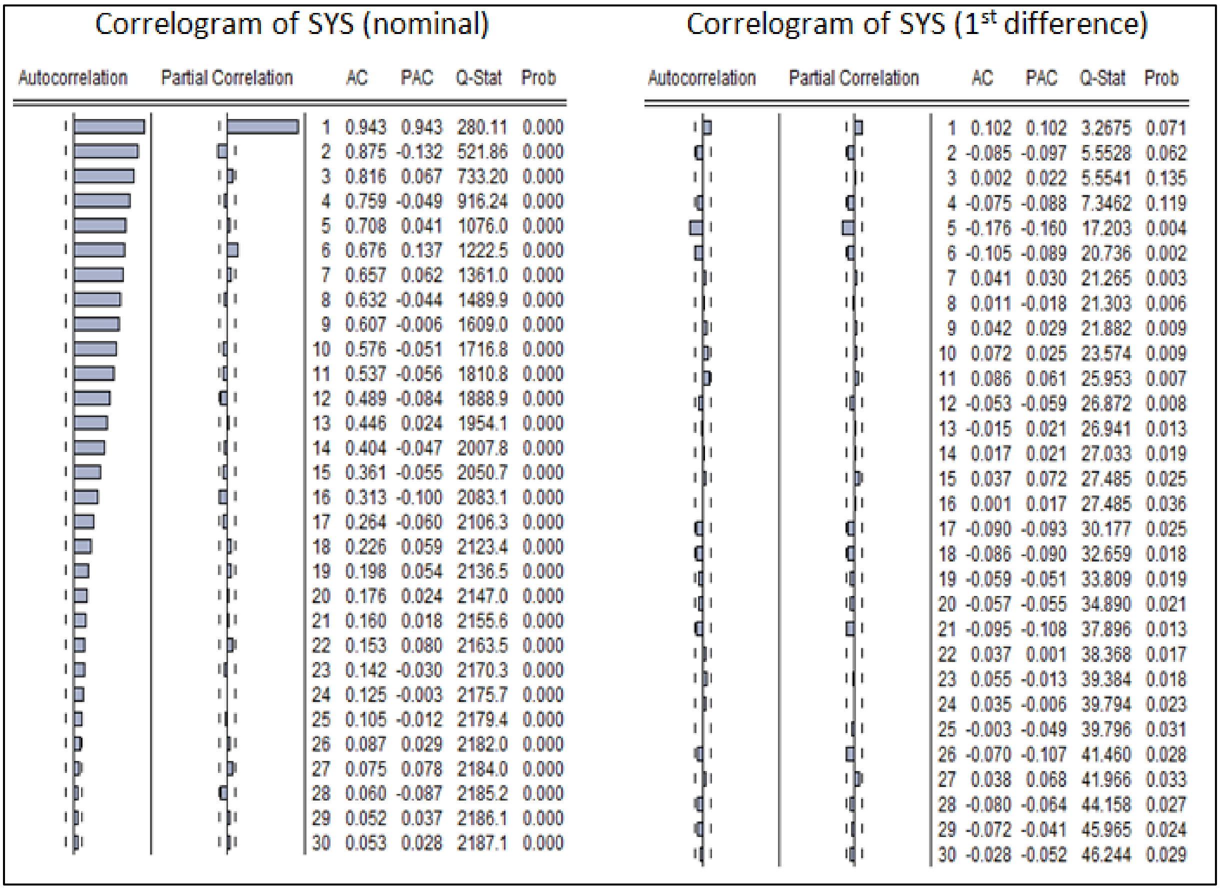
Table 7.4 DESCRIPTIVE STATISTICS, SPIKES AND NORMALITY: Weekly Spot- and futures prices 2007-2012.

7.1.3 Autocorrelation

Note that the Breusch-Godfrey test that was introduced to test for autocorrelation is used only on the residuals. For analysis of the time series we use the Ljung-Box test, which tests the null hypothesis of no autocorrelation. For the test result values, it is referred to the tables in the Appendix at the end of the thesis.

All of the nominal- and log time series reject the null hypothesis, and states that all of the samples exhibit autocorrelation. Even though the log differentiated time series have removed the autocorrelation from their respective data series, the nominal values will be used in the regression analysis. If autocorrelation is found in the residuals, the standard errors will be adjusted instead of removing the autocorrelation. Figure 7.7 compare the 30 lagged auto-correlation of the nominal system price with the 1st difference.

Autocorrelation in the weekly system prices implies that this week's price is dependent on last week's price. Further next week's price will be dependent on this week's price. Thus it implies that the future prices are predictable, to some extent. In contrast the weekly changes are not auto-correlated. Whether or not the next week's price will move up or down compared to this week's price, is independent on whether or not the price-move from last week to this weeks. The results are intuitive and expected. Autocorrelation in the system price is found in other studies such as Berg (2010) and Bernseter (2003).



Correlogram of SYS (nominal)

Lag	AC	PAC	Q-Stat	Prob
1	0.943	0.943	280.11	0.000
2	0.875	-0.132	521.86	0.000
3	0.816	0.067	733.20	0.000
4	0.759	-0.049	916.24	0.000
5	0.708	0.041	1076.0	0.000
6	0.676	0.137	1222.5	0.000
7	0.657	0.062	1361.0	0.000
8	0.632	-0.044	1489.9	0.000
9	0.607	-0.006	1609.0	0.000
10	0.576	-0.051	1716.8	0.000
11	0.537	-0.056	1810.8	0.000
12	0.489	-0.084	1888.9	0.000
13	0.446	0.024	1954.1	0.000
14	0.404	-0.047	2007.8	0.000
15	0.361	-0.055	2050.7	0.000
16	0.313	-0.100	2083.1	0.000
17	0.264	-0.060	2106.3	0.000
18	0.226	0.059	2123.4	0.000
19	0.198	0.054	2136.5	0.000
20	0.176	0.024	2147.0	0.000
21	0.160	0.018	2155.6	0.000
22	0.153	0.080	2163.5	0.000
23	0.142	-0.030	2170.3	0.000
24	0.125	-0.003	2175.7	0.000
25	0.105	-0.012	2179.4	0.000
26	0.087	0.029	2182.0	0.000
27	0.075	0.078	2184.0	0.000
28	0.060	-0.087	2185.2	0.000
29	0.052	0.037	2186.1	0.000
30	0.053	0.028	2187.1	0.000

Correlogram of SYS (1st difference)

Lag	AC	PAC	Q-Stat	Prob
1	0.102	0.102	3.2675	0.071
2	-0.085	-0.097	5.5528	0.062
3	0.002	0.022	5.5541	0.135
4	-0.075	-0.088	7.3462	0.119
5	-0.176	-0.160	17.203	0.004
6	-0.105	-0.089	20.736	0.002
7	0.041	0.030	21.265	0.003
8	0.011	-0.018	21.303	0.006
9	0.042	0.029	21.882	0.009
10	0.072	0.025	23.574	0.009
11	0.086	0.061	25.953	0.007
12	-0.053	-0.059	26.872	0.008
13	-0.015	0.021	26.941	0.013
14	0.017	0.021	27.033	0.019
15	0.037	0.072	27.485	0.025
16	0.001	0.017	27.485	0.036
17	-0.090	-0.093	30.177	0.025
18	-0.086	-0.090	32.659	0.018
19	-0.059	-0.051	33.809	0.019
20	-0.057	-0.055	34.890	0.021
21	-0.095	-0.108	37.896	0.013
22	0.037	0.001	38.368	0.017
23	0.055	-0.013	39.384	0.018
24	0.035	-0.006	39.794	0.023
25	-0.003	-0.049	39.796	0.031
26	-0.070	-0.107	41.460	0.028
27	0.038	0.068	41.966	0.033
28	-0.080	-0.064	44.158	0.027
29	-0.072	-0.041	45.965	0.024
30	-0.028	-0.052	46.244	0.029

Figure 7.7 WEEKLY SYSTEM PRICE, CORRELOGRAM: 2007-2012

7.1.4 Mean Reversion (Stationarity)

The results from the ADF-tests which is performed in order to test for stationarity, is summarized in Table 7.5. Recall that the number of lags is decided by BIC. Furthermore, it had to be decided whether to add a constant, a trend or both.

There were no clear signs of trends, when the time series was plotted against its mean, but the constants had significant influence both on the system price and the futures price when the data was represented in levels. Only the level test of the system price suggested introducing a lag. However, when a similar test was carried out and manually adjusting the maximum number of lags equal to zero, the results still showed stationarity.

The test for a unit root on level data series showed that both the system price and the futures price hold stationarity when a constant was included, since the null hypothesis of a unit root could be rejected. This means that we don't have to be afraid of spurious results from the regression analyses even though we do not include lags. Note that the results from the first difference show that the p-level is significantly reduced for these unit root tests, which makes them more reliable than the level data.

The results from the remaining data is not provided, since all the spot data are very similar to the system price, and all the futures data are very similar to the one-week futures price series. This also applies to the sub samples.

Sample 2007-2012	Lags	Constant	ADF	Critical value (95 %)	p-value	n
SYS weekly price (Level)	1	yes	**-3,40**	-2,87	0,0116	312
	0	no	**-0,99**	-1,94	0,2890	312
SYS weekly price (d1)	0	yes	**-15,82**	-2,87	0,0000	312
	0	no	**-15,84**	-1,94	0,0000	312
F1 weekly price (Level)	0	yes	**-2,98**	-2,87	0,0375	312
	0	no	**-1,02**	-1,94	0,2752	312
F1 weekly price (d1)	0	yes	**-17,77**	-2,87	0,0000	312
	0	no	**-17,77**	-1,94	0,0000	312

Table 7.5 DESCRIPTIVE STATISTICS, ADF TEST: Sys- and one-week futures price. Level and first differentiated 2007-2012

Figure 7.8 displays the difference between the test of level and the test of the first difference of the system price. Since the level is already stationary and without a trend, the two graphs are quite similar, but still we see that the first difference makes the data move around a constant to a greater extent than the level test do.

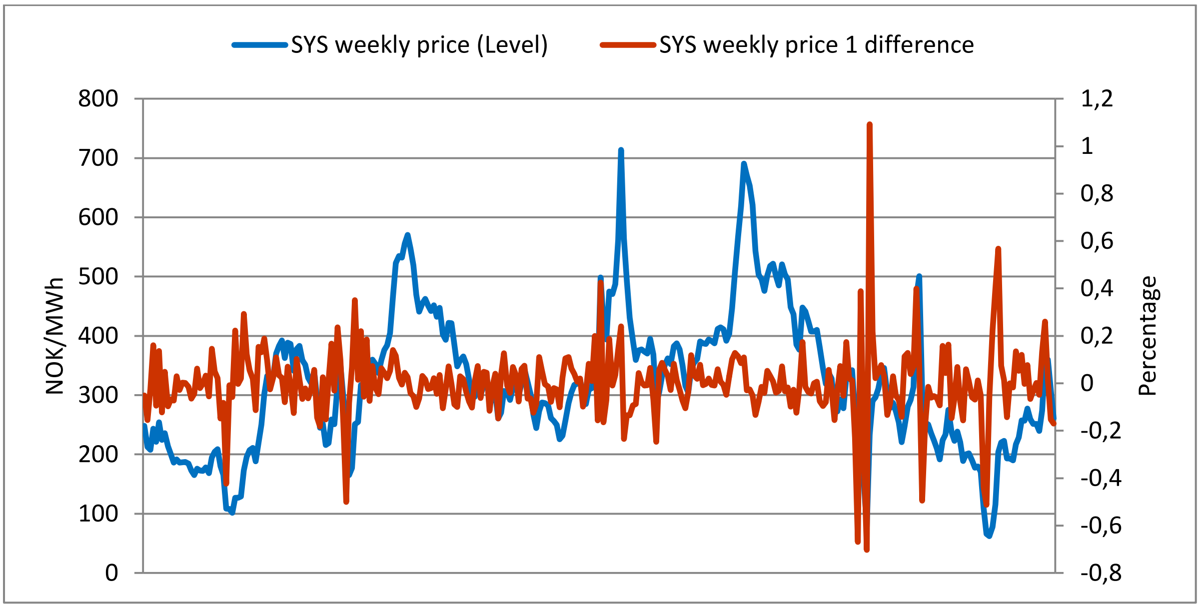


Figure 7.8 DESRIPTIVE STATISTICS, MEAN REVERSION: Sys weekly price in level (NOK) compared to the first difference (%) 01.01.2007.31.12.2012

The previous studies that were discussed in Chapter 5.2.1 argued that the system price should be mean reverting because the price determining factors, such as the weather, is mean reverting. Our results confirm these assertions. Though, we will not further investigate the reason for this.

7.1.5 Cointegration Results

Since the ADF results are quite close to the critical values, it is tested for cointegration between the system price and the futures price, in order to find the potential long run equilibrium.

The Johansen cointegration test requires that the data must be non-stationary and must be integrated of the same order. Since the ADF results of the levels show that both the system price and the futures price are non-stationary when a constant is not included, we make this assumption in the Johansen cointegration test. Furthermore, both data series become stationary in first difference. Based on the other results an assumption of no lags was made.

Both the Trace test and the Maximum Eigenvalue are higher than the critical value, and thereby reject the null hypothesis. The null hypothesis of “at most 1” cannot be rejected, implying that there exists one cointegrated equation between the system price and the futures price. An excerpt of the test result is provided in the Table 7.6.

Included observations: 311 after adjustments
Trend assumption: No deterministic trend
Series: SYS F1
Lags interval (in first differences): No lags

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.684175	359.4986	12.32090	0.0001
At most 1	0.003370	1.049951	4.129906	0.3550

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.684175	358.4487	11.22480	0.0001
At most 1	0.003370	1.049951	4.129906	0.3550

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Table 7.6 DESCRIPTIVE STATISTICS, JOHANSENS TEST: Sys price and one-week futures contract 2007-2012.

8 Derivations and Models

Recall our introduction of the commodity spot and futures relationship through The Theory of Storage and The Theory of Risk Premium. We will now develop this further in order to perform various empirical analyses on the data we described in Chapter 1.

8.1 Ex-post Forecast Errors and Basis Risk

In this section, equations will be derived in order to investigate the biasedness of the futures contracts. This is also called the forecast error (Gjølberg & Brattestad, 2011), since it actually calculates the difference between the expected future spot price through the price paid for the futures contract, with the materialized spot price. The payoff from a position that is held to maturity and reversed will be equivalent to this forecast error.

When assuming a short position in a futures contract, the payoff from one unit of an asset is calculated as:

$$Payoff = K - S_T$$

Equation 8.1

where K is the delivery price (contract price) and S_t is the spot price of the asset at maturity of the contract (Hull, 2009). This is the same as:

$$Forecast\ error = F_t - S_T$$

Equation 8.2

where t represents the time to maturity. The forecast error will be calculated for t=1, 4 and 6 (week(s) prior to maturity). If the expected spot price is underestimated (overestimated), the forecast error will be negative (positive).

The equations for the ex-post basis risk are similar as for the ex-post forecast Error, except that the spot price at delivery T is replaced with the spot price at time t. Hence, the spot price and the futures price on the same date t are compared. The spot price on the last day of trading one-, four- and six- week(s) prior to maturity will be used to calculate the basis.

8.2 Ex-post and Risk Premium Convenience Yield

Recall Equation 4.3 introducing The Theory of Risk Premium. Assuming that the market is efficient and that the futures price is an unbiased predictor of the future spot price, the risk premium can be expressed as:

$$-P_t = \ln \frac{E_t(S_{t+T})}{F_{t,T}} \qquad \textbf{Equation 8.3}$$

Since it is hard to observe expected prices (Gjølberg & Brattestad, 2011), it is normal to compare the futures price at t, with the materialized delivery spot price at T[33]. Thus, when historical data is analyzed the expected future spot price at maturity can be replaced with the materialized spot price at maturity. Hence, we get the following equation[34]:

$$P_t = \ln \frac{F_{t,T}}{S_T} \qquad \textbf{Equation 8.4}$$

The price at time t of the futures contract with maturity at time T will then have the following relationship to the spot price at maturity T:

$$F_{t,T} = S_T \ e^{P_T} \qquad \textbf{Equation 8.5}$$

It can be shown that the by using The Theory of Risk Premium, the results will be similar to the ones from the forecast error. The relative forecast error is defined as:

$$Relative\ forcast\ eror = \frac{F_{t,T} - S_T}{S_T} \qquad \textbf{Equation 8.6}$$

This equals:

$$\frac{F_{t,T} - S_T}{S_T} = \ln F_{t,T} - \ln S_T = \ln\left(\frac{F_{t,T}}{S_t}\right) = P_t \qquad \textbf{Equation 8.7}$$

Consequently we have that:

$$e^{P_t} = 1 + (\frac{F_{t,T} - S_T}{S_T}) \qquad \textbf{Equation 8.8}$$

This can be used to derive the following equation:

[33] T=t+i, thus t will be the time before delivery/maturity.

[34] Note that: $-1\left[\ln\frac{a}{b}\right] = \ln\frac{b}{a}$

$$F_{t,T} = S_T\left(1 + \left(\frac{F_{t,T} - S_T}{S_T}\right)\right) \qquad \text{Equation 8.9}$$

Hence, the relative forecast error can be used as a measure of the percentage difference between the realized spot price at time T and the futures price at time t, and is thereby a measure of the risk premium as a percentage of the spot price. This reveals a new issue; whether the forecast error exclusively is a result of a risk premium, or if it is a deviation because of other factors, like an immature market. This will be touched by one of the regression models and further discussed later in the thesis.

Now that it is shown that the risk premium can be interpreted as a forecast error, we move on to The Theory of Storage in order to interpret the convenience yield. Recall that Botterud et al.(2010) define the convenience yield as the benefit from owning the physical commodity that is not obtained by holding a futures contract. Equation 4.2 can be expressed as:

$$cv_{t,T} = y_{t,T} - u_{t,T} = \ln\left(\frac{S_t}{F_{t,T}}\right) \qquad \text{Equation 8.10}$$

where $cv_{t,T}$ is the net-convenience yield in week t, for the holding period until T. S_t is the average spot price in week t, and $F_{t,T}$ is the futures price in week t of a contract with delivery in week T. Note that the risk free interest rate is assumed to be zero. This is done for simplicity reasons and is not unreasonable since it is close to zero for the short periods that the weekly futures contracts are held. The relationship between the basis risk and the convenience yield can easily be seen through Equation 8.10.

To sum up, we can conclude that the basis risk can be interpreted as the convenience yield, while the forecast error can be interpreted as the risk premium. Note that since we assumed a short position for the forecast error and the risk premium, the interpretation requires the signs to be opposite.

8.3 Regression Models

Regression models will now be presented in order to uncover more from the relationship between the spot- and futures prices. The forecast is said to be unbiased if the beta equal unity while a constant different from zero is interpreted as a risk premium (Gjølberg & Brattestad, 2011). Hence, the two first model tests in nominal values and in logarithms respectively, if the future spot price at maturity can be expressed as a function of the futures contract price. Recall that we use the materialized spot price with maturity at time T, instead of the expected future spot price at time t.

$$S_T = \alpha + \beta F_{t,T} + \epsilon_T \quad \textbf{Model 8.1}$$

$$ln\, S_T = \alpha + \beta lnF_{t,T} + \epsilon_T \quad \textbf{Model 8.2}$$

Gjølberg & Brattestad (2011) claim that there are fundamental problems related to this approach, as the risk premium may not be constant, making the alpha value a mixture of time-varying risk premiums, which again influences the estimated slope coefficients. Thus, they propose a model where the spot-price change in monetary terms or percentage terms is estimated as a function of the basis, or the relative basis. The null hypothesis of the next models is that beta equals unity, while alpha may be different from zero as a result of net-short or net-long hedging demand generating a constant risk premium.

$$(S_T - S_t) = \alpha + \beta\left(F_{t,T} - S_t\right) + \epsilon_T \quad \textbf{Model 8.3}$$

$$(ln\, S_T - lnS_t) = \alpha + \beta\left(lnF_{t,T} - lnS_t\right) + \epsilon_T \quad \textbf{Model 8.4}$$

The futures prices should capture all relevant information inherent in historic price observations, in a well-functioning and efficient market (Gjølberg & Brattestad, 2011). Consequently, they suggest adding a previous price into the model in order to test this. The forecast performance of the futures price should then <u>not</u> be improved by this model, unless there is a relationship between previous prices and the risk premium. If assuming no such systematic risk Equation 8.4 should not be improved by the following equation:

$$(ln\, S_T - lnS_t) = \alpha + \beta\left(lnF_{t,T} - lnS_t\right) + \gamma\, lnS_t + \epsilon_t \quad \textbf{Model 8.5}$$

The last model presented is concerned on the same issue as Model 8.5 and builds on Model 8.1. In addition to the futures contract price, it includes the lagged spot prices of the delivery week in previous years. If including lagged spot prices improve the performance of Model 8.1 we have basis to claim that the futures prices are not the best estimates of the future spot price.

$$S_T = \alpha + \beta_0 F_{t,T} + \sum_{i=1}^{n} \beta_i S_{T-iY} + \epsilon_T$$

Model 8.6

9 Empirical Analysis and Results of Spot-Futures Relationship

9.1 Ex-post Forecast Errors and Basis Risk Results

The relative forecast errors for each of the three time horizons are displayed in Figure 9.1 while the similar relative basis risk is displayed in Figure 9.2. Extreme observations in both figures at the end of 2011 and mid-2012, complicates the illustration[35]. Consequently, the y-axis is compressed in order to get a better visual of the major part of the fluctuations, instead of trimming the data series. The complete results from the calculation of the forecast errors, relative forecast errors and relative risk premiums are summarized in Table 9.1.

Extreme forecast errors occur quite often, and the maximum- and minimum values reveal overestimation errors of 114% for the one week positions and 377% for the 6 week positions. The underestimations are not that frequent and far from as extreme with minimum values of 26% for the one week positions and 46% for the six week positions. The errors tend to increase with the time horizon, which was expected as the shorter horizons should generally hold more information about the expected price and hence reduce the error.

The means are all positive and imply that the futures prices tend to overestimate the future spot prices. Short positions in the futures market through this period would give a profit for all of the three horizons analyzed. The overestimates for the one, four and six week horizon are respectively around 2%, 9% and 12%. In other studies (Bernseter, 2003) show that the weekly futures contracts have overestimated the future spot price with 0,7% one week prior to maturity, in the period from 1995 to 2003. Gjølberg & Brattestad (2011) show that the four-week forecast error is 7,4% and the six-week forecast error is 8,2% in the period 1995-2008, and respectively 9,3% and 10,8% in the period 2003-2008. Further comparison with other commodities is difficult since such errors require that the commodity cannot be stored, or else arbitrage opportunities occur.

[35] Information about the extreme values can be found in the data tables as maximum values.

The basis has had similar extreme values as the forecast errors, also with more extreme positive than negative values and with positive skewness. The basis is positive for all three horizons and seems to decrease as delivery approaches. This is expected and consistent with the theory we introduced about the relationship between the futures price and the spot price, illustrated in Figure 4.2. Note that positive basis in this case means that the current futures price is higher than the current spot price.

One week prior to maturity, the analyzed contracts have a relative basis of 0,9% while it is 7,3% four weeks prior to maturity and 9,5% six weeks prior to maturity. These values are similar to the results Gjølberg & Brattestad (2011) calculated in their study of the period 1996-2009.

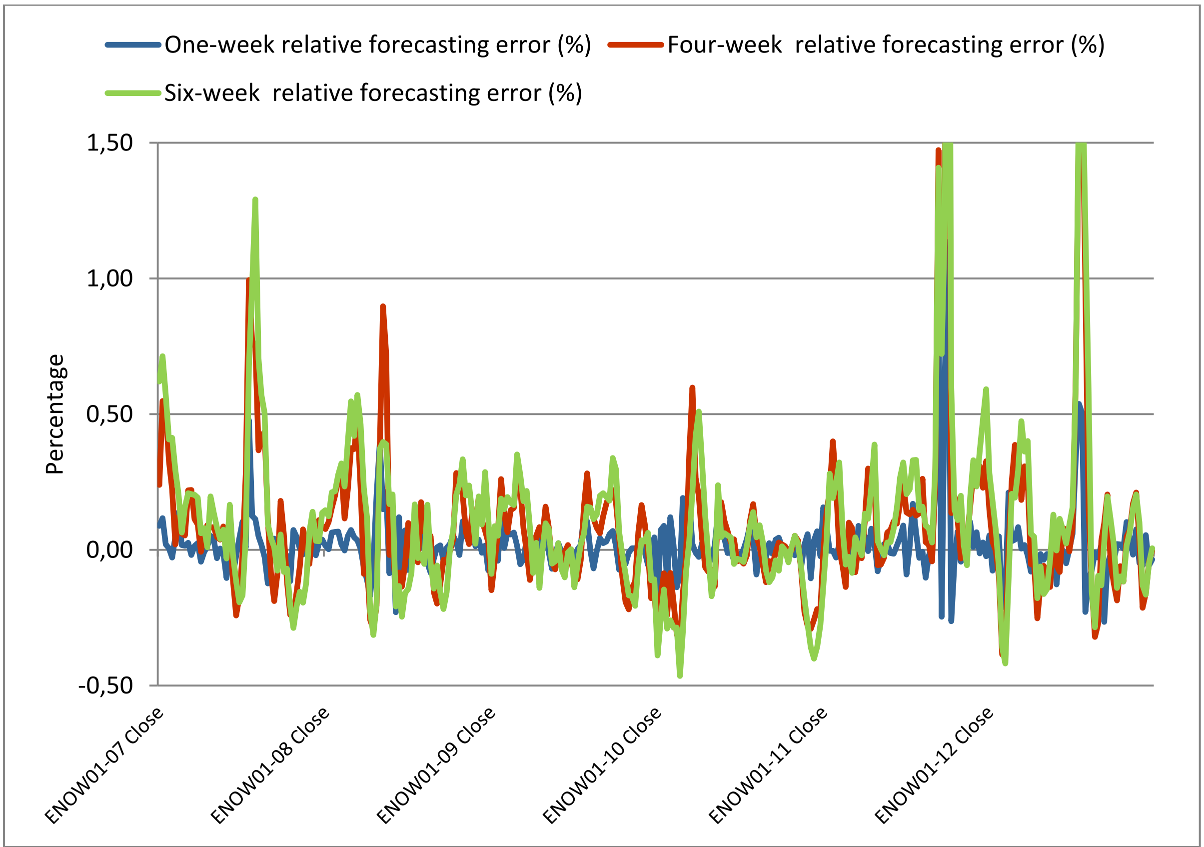


Figure 9.1 RELATIVE FORECAST ERRORS: $(F_{t,T}-S_T)/S_T$ 2007-2012.

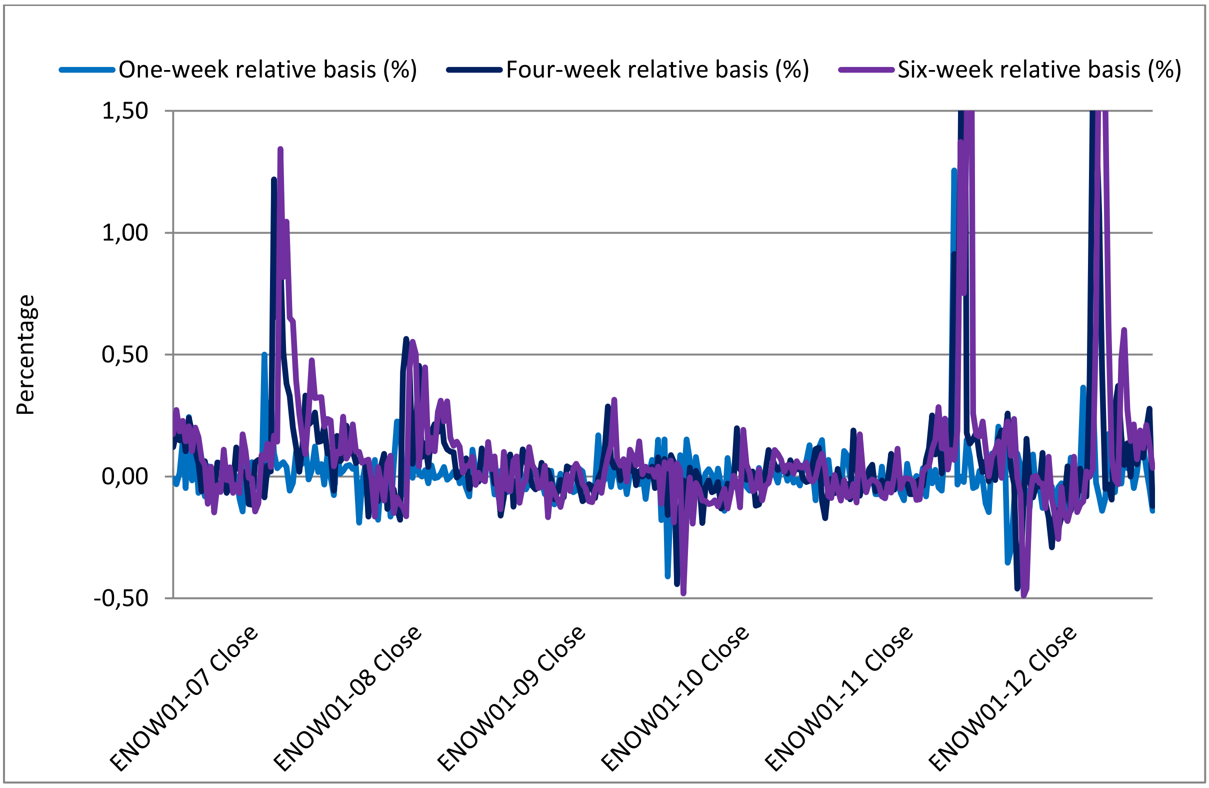


Figure 9.2 RELATIVE BASIS RISK: ENOW01-07 – 52-12. (F_t, T-S_T)/S_T.

Sample ENOW01.07-51.12	Mean	St.dev.	Min.	Max.	Skewness	Kurtosis	Jarque-Bera	Ljung-Box	n
One-week forecast error (NOK)	3,68	27,151	-107	125	0,227	4,440	248*	0,199***	312
Four-week forecast error (NOK)	13,15	64,743	-243	244	-0,219	2,409	74*	169*	312
Six-week forecast error (NOK)	16,87	75,530	-331	294	-0,726	2,893	131*	199*	312
One-week relative forecast error	0,021	0,127	-0,265	1,135	4,070	28,511	11072*	8,04**	312
Four-week relative forecast error	0,092	0,317	-0,385	3,116	4,334	31,413	133374*	122*	312
Six-week relative forecast error	0,116	0,357	-0,464	3,761	4,556	37,586	18834*	134*	312
One-week relative basis	0,009	0,118	-0,411	1,256	4,101	41,325	22344*	3,48**	312
Four-week relative basis	0,073	0,280	-0,461	2,949	5,314	42,374	24037*	108*	312
Six-week relative basis	0,095	0,329	-0,489	3,383	4,954	35,620	17218*	126*	312

*p=0,0000, **p<0,05, ***p=>0,05

Table 9.1 DESCRIPTIVE STATISTICS, FORECAST ERRORS AND BASIS RISK: nominal errors ($F_{t,T}$-S_T), relative errors ($F_{t,T}$ – S_T)/S_T, and relative basis ($F_{t,T}$-S_t)/S_t. ENOW01-07 to ENOW52-12.

The high standard deviations imply that they possess a high degree of uncertainty. One sample, one sided t-tests can be performed to analyze if we can conclude that the forecast errors really are positive. However, neither of the nominal (1-, 4-, 6-week forecast errors) nor the relative (1-, 4-, 6-week forecast errors) data series are close to being normal distributed, as all of the observed Jarque-Bera values clearly exceed their critical value, hence rejecting the null hypothesis of normal distribution. The nominal values are closer to being normal. Consequently, we choose these samples for the t-test, but the results from the tests must be interpreted with caution and non-parametric tests should ideally be performed to increase the confidence of the results. The complete test statistics is summarized in Table 9.2.

Since all of the three t-tests conclude to reject H0 with a significance level of 5 %, there is statistical evidence to say that the futures prices overestimate the future spot price six-, four- and one- week(s) prior to maturity.

Variable	Test Interpretation	df	T (observed)	t (critical)	p-value	Confidence int. Lower	Upper	α
One week forecasting error (NOK)	H0: $\mu = \mu_0$ H1: $\mu > \mu_0$	311	2,397	1,650	0,009	1,148	∞	5 %
Four week forecasting error (NOK)	H0: $\mu = \mu_0$ H1: $\mu > \mu_0$	311	3,589	1,650	0,0002	7,106	∞	5 %
Six week forecasting error (NOK)	H0: $\mu = \mu_0$ H1: $\mu > \mu_0$	311	3,945	1,650	<0,0001	9,816	∞	5 %

Table 9.2 T-TEST STATISTICS, FORECAST ERRORS: ENOW01-07 to ENOW52-12. Test concluding interpretation highlighted in green.

9.2 Interpreting the Results as Risk Premiums and Convenience Yield

In order to show that the forecast errors can be interpreted as risk premiums, the risk premium results following Equation 8.2 are summarized in Table 9.3. These results are expected to be identical with the forecast error results in **Error! Reference source not found.**. Through the derivation in chapter 8.1, it was showed that:

$$e^{P_t} = 1 + (\frac{F_{t,T} - S_T}{S_T}) \quad \textbf{Equation 9.1}$$

This can be written:

$$\frac{F_{t,T} - S_T}{S_T} = e^{P_t} - 1 \quad \textbf{Equation 9.2}$$

When the calculated relative values for the six week horizon are inserted we get:

$$0{,}116 \neq e^{0{,}075} - 1 = 0{,}078 \quad \textbf{Equation 9.3}$$

Thus, subtracting one from the exponential function of the risk premium should equal the average of the relative forecast error. However, Equation 9.1 shows that this is not the case.

Following this result, it seems that the derivation of the relationship was wrong. Further investigation has nevertheless shown that it is correct if single observations are compared. Thus, Equation 9.2 is valid when comparing single observations. This implies that the derivation, and thereby the interpretation is correct. It is not further investigated why a deviation between the two equations occurs when comparing more than one pair of observations, but it is assumed that the deviation will increase with the number of observations. The same problem is expected to occur when interpreting the basis risk as the convenience yield.

For the one-, four- and six- week horizon, the average of all the risk premiums give a forecast error of respectively 1,5% $(e^{0,015} - 1)$, 6,1% $(e^{0,059} - 1)$, and 7,8% $(e^{0,075} - 1)$, while they in fact are supposed to be 2,1% , 9,2% and 11,6%.

Sample ENOW01.07-51.12	Mean	St.dev.	Min.	Max.	Skewness	Kurtosis	n
One-week risk premium	0,015	0,107	-0,308	0,759	2,180	13,671	312
Four-week risk premium	0,059	0,225	-0,486	1,415	1,506	6,433	312
Six-week risk premium	0,075	0,249	-0,624	1,560	1,132	5,247	312

Table 9.3 DESCRIPTIVE STATISTICS, RISK PREMIUMS: ENOW01-07 to ENOW52-12 (lnFt-lnST).

9.3 Regression Results

This chapter starts with an evaluation of the residual diagnostics before the results from the regression models, introduced in chapter 8.1, will be presented and discussed.

9.3.1 Residual Diagnostics

The fundamental assumptions behind the OLS regression seem to be fulfilled for all of the models, since the linear fit is good, the error term has an average of zero and the four first models have only one explanatory factor, excluding the problem of linear dependence. Model 8.5 and Model 8.6 has more than one explanatory variable. Neither of them is assumed to exhibit collinearity, and since we are only interested in the R-squared values we will not investigate this any further.

In contrast, the additional assumptions, for the models to be BLUE, seem to be violated. Gjølberg & Brattestad (2011) claim that when using Model 8.1 and Model 8.2, we are typically confronted with problems related to non-stationary variables. Despite this, our results from the descriptive analysis of the spot and futures prices in chapter 6.4.1 show that the variables are stationary. In addition, the spot- and the futures price have long term equilibrium as they are cointegrated, see chapter 6.4.2 .

Furthermore, residual diagnostics has been performed using the Jarque-Bera test for normality, the Breusch-Pagan test for heteroskedasticity and the Breusch-Godfrey test for autocorrelation.

Complete residual diagnostics results can be found in Table 9.4. The assumption of normality is violated for all of the models in all of the time horizons. The assumption of no autocorrelation is violated for all of the models in the four- and six- week horizon, but not in the one- week horizon. Homoscedasticity seem to be a bigger problem in the shorter contracts than in the longer contracts, and Model 8.3 does not suffer from heteroskedasticity in any of the time horizons.

Since there are consistent signs of both autocorrelation and heteroskedasticity, all of the regressions were recalculated and adjusted so that the t-values are based on the Newey-West heteroskedastic and autocorrelation consistent estimators. The t-HAC values are added to the regression results in **Error! Reference source not found.** along with the estimated t-values.

Table 9.4 has been color coded as following: if red; the assumption is violated, indicating non-normality, autocorrelation or heteroskedasticity. If green; the assumption is fulfilled, indicating normality, no autocorrelation or homoskedasticity.

	One week horizon			Four week horizon			Six week horizon		
	$\varepsilon \sim N$	$Cov(\varepsilon_i, \varepsilon_j) = 0$	$Var(\varepsilon) = constant$	$\varepsilon \sim N$	$Cov(\varepsilon_i, \varepsilon_j) = 0$	$Var(\varepsilon) = constant$	$\varepsilon \sim N$	$Cov(\varepsilon_i, \varepsilon_j) = 0$	$Var(\varepsilon) = constant$
	$S_T = \alpha + \beta F_{t,T} + \epsilon_T$								
8.1	JB=281	F=0,37	F=6,63	JB=104	F=223	F=15,84	JB=205	F=308	F=5,65
	P=0,00	P=0,69	P=0,01	P=0,00	P=0,00	P=0,00	P=0,00	P=0,00	P=0,02
	$\ln S_T = \alpha + \beta \ln F_{t,T} + \epsilon_T$								
8.2	JB=2575	F=1,86	F=17,97	JB=642	F=187	F=4,89	JB=424	F=250	F=3,04
	P=0,00	P=0,16	P=0,00	P=0,00	P=0,00	P=0,03	P=0,00	P=0,00	P=0,08
	$(S_T - S_t) = \alpha + \beta(F_{t,T} - S_t) + \epsilon_T$								
8.3	JB=245	F=0,32	F=0,23	JB=73	F=208	F=0,93	JB=127	F=286	F=2,00
	P=0,00	P=0,73	P=0,63	P=0,00	P=0,00	P=0,33	P=0,00	P=0,00	P=0,16
	$(\ln S_T - \ln S_t) = \alpha + \beta(\ln F_{t,T} - \ln S_t) + \epsilon_T$								
8.4	JB=2577	F=1,90	F=7,02	JB=646	F=184	F=0,00	JB=416	F=243	F=0,56
	P=0,00	P=0,15	P=0,01	P=0,00	P=0,00	P=0,98	P=0,00	P=0,00	P=0,46
	$(\ln S_T - \ln S_t) = \alpha + \beta(\ln F_{t,T} - \ln S_t) + \gamma \ln S_t + \epsilon_t$								
8.5	JB=2564	F=1,96	F=11,77	JB=644	F=185	F=2,26	JB=425	F=247	F=1,85
	P=0,00	P=0,14	P=0,00	P=0,00	P=0,00	P=0,11	P=0,00	P=0,00	P=0,16

Table 9.4 RESIDUAL DIAGNOSTIC RESULTS, MODEL 8.1-8.5: 2007-2012. Red=violation of BLUE assumption.

9.3.2 Regression Coefficients and Adjusted R-squared

Table 9.5 summarizes the regression results. Each of the models will now be briefly explained in order to stress their meaning, before their respective results will be discussed. A Wald-test has been performed on each of the regressions to find the probability of the beta coefficient to be different from the value in the null hypothesis. These p-values are included in the among the other regression results. Note that it is the HAC-values that is used in order to test if alpha equal 0, and for the Wald-test of (say) beta = 1.

Model 8.1 and 8.2

Model 8.1 (nominal) and Model 8.2 (logarithm) test if the futures contract price is an unbiased predictor of the future spot price. A beta coefficient equal to one implies that it is an unbiased predictor of the future spot price, while an alpha coefficient significantly different from zero can be interpreted as a forecast error. Thus, we test the null hypothesis of α=0 and β=1.

As expected, the adjusted R-squared is high for the one week horizon and decreasing when time to maturity increase. Furthermore, both models give somewhat ambiguous results. If $\beta = 1$, the forecast error will be constant and independent of the futures price level. The value of the forecast error $(F_t - S_T)$ will then be equal the alpha but with opposite sign[36].

Model 8.2 fails to reject the null hypothesis on all three horizons. This means that the forecast error will be constant independent of the futures price level, but since the alpha value is not significant different from zero, we cannot claim that there is a forecast error.

If then $\beta < 1$ (and significant), the forecast error will increase with the futures price level. Furthermore, when $\beta < 1$ and is combined with an alpha that is higher than zero, this implies that the forecast error $(F_t - S_T)$ will become negative (alpha with opposite sign) when the futures price is low. When the futures price increase, it will eventually make the forecast error positive. Hence, we can state that $\beta < 1$ combined with $\alpha > 0$ implies that the futures price tends to underestimate the future spot price at low levels, and overestimate it at higher levels. Even though the null hypothesis of alpha =0 cannot be rejected, the alpha values seem to be positive and increase with increasing time to maturity. But since none of the alpha values are significant higher than 0, we fail to state that low futures prices underestimate the future spot price, but we still can conclude that the forecast error increases with increasing futures price level for the one and the six week horizon. For the same reasons ($\alpha = 0$) we fail to conclude that there is a forecast error.

Model 8.3 and 8.4

Model 8.3 (nominal) and Model 8.4 (relative) tell us if the basis is an unbiased predictor of the spot price change. The basis risk will be an unbiased estimator of the spot price change if beta equals one, while an alpha significantly different from zero can be interpreted as a result of net-short or net-long hedging demand (Gjølberg & Brattestad, 2011). Thus, we test the null hypothesis of α=0 and β=1.

Relative low adjusted R-squared values $(adjR^2 < 0{,}6)$ indicate that the basis is not an ideal descriptor of the spot price changes. From the nominal results we find that there is a substantial drop in the value when moving from the one-week horizon to the four-week horizon. In contrast, we find that the relative values are much more stable, but starting off at

[36] $S_T = \alpha + \beta F_{t,T} + \epsilon_T \rightarrow F_t - S_T = -\alpha$. Beta and error term = 0 for simplicity reasons.

a lower level in the one week horizon. Furthermore, Model 8.4 and Model 8.5 provide quite unambiguous results.

If β=1, the forecast error[37] will neither rise nor fall when the basis changes, but simply have the constant level equal to the alpha value. When $\beta < 1$, the forecast error will increase with increasing basis, while negative increasing basis will make the forecast error tend towards negative infinity. Note that since alpha is negative it takes a certain size of the negative basis before the forecast error becomes negative.

However, since neither of the basis's comes with beta values that are significantly different from one, it cannot be concluded that the forecast errors increase (decrease) with an increase (decrease) in the basis $\left(F_{t,T} - S_t\right)$. Consequently the forecast error will be constant, and equal to the significant alpha level. Note that this is independent of whether the basis is positive or negative. Since all of the alphas are significantly lower than zero (except Model 8.4 on the six week horizon), we can conclude that the forecast errors are positive for all horizons[38].

Further, the results imply that the following three scenarios will make the spot price fall towards maturity; as long as the basis is less than the alpha value, when the basis is zero, or when the basis is negative. The interpretation of this will be discussed in Chapter 13.

Model 8.5 and 8.6

Model 8.5 is included in order to see if the forecast performance is improved when including a coefficient with historical price information inherent. Since the adjusted R-squared value does not seem to improve compared to the similar Model 8.4, we can conclude that the futures prices include relevant price information in historical prices and hence is a sign of market efficiency.

From Model 8.6[39] we are only interested in the performance compared to Model 8.1. The data access restricted the number of lags to 7 (years), but this is probably more than enough

[37] The forecast error (Ft-ST) must not be confused with the change in spot price (ST-St). The relationship saying that a rise in the basis risk will give a rise in the forecast error if beta<1, must be derived from the regression equation (see appendix)
[38] It may seem strange that negative alphas imply positive forecast errors (Ft-ST). A derivation of this relationship is therefore included in the appendix A3.
[39] Note that the complete regression results are not provided since only the R-values was of interest.

since the market undergoes such large changes that older prices are less relevant. The results show that the forecast of the one-week expected future spot price was not significantly improved. This was to some extent expected since the amount of information available one week up front should give better prediction power than other previous information. Additionally this may also indicate that previous price information is already inherent in the futures contact and thereby according to the results from Model 8.5. The six week horizon was of more interest as the information and especially the weather forecast are of less accuracy. In contrast to the one week horizon that did not get improved when including up to 7 lags, the six week horizon model improved from a adj. R-squared of 0,59 to 0,65. From this it seems like the futures contract price is the better predictor of the future spot price one week up front, while the estimate gets improved when including previous price information in the longer horizons.

	One week horizon				Four week horizon				Six week horizon			
	α	β	γ	Adj R^2	α	β	γ	Adj R^2	α	β	γ	Adj R^2
	$S_T = \alpha + \beta F_{t,T} + \epsilon_T$											
	7,18	0,97	-	0,95	17,19	0,91	-	0,70	28,62	0,87	-	0,59
8.1	(1,59)	(74,00)	-	-	(1,44)	(26,63)	-	-	(1,98)	(21,16)	-	-
	(1,47)	(66,21)			(0,96)	(15,45)			(1,46)	(13,78)		
		P=0,03				P=0,12				P=0,03		
	$lnS_T = \alpha + \beta lnF_{t,T} + \epsilon_T$											
	-0,02	1.00	-	0,93	-0,03	0,994	-	0,68	0,04	0,98	-	0,60
8,2	(-0,22)	(62,55)	-	-	(-0,12)	(25,54)	-	-	(0,16)	(21,71)	-	-
	(-0,15)	(43,82)			(-0,07)	(14,17)			(0,09)	(12,20)		
		P=0,96				P=0,94				P=0,80		
	$(S_T - S_t) = \alpha + \beta(F_{t,T} - S_t) + \epsilon_T$											
	-3,71	0,98	-	0,60	-13.03	0,99	-	0,36	-16,51	0,97	-	0,34
8.3	(-2,41)	(21,68)	-	-	(-3,50)	(13.31)	-	-	(-3,77)	(12,74)	-	-
	(-2,47)	(13,53)			(-2,09)	(9,10)			(-1,95)	(7,23)		
		P=0,77				P=0,98				P=0,82		
	$(lnS_T - lnS_t) = \alpha + \beta(lnF_{t,T} - lnS_t) + \epsilon_T$											
	-0,02	1,00	-	0,48	-0,06	1,08	-	0,46	-0,08	1,07	-	0,46
8.4	(-2,45)	(17,09)	-	-	(-4,82)	(16,17)	-	-	(-5,39)	(16,38)	-	-
	(-2,28)	(15,57)			(-2,89)	(11,51)			(-2,93)	(14,23)		
		P=0,93				P=0,41				P=0,36		
	$(lnS_T - lnS_t) = \alpha + \beta(lnF_{t,T} - lnS_t) + \gamma\, lnS_t + \epsilon_t$											
	-0,02	1,00	0,00	0,48	-0,07	1,08	0,00	0,45	0,00	1,05	-0,01	0,46
8.5	(-2,22)	(15,99)	(0,02)	-	(-0,32)	(12,93)	(0,04)	-	(0,01)	(12,38)	(-0,31)	-
	(-0,15)	(14,60)	(0,04)		(-0,17)	(7,71)	(0,02)		(0,00)	(7,76)	(-0,17)	
		P=0,95				P=0,57				P=0,70		

Table 9.5 REGRESSION RESULTS, SPOT- AND FUTURES PRICES: 2007-2012. Null hypothesis of alpha=0 and beta=1. Red=reject null hypothesis, Green=keep null hypothesis. The upper bracket gives the estimated t-values, while the lower bracket gives the HAC estimators. The p-values comes from the Wald-test with null hypothesis of beta=1.

Figures that combine the residual plot, the actual line and the fitted line for the regression Models 8.1-8.4 are displayed in Figure 9.3.

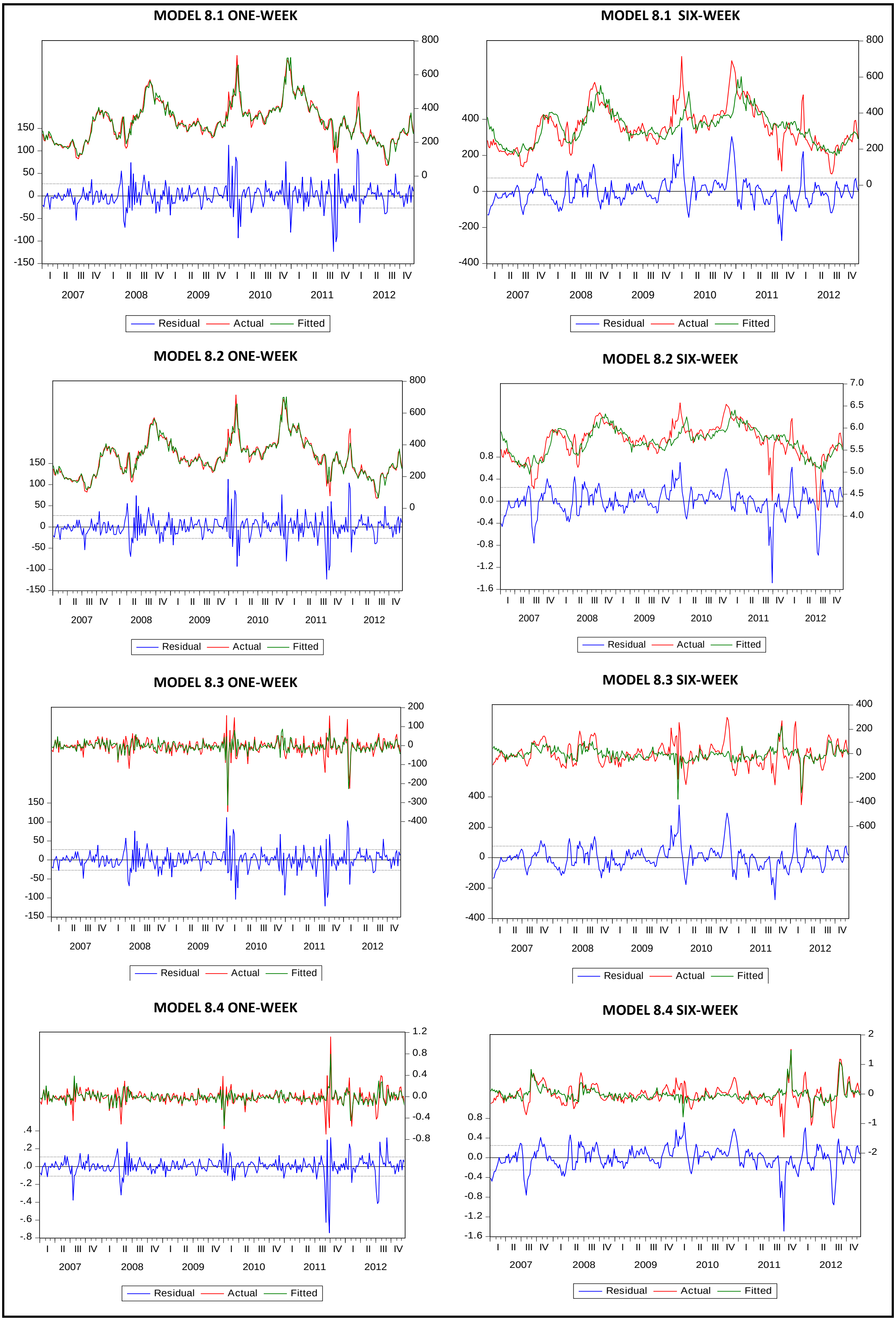


Figure 9.3 REGRESSION MODEL 8.1-8.5 PLOT: Blue line are residual, red is actual plot and green is fitted line. 2007-2012

10 Analysis of Seasonal Trends and Area Prices

Until now we have seen that the prices, errors, and basis vary considerably through the sample period. Furthermore we will make some plots against the calendar weeks and perform further testing of the results in order to find possible seasonal trends or detect whether it is just random variation. A potential difference between what Nord Pool defines as summer (week 14-44) and winter (the rest of the year) is of primarily interest. In addition we will analyze potential effects of the restructuring of the bidding areas.

10.1 Seasonal System- and Area Prices

In order to see how the spot prices change during the year, the average system price of each calendar week is calculated and displayed in Table 10.1. Quite clearly we see that the system price is lower during summer than during winter. The spot price seems to reach maximum around year end and minimum during July. Hence, it decreases during the first year-half and increases during the second year-half.

The summer period is actually normally distributed, while the winter period is close to being normally distributed. Hence, we can with confidence use parametric t-tests. Following the results from the t-test (T=5,99 > t=1,65) we can conclude that the winter price is significantly higher than the summer price. Furthermore the results show that winter period has higher skewness than the summer period. It also indicates that the variation is higher during the winter period, but we are not able to find significance for this. Based on the volatility plot, we cannot find any clear pattern throughout the year. Volatility might be a little higher during late summer and fall, but this is not further analyzed.

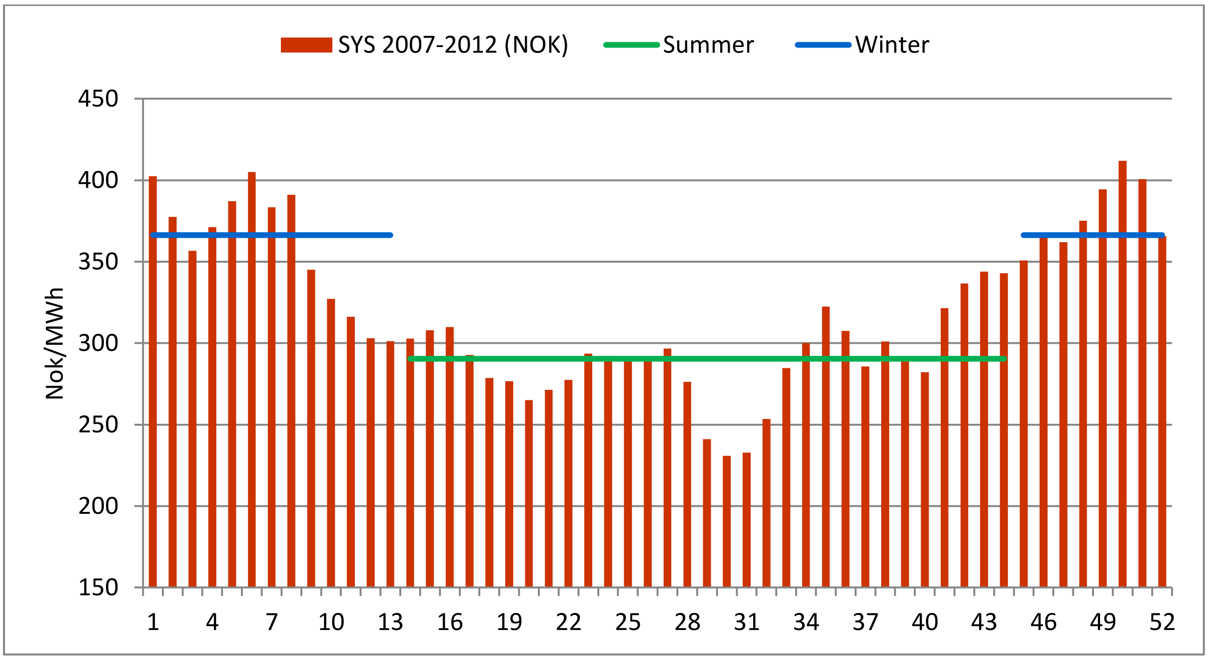


Figure 10.1 SEASONAL TREND, SYSTEM PRICE: Calendar week average price (NOK/MWh) 2007-2012.

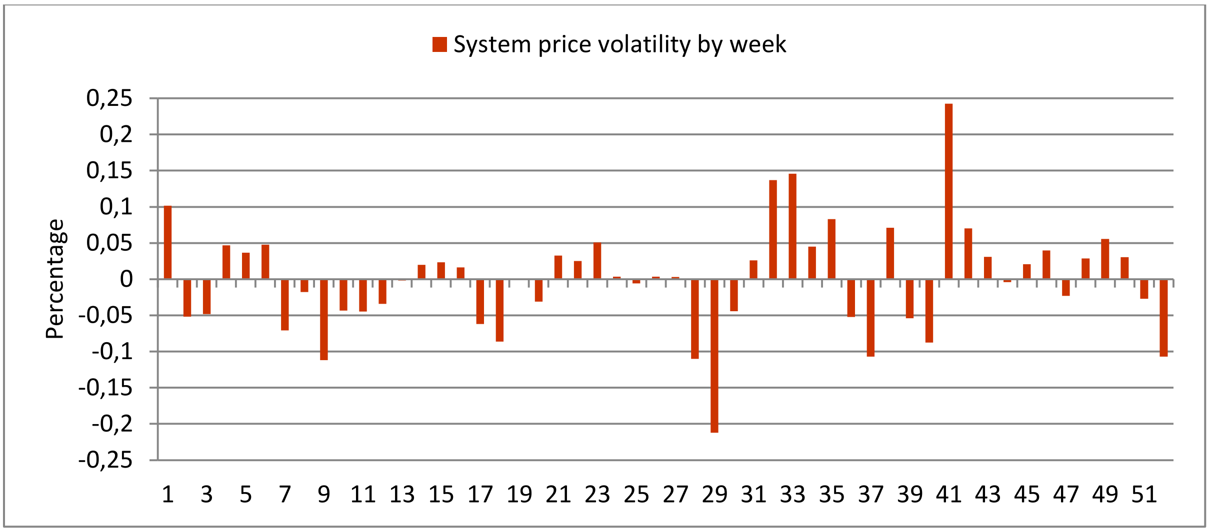


Figure 10.2 SEASONAL TREND, SYSTEM PRICE VOLATILITY: Calendar week average volatility 2007-2012.

Sample 2007-2012	Mean	St.dev.	Min.	Max.	Skewness	Kurtosis	Jarque-Bera	n
SYS Winter period (NOK)	366,3	119,4	186,1	714,0	0,67	2,95	9,52**	126
SYS Summer period (NOK)	290,3	103,2	62,1	570,5	0,21	2,85	1,57***	186

**p<0,05, ***p=>0,05

Table 10.1 DESCRIPTIVE STATISTICS, SEASONAL WEEKLY SYSTEM PRICE: 2007-2012.

10.2 System Price vs. Area Prices N01 and N02

In this section we investigate if there is a pattern in the deviations between the area prices and the system price.

The relative difference between the system price and the N02 price is displayed in Figure 10.3. The N02 price is lower than the system price most of the year, except for the period from April-August, where the prices are close to each other and the N02 once in a while exceeds the system price.

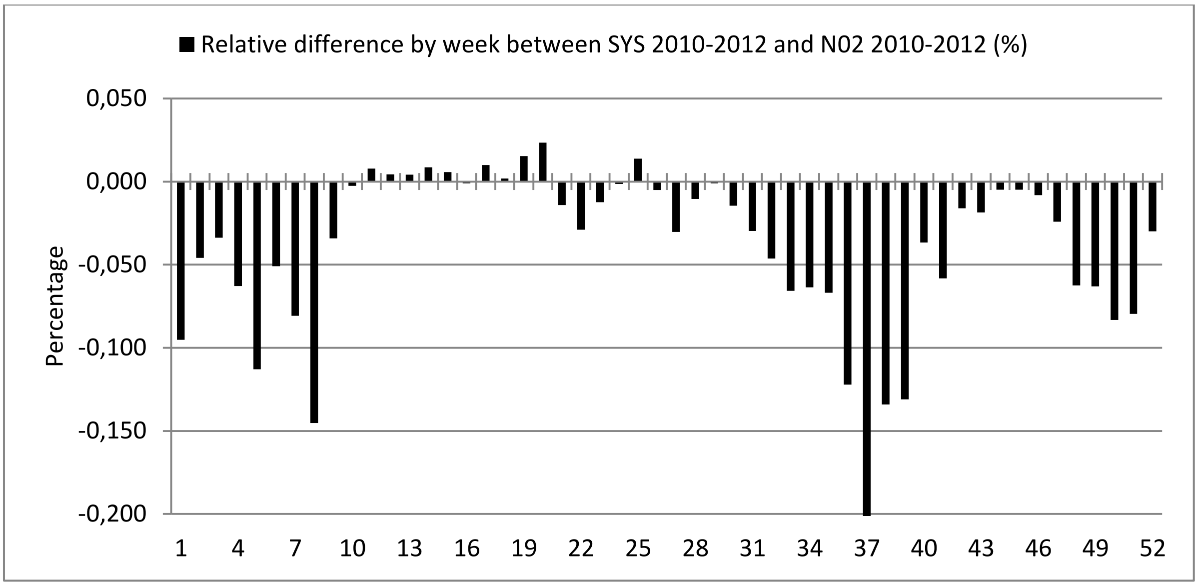


Figure 10.3 SEASONAL RELATIVE DIFFERENCE IN PRICE, N02-SYS: by week between SYS 2010-2012 and N02 2010-2012 (N02-SYS)/SYS.

Since the number of observations in each week is small[40], especially for the N02 price, the results should be used with caution, as single observations have high influence. We have not included the relative difference between the N01 price and the SYS because they showed similar results as Figure 10.3.

Table 10.2 summarizes the statistics of the relationship between the area prices and the system price before and after the restructuring in 2010. Before 2010, the difference was significantly higher than in both of the new areas. Negative means implies that the area prices are lower than the system price. We do not have significance to conclude that the N02 price is lower than the N01, compared to the system price. Negative skewness values imply that the area prices most likely will be lower than the system price. This reinforces the

[40] 6 observations of the system price and 3 observations of the N02 price in each calendar week.

picture painted by the figure, that the area prices are very seldom higher than the system price.

Sample 2007-2010	Mean	St.dev.	Min.	Max.	Skewness	Kurtosis	Jarque-Bera	n
Relative difference N01-SYS	-0,10	0,17	-0,77	0,07	-2,26	7,65	272*	156
Sample 2010-2012								
Relative difference N02-SYS	-0,04	0,09	-0,51	0,10	-2,33	10,00	460*	156
Relative difference N01-SYS	-0,03	0,09	-0,51	0,29	-2,14	12,10	658*	156

*p=0,0000

Table 10.2 DESCRIPTIVE STATISTICS, RELATIVE DIFFERENCE AREA PRICE-SYS: (area-sys)/sys 2007-2010 and 2010-2012

10.3 Seasonal Forecast Errors and Basis Risk

Figure 10.4 displays the average relative forecast error through the calendar weeks of a year. The average error is calculated as the average of each weekly futures contracts subsequent relative forecast errors one-, four- and six- weeks prior to maturity. The average of the relative forecast errors during the summer period and for the winter period is also calculated. Since the results are calculated on few observations, they must be interpreted with caution.

At first glance, we can tell that the futures price tends to overestimate the future spot price during most of the year, and by more during the summer period than during the winter period. A t-test is performed in order to test if the forecast error during summer is higher than during winter. The descriptive statistics in **Error! Reference source not found.** confirms that neither of the summer data series nor the winter series is normally distributed. Ideally non-parametric tests should have been performed to increase the confidence of the results.

The two-sample one-sided t-test gave a t-value of 1,53. Since the critical value is 1,65, we do not have statistical basis to claim that the summer period error is larger than the winter period error. However, the value is close to the critical value, and combined with that we know the parametric test can be imprecise when the data series are not normally distributed we keep the null hypothesis under doubt. Nevertheless, both the winter- and summer-forecast error is significantly higher than zero (T_{Winter}=6 3, T_{Summer}=6.1).

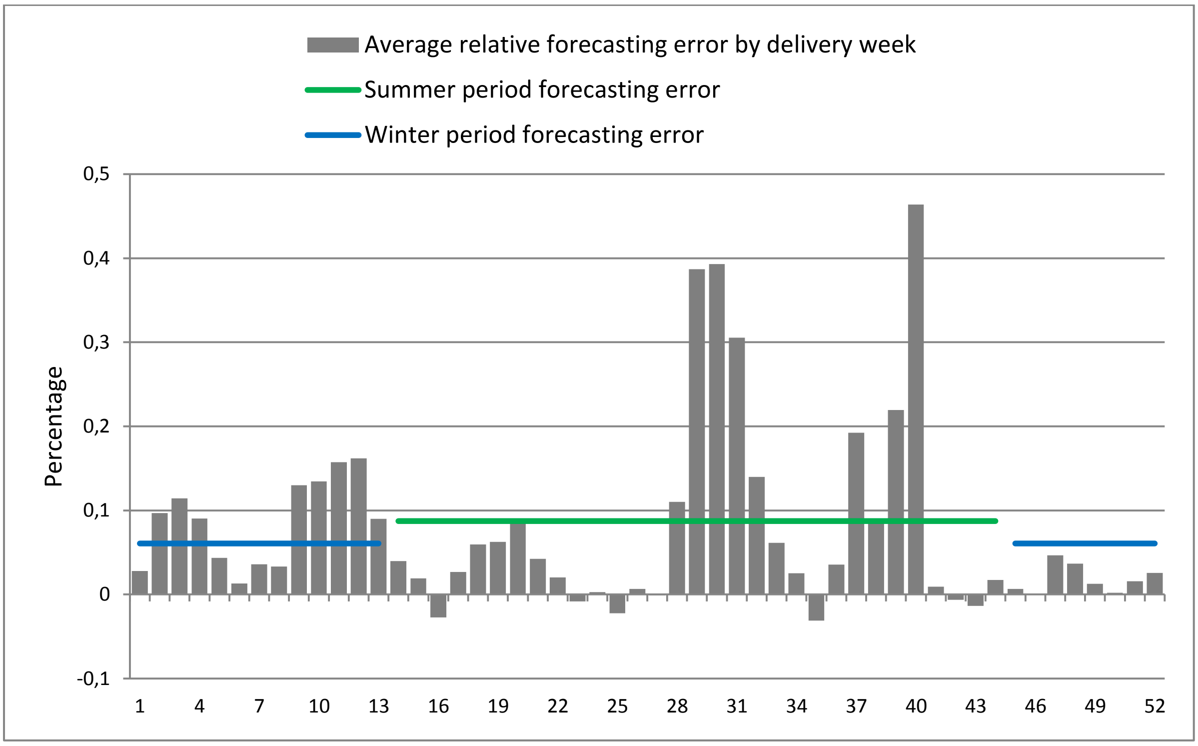


Figure 10.4 SEASONAL RELATIVE FORECAST ERRORS: by calendar week (Ft/ST)/ST 2007-2012.

Furthermore, we calculate the average relative basis similar as for the average relative forecast error. This is displayed in Figure 10.5. The first year half seems to have longer periods where the spot prices are higher than the futures prices, hence, it is exhibiting normal backwardation. In contrast the futures prices seem to be considerable higher than the spot price during the second half of the year, and thereby making the market exhibit Contango.

In order to provide statistical confident results, a t-test is performed to test if the basis is higher during summer than during winter. The descriptive statistics in Table 10.3 confirms that neither of the summer data series nor the winter summer series is normally distributed. Ideally non-parametric tests should have been performed to increase the confidence in the results.

The two-sample one-sided t-test gives us a t-value of 1,99 which exceed the critical value of 1,65. We can with significance claim that the basis is higher during summer than winter[41].

[41] Note that it is done a parametric test on a non-parametric sample, and that the results must be interpreted with caution.

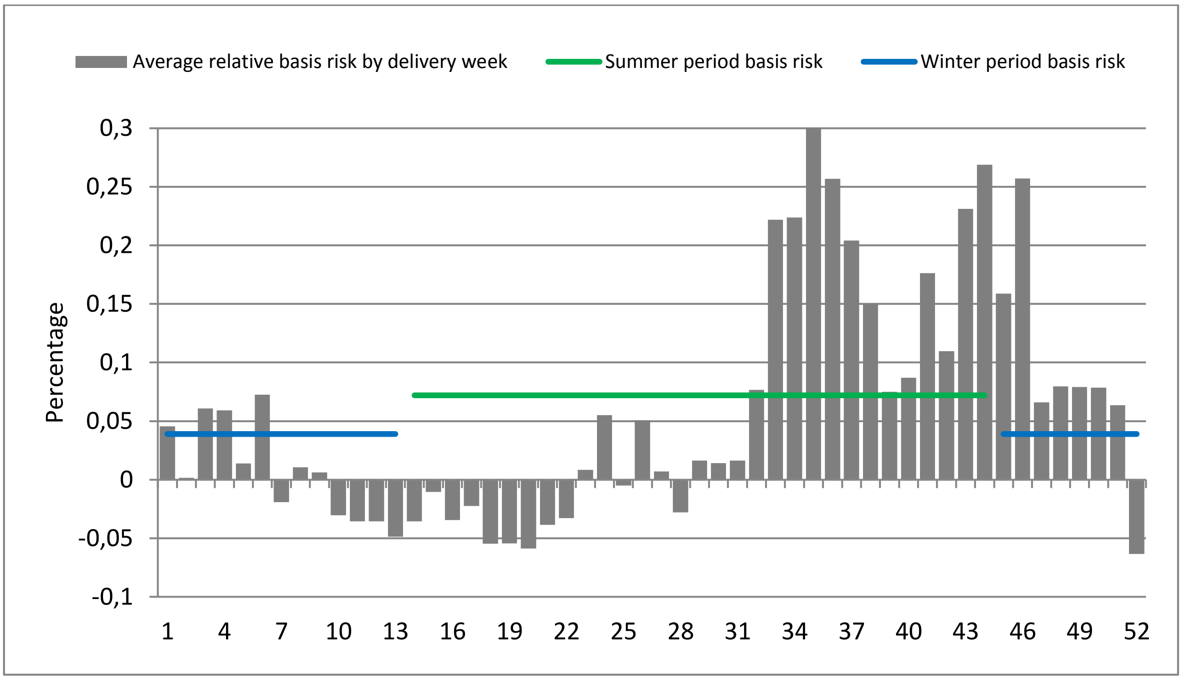


Figure 10.5 RELATIVE BASIS RISK BY CALENDAR WEEK 2007-2012 (FT-ST)/ST

Despite this, we can readily see that the real regime switch is independent of the season defined by Nord Pool. The figure indicates two or maybe three regimes during the year. As of approximately August (week 32) the basis is at its definitely highest until approximately mid-November. Then it experiences a heavy drop, but is still positive until end of January. Then it decreases and turns negative or low positive until the dramatic increase in August.

In order to get results that are easy to compare with other results, we define two new periods, first year-half (week 1-26) and second year-half (week 27-52). From **Error! Reference source not found.** we see that the first year-half has a slight negative basis, while the second year-half has got a positive basis. This was as expected following the figure. There is a clear significantly difference between the two periods (T=7,7). The second period is clearly significant positive (T=7,90), but we were not able to find significance for the first year-half to exhibit negative basis (T=-0,87). At last we were able to find significant negative basis (T=-5,62) when defining the period March-May.

Sample 2007-2012	Mean	St.dev.	Min.	Max.	Skewness	Kurtosis	Jarque-Bera	n
Winter period relative forecasting error	0,06	0,19	-0,46	0,71	0,26	3,86	15,92*	378
Summer period relative forecasting error	0,09	0,34	-0,32	3,76	5,20	43,12	39941*	558
Winter period relative basis	0,04	0,22	-0,49	3,28	8,91	129	254028*	378
Summer period relative basis	0,07	0,29	-0,29	2,95	4,68	33	23106*	558
First year-half relative basis	-0,01	0,12	-0,49	0,56	0,27	7,30	366*	468
Second year-half relative basis	0,12	0,34	-0,18	3,28	4,97	35,7	22793*	468
March-May relative basis (week 9-22)	-0,03	0,10	-0,49	0,43	-0,67	9,03	401*	252

*p=0,0000

Table 10.3 DESCRIPTIVE STATISTICS, SEASONAL FORECAST ERROR AND BASIS RISK: 2007-2012

11 Hedging the Area Price

In general the high volatility of the Nordic energy market makes risk management an important tool in order to deal with price risk. A portfolio consisting of spot exposure and futures contracts can be used to reduce some of this volatility. This requires an optimal ratio between the two positions in the portfolio.

The fact that area prices tend to lay below the system price could make hedging attractive for the producers in these areas. We will use the N02 area as an example in this thesis, but it is assumed that the results could provide good indications also for other areas that have lower prices than the system price[42]. In addition we have calculated the similar hedges, but with spot exposure through the system price. This hedge is included as a benchmark.

The objective with our hedge is that a loss in the spot market will be offset by a gain in the futures market. A perfect hedge requires the basis to equal zero at expiration. In general we have:

$$Basis = Spot\ price\ of\ asset\ to\ be\ hedged - Futures\ price\ of\ contract\ used$$

In our case, we have to consider some aspects that complicate the hedge (Hull, 2009);

- The asset whose price is to be hedged (N02) is not exactly the same as the asset underlying the futures contract (SYS).
- The hedger is not certain to which exact date when the asset (N02) will be sold.
- The hedge may require the futures contract to be closed out before its delivery week.

Recall Figure 4.2, illustrating the price of the futures contract converging against the spot price at maturity. This resulted in a basis equal to zero, explained by the arbitrage argument. However, since we don't have the same underlying asset in both the spot (N02) and futures contract (SYS), the basis will not necessarily be equal to zero at maturity. In addition, to this the futures contract has to be closed out one week prior to maturity. This implies that even though the underlying asset is the same[43] the basis will be equal to the forecast error of the last day of trading and will thereby only be zero if the one week horizon forecast error is

[42] For many other of the bidding areas there exist contracts for difference (cfd's), but these does not exist for the N02 area.
[43] In a situation where the system price is hedged using futures with the system price as underlying.

zero. Optionally, the contracts can be settled at the last day of trading, but the basis will most likely not still be zero. Hence, when hedging the spot price, the basis at maturity can be written as:

$$Basis = Forecast\ error = S_T - F_{t,T} \qquad \text{Equation 11.1}$$

Thus, we have to find the futures contract that gives the lowest basis risk when combined in a portfolio with the spot price. Furthermore, the optimal weight of contracts in the portfolio must be assessed. Following our analysis, we are interested in short positions in the futures market. Short positions will in general be improved if the basis unexpectedly rises and vice versa (Hull, 2009).

Furthermore, we will discuss the important choices to be made before we present different types of hedging.

11.1 Cross Hedging the N02 price

A perfect hedge is a hedge that completely eliminates the risk, but as perfect hedges are rare, we often concentrate to construct hedges so that they perform as close to perfect as possible (Hull, 2009). As mentioned, there is no traded futures contract that uses the N02 price as underlying asset. Therefore, we use the traded futures contracts with the system price as underlying asset to construct a cross hedge.

When choosing a product with a different underlying asset, we must analyze futures prices of various assets to find the one that is best correlated with the N02 price. Since all trades of futures contracts in the Nordic market have the system price as underlying asset, we have a narrow range of products to choose from. We will test the correlation between the N02 spot price and the futures contract with the system price as underlying asset, which is considered to be the best match.

Furthermore, the weekly futures contracts are delivered one week later than the last day of trading. Hence, we choose to use the basis at the last day of trading as delivery of the hedge. This implies that the futures contract price at the last day of trading that specific contract will be compared to the daily average N02 price the same day. This is then continued through the hedging period by buying short positions at that day and rolling those over to the next contract the coming week. Note that this is a simplified hedging strategy as we will not adjust it once it has been constructed.

11.2 Optimal Hedge Ratio Models

The optimal hedge ratio is the number of futures per unit of exposure in the spot market that minimizes total return variance. Our hedge will take a futures position at the beginning of the life of the hedge, and close out the position at the end of the life of the hedge.

There are various models that can be used to find the minimum-variance hedging ratio. In this thesis we will look at the traditional hedging method, also called naïve hedging, in addition to the OLS hedge. What could be a disadvantage of the OLS hedging model is that it gives a constant hedge ratio, which is not ideal if there is a trend or heteroskedasticity in the volatility. Previous studies like Berg (2010) have found that the VAR hedging model does not improve the OLS hedging model efficiency. Nor have we found the N02 volatility or the one week futures price volatility to be time varying. It is therefore no need to include different types of ARCH models.

In order to evaluate the hedges we calculate the hedging efficiency, given by the following equation:

$$HE = 1 - \frac{Variance_{hedged\ Portfolio}}{Variance_{\ unhedged\ Portfolio}} \qquad \textbf{Equation 11.2}$$

The variance is a standard measure of risk in finance and is a dominant measure of hedging effectiveness (Madaleno & Pinho, 2008).

11.2.1 Naïve Hedge

The naïve hedge is traditionally the best hedge and assumes a one-to-one hedge ratio. This implies equal but opposite positions. In our situation this is gained by equal position in spot exposure and in futures contracts. Since producers in the N02 area usually get lower prices than the system price, the idea is that an increase in the deviation between the system- and the N02 price $(N02 - SYS < 0)$ will be offset by a gain through shorting futures contracts with the system price as underlying asset. This hedge is good if the prices are perfectly correlated, and with same mean and variance.

The variance reducing effect of a naïve hedge is simply given by the variance of the futures position, divided by the variance of a pure spot exposure.

$$Naive\ Hedging\ Effictiveness = \frac{\sigma_F^2}{\sigma_S^2}$$ **Equation 11.3**

11.2.2 Minimum-Variance Hedging Ratio with OLS Regression

It can be showed that the minimum-variance hedge ratio is given by:

$$h^* = \frac{Cov(\Delta S, \Delta F)}{\sigma_{\Delta F}^2} = \rho \frac{\sigma_S}{\sigma_F}$$ **Equation 11.4**

Where h^* is the hedge ratio that minimizes the variance of the hedger's position, ΔS is the change in spot price, ΔF is the change in futures price, ρ is the coefficient of correlation betweenΔS and ΔF, σ_S is the standard deviation of ΔS and σ_F is the standard deviation of ΔF.

Further, it can be showed that the optimal hedge ratio h^* is the slope of the best-fit line when ΔS is regressed against ΔF. The optimal hedge ratio h^* will then correspond to the optimal portfolio ratio at any point on the line. This should be intuitively reasonable (Hull, 2009), and leads us to the following regression model:

$$\Delta S_T = \alpha + \beta \Delta F_{t,T} + \epsilon_T$$ **Equation 11.5**

The variance reducing effect of the hedge will then equal the R-squared value of the regression, i.e. the proportion of the variance that is eliminated by hedging. And can be showed since (Hull, 2009):

$$OLS\ Hegding\ Effectiveness = \rho^2 = h^{*2}\left(\frac{\sigma_F^2}{\sigma_S^2}\right) = R^2$$ **Equation 11.6**

This can be further developed to show the exact number of futures contract that is required to optimize the portfolio, given the ratio and the spot exposure (such as 100MW/h). It is however, out of the scope of this thesis.

12 Empirical Analysis and Results of Cross Hedging

The results of the different hedging models are summarized in Table 12.1. Recall that our focus is hedging the N02 price, and the system price hedge is given only as a benchmark.

Model	Minimum-Variance Hedge Ratio (F:S)	Variance Reduction Effectiveness
Naïve Hedge		
N02	1:1	26 %
SYS	1:1	56 %
OLS Hedge		
N02	1:1,4	51 %
SYS	1:0,95	50 %

Table 12.1 HEDGING RESULTS: Basis equals difference between Weekly futures with one week to maturity and N02 spot price, 2010-2012.

Berg (2010) claims that there has been produced few studies on this subject, but refers to Byström 2003 and Yang, Zhang, Liu & Luo 2009. They both found that hedging gave risk reducing effects, but Yang et al. stressed the high basis risk. Berg himself found a MGARCH model to give the best risk reducing effect with 34 %, but still the Naïve hedge and the OLS hedge were not far behind with a reduction effect of 25 % and 28 % for the period 1995-2009. Note that Berg hedged with the system price as spot exposure. Our results will now be discussed further in the next sections.

12.1 Naïve Hedging

Even though a naïve hedge reduces variance with 26 %, this hedge could give unreliable results since the correlation between the N02 price and the futures contract with the system price as underlying asset is only 72 %. The correlation is actually more or less the same between the system price and the futures contract, but since the changes in the system price has a lower standard deviation, the effectiveness of this hedge is still much better with its 56%. Note that the low correlation factor still gives a significant chance of unreliable results. The results seem to be quite similar with the ones produced by Berg (2010).

12.2 OLS Hedge

The OLS hedge calculates the optimal constant hedge ratio to be 1,4. This implies shorting one futures contract for every 1,4 portion of exposure in the spot market. This position is assumed to be held through the hedging period by rolling over the positions every week. The

MVHR for hedging the system price is 0,95. The fact that the N02 ratio is higher than 1, and higher than the SYS ratio was expected, since the N02 spot price is lower than the system price. This loss is offset by shorting the futures contracts.

The slope of the regression line confirms that one should go short in the futures contracts, with its positive beta coefficient. Furthermore we find the R-squared to be 0,51, which imply a variance reduction of 51 % compared to being completely exposed in the spot market. As long as the effectiveness is above 50 % there is more diversifiable risk than basis risk.

The Wald-test shows that the β-coefficient for N02 is different from 1 on a 5 % significance level. In contrast the β-coefficient of the system price is not found to be significant different from one. This implies that we do not have significance to claim that the OLS regression is different from the naïve hedge, which again explains the rather strange result that the naïve hedge should give a better hedge than the OLS hedge. An excerpt of the regression results and the residual diagnostics are summarized in Table 12.2.

	α	β	R^2	$\varepsilon \sim N$	$Cov(\varepsilon_i, \varepsilon_j) = 0$	$Var(\varepsilon) = constant$
N02	0,003 (0,168)	**1,4065** (12,66)	**0,5133**	JB=1996 P=0,0000	F=27,7 P=0,0000	F=0,18 P=0,6728
Wald-test H0: β=1	-	3,66 P=0,00	-	-	-	-
SYS	-0,002 (-0,220)	**0,948** (12,44)	**0,5045**	JB=642 P=0,0000	F=13,1 P=0,0000	F=8,25 P=0,0047
Wald-test H0: β =1	-	-0,6759 P=0,50	-	-	-	-

Table 12.2 OLS HEDGE REGRESSION RESULTS AND RESIDUAL DIAGNOSTICS. SAMPLE 2010-2012.

The residual diagnostics show that none of the regressions are BLUE. Note that since the residuals violate the assumption of no autocorrelation the standard errors should ideally be adjusted prior to the Wald-test. The fact that N02 is homoskedastic indicates that there is no time-varying volatility, and therefore no ARCH affect, hence no time-varying risk ratio. We will therefore not perform a MGARCH on the N02 hedge. In contrast the SYS hedge ratio seems to be time varying.

13 Final Discussion of Empirical Results

We have found that the futures prices overestimate the expected future spot price with respectively 2,1%, 9,2 % and 11,6% for the one-, four- and six- week horizon. This implies that people buy futures contracts at a higher price than they could pay in the spot market for the same underlying asset. A normal explanation for this behavior is risk-aversion, where you buy insurance to avoid unexpected loss. These market participants are called hedgers and will have a net-long demand of positions in futures contracts. Translated to the Nordic power market, this means that people buy futures contracts as insurance against even higher electricity prices.

This behavior could actually seem reasonable when considering that the spot price could multiply itself in short time. We found extraordinary high volatility in the market with a weekly volatility of the system price of 15% (107% annualized) and that higher values occur frequently. The most extreme change from one week to another was as much as 109%.

Even though we experienced some problems finding significant forecast errors through some of the regression models, other interesting aspects were uncovered. We found the errors to increase with increasing price level and increasing time to maturity[44]. Furthermore, the results indicated that they become negative when the price level of the futures is low, but since we did not find significance we had to keep the null hypothesis under doubt.

Despite uncovering a pitfall when interpreting the forecast errors as risk premiums, we finally managed to show that positive errors equal negative risk premiums in the Nordic energy market. When comparing the results to the discussion of risk premium in a hydro dominated market, it seems legitimate to interpret that this is a result of the unbalanced situation where power producers can adjust production in short notice, while customers have inelastic demand. Following that customers fear price increases and buy insurance through derivatives, while the producers does not fear price drops as they can simply reduce production.

The fact that we found the skewness of the electricity prices to be positive and higher during winter, enforces the consumer’s incentives to hedge, especially during the winter period. In contrast, positive skewness serves the producer’s interests in the spot market. This because

[44] The annualized forecast errors may be reduced when time to maturity is increased but this is not analyzed.

producers does not have the same fear for extreme prices since the most extreme values comes as high prices in addition to that extreme high prices are more frequent than the extreme low prices.

Hence, producers can benefit from flexibility and positive skewness, and are therefore not meeting the customers demand for long positions with supply of short positions. The risk premium will then occur as the difference between the pure competition equilibrium and the actual equilibrium. Whether this we refer to as the risk premium actually is a risk premium or not, is another interesting discussion. But based on our arguments, we find likely that it to a large extent is a risk premium.

If it is really a risk premium, the market participants in the Nordic power market are willing to take expected losses in order to avoid unexpected losses through paying risk premiums. On the other hand, this deviation could be a result of an immature market with pricing inefficiency, as alluded by Gjølberg & Brattestad (2011). When simply testing this through regression, we found no indications of a pricing inefficiency in the one-week positions, since the futures prices seemed to include relevant information in historical prices. However, in the six-week positions the forecast was improved when including lagged variables of prices of the same week in previous years.

From the seasonal analysis, we found the basis risk (i.e. net convenience yield) to be time varying, and the net-convenience yield for the full sample to be significant negative. This implies that the Nordic energy market exhibits Contango, as the futures price lay above the current spot price. According to the background theory, the risk of overflows and spillage is larger than the benefit of holding water in reservoirs. A plot of the basis (i.e. net convenience yield) over the year showed that the market exhibits normal backwardation in the period March-May. When comparing the periods defined by Nord Pool for summer and winter we found the net convenience yield to be lower during summer than during winter. This implies that the market is closer to normal backwardation during winter, but that it still exhibits Contango.

Using background theory, we have stated that backwardation is connected to low reservoirs and that the reservoirs generally are lower during winter. It is therefore reasonable to conclude that there is a good fit between the theory of storage and the results that we found.

Spring flood gives the producers higher incentives for hedging because of the risk of overflows and a decrease in the price of electricity. On the other hand, the consumers get their hedging demand reduced as their fear of high prices is reduced in addition to a decreasing demand as summer approaches. Our analysis show decreasing risk premium after the spring flood, and thereby confirm this market situation.

Furthermore we found the risk premiums to (negatively) increase substantially as of late summer. However, this could be connected to that the consumers again start to fear higher prices during winter combined with an increased demand as temperatures decrease. Even though we did not find it to be significant, it seemed like the risk premium for the summer period was larger than the winter period. This indication was somewhat unexpected since previous studies, like Gjølberg & Brattestad (2011) and Lucia & Torro (2008), find the risk premium smaller during summer (May-Aug). It could be explained by few observations, combined with some extreme observations during late summer. In addition the summer period defined by Nord Pool, that we have used, stretches until the end of October. Nevertheless we still found both periods to have significant negative risk premiums.

We failed to prove that the level of net-convenience yield affects the size of the risk premiums. Still the net-convenience level gave some interesting results in order to explain the spot price development. The regression results showed that a high basis (i.e. high Contango) makes the spot price increase towards maturity. Following the theory of storage a Contango situation finds place when the net-convenience yield is negative. We have already linked Contango to filled reservoirs, since the net-convenience yield is negative when the risk of overflows is present. This leads us to the somewhat strange result that the spot prices will increase when the reservoirs are filled. The reason for this is the core of the Theory of Storage. Filled reservoirs give low electricity prices, consequently there will be an expectation that the prices must increase in the future, as a result of an expected decrease in the reservoirs. In contrast the regression results showed that the price is expected to increase when the market exhibits a normal backwardation. Similar analogy is used to explain this; the prices are high due to low reservoirs and are expected to fall when the reservoirs are filled at some time in the future.

The regression results have good match with the fact that we, as mentioned, found normal backwardation during the spring floods. Since the reservoirs are low and the prices are high, but decreasing, as the reservoirs are filled during the spring. Furthermore, the regression implies that prices will fall when net-convenience yield is positive, while prices will increase when the market exhibits Contango. These relationships are confirmed by our spot price analysis that shows that the electricity price seems to peak at year end, decrease the first year-half and increase the second year-half. Simultaneously is Contango at its highest in the second year-half and the first year-half is close to exhibiting normal backwardation. The basis seems to peak during fall, which is when the reservoirs should be at its highest. Hence the storage costs and risk of overflows are at its highest.

The analysis of the relationship between the area prices and the system price showed that the area prices are almost exclusively lower than the system price. However, they were closer to the system price during spring, and actually higher at some points. The difference seems to be greatest from August to the end of February. These results are according to Marckhoff & Wimschulte's (2009) arguments. They argue that producers in hydro dominated areas want to hedge because they experience lower prices than the system price since transmission congestions prevents the cheap hydropower to spread across to other areas. Furthermore, we found that the largest deviations between the system price and the area prices appeared during the restructuring of the bidding areas. When N01 included the hydro dominated Bergen-area[45] in 2008, the N01 price fell below the system price. In contrast the N01 price increased above the system price in 2010 when the hydro dominated Kristiansand/Stavanger area was excluded. We do not have basis to further connect these events, but the findings are interesting in this setting considering the findings of (Marckhoff & Wimschulte, 2009).

The hydro dominated areas effect from cross hedging with the system price as underlying asset was the subject of our last analysis. This provided some remarkable variance reducing effects. However, since the correlation coefficient is low, the naïve hedge is not

[45] The Bergen area and Kristiansand/Stavanger area has a substantial higher share of hydropower than the Oslo area (Nordpoolspot, 2013h).

recommended since it could give unreliable results. The OLS hedge concluded that the N02 area should have a portfolio consisting of more short position in futures contracts, than spot market exposure. But since the hedging effectiveness is close to 50%, there is still much basis risk in the portfolio. High negative skewness of the relationship between the N02 and the system price implies that the N02 is seldom higher than the system price, and when it is higher, it only marginal. This is a good indication of that the N02 producers do not have to fear a considerable lost up-side through hedging. If producers hedge through short positions, this will reduce the net-long demand in the Nordic energy market and perhaps contribute to reduce the negative risk premium.

14 Conclusions and Final Remarks

All in all we have got more or less the results we expected and have thereby confirmed various results from other studies. The work has been challenging and new issues appeared as the study progressed. Many topics have been touched, that would have been interesting to investigate further. We will now briefly answer the main issues presented in the introduction.

First we presented background theory and found that the characterizations of electricity make every power market challenging considering price- formation and expectations. Electricity cannot be stored, implying that production must meet demand at any time. In addition it requires extensive infrastructure to be consumed. So far are all power markets similar, but the hydro dominance in the Nordic power market is what distinguishes it from most others. The dependence of precipitation is what makes price expectation uncertain, since weather forecasts are uncertain, especially the long-term forecast. In order to meet these challenges, the Nordic energy market was early regulated and Nord Pool Spot was created to organize the trade of electricity. Area prices have been introduced in order to equal the geographical differences between prices. And increasing connection between areas through cables makes sure that the reliability of supply gets better and that the benefits of the different production sources are utilized.

Further we found the situation described to be reflected through the electricity prices. The high volatility is what mainly characterizes the Nordic electricity price. The hydro dominance makes the price fluctuations extreme. The prices do not follow normal distributions since they tend to be skewed to the right. Hence, extreme high prices are more likely than extreme low prices. Despite large spikes, they still seem to be mean reverting. The system price has increased marginally the last decade, while the volatility has decreased marginally the last six years. This could be explained through higher demand and export, than new production and import. While the reduced volatility could be explained through the increasing cable connections. The weekly futures prices tend to exhibit much of the same patterns as the spot prices, but are less volatile.

The price volatility and positive skewness could be the reason why the weekly futures contract prices tend to overestimate the spot prices. Hence, they are biased estimators of the future spot price. Due to the market characterizations we have implied these as negative risk premiums, created by the consumers net-long demand for futures contracts. We found the market to exhibit Contango most of the year, except during the spring floods when it exhibits normal backwardation. This was successfully interpreted with the Theory of Storage, making a negative net-convenience yield through most of the year. However, the size of the risk premium was not found to be dependent of the futures curve, but nevertheless increasing with rising price level. Despite being unbiased predictors of the future spot price, the one-week horizon weekly futures did not improve when additional historical information was included in the model. In contrast the six-week horizon predictor was improved when adding historical price information.

We have found the area price to be almost exclusively lower than the system price, which gives such producers incentives for hedging. Through creating a portfolio by cross hedging the N02 spot exposure through short positions in weekly futures contracts, with the system price as underlying asset, we found significant reduction of variance.

14.1 Critics

Some of the background theory and market characterizations have not been confirmed through new empirical analysis. The reservoir level could have been used as an explanatory variable in order to support the analysis since arguments and conclusions throughout the thesis relies on its relationship to the electricity prices.

The amount of data I had access to has restricted my analysis to some extent, which resulted in having to adjust my issues according to the data and gave the thesis more of a general price description than intended. Even though some trends through the period have been found, it has not been prioritized to comment on the development through the sample period. In addition, the small amount of data from the new N02 Kristiansand area has given uncertainty to parts of the thesis results. These issues should be analyzed further with an increased amount of data readily. The rapid changes of the bidding areas make these types of analysis challenging.

Peak load futures contract are settled against the 60 hours between Monday-Friday 08.00-20.00 during delivery week. However, since I was provided system prices which are calculated from the 168 average hours (base load) during delivery week, this could have influenced the preciseness in the results. It should not have led to large deviations as the prices are assumed to be quite similar. I did not become aware of this until the end and did not have time to adjust the analysis.

The introduction of the HAC standard errors has probably made the thesis more statistical correct, but this could have been on the expense of more economical correct answers since I experienced some problems getting significant answers from some of the regression models. This must be considered when comparing the results with other studies.

On the other hand, the use of parametric tests on non-normal data series has reduced the statistical quality of the thesis.

The hedging section could have been developed further. An out-of-sample analysis could for instance been performed to control the confidence of the results.

14.2 Further work

It should be proved mathematically why the mean of the forecast error is different from the mean of the exponential function of the risk premium. Further it would be interesting to investigate if there is awareness of this in previous studies when the results of these two methods are indiscriminately compared.

Unfortunately, this thesis has not gone any deeper in to the obligations following the licenses in the regulated Nordic power market. It would be of interest whether the extent to which these contribute to reduce the unbalanced market. And in that case if, and potentially how, the power producers are prevented from speculating in high electricity prices through their reservoirs. Further, whether reservoirs are emptied in order to increase price, or if export is used actively to increase the price. Are we going toward are more liberalized energy market in Europe, or are the regulations necessary due to the market characteristics?

While the fact is that producers could profit on shorting futures contracts, many have signed fixed-price contracts for delivery of electricity, with their power distributor. If would be interesting to see to which extent these products reflect the distributors fear of high prices and whether simple consumers have benefits of such agreements.

In time, when the data samples increase, it would be interesting to further investigate the relationship between the N02 area, or bidding areas in general, and the system price. And with particular regard of the producers risk awareness.

It would also be interesting to further investigate the price formation in the bidding areas, compared to the unconstrained system price. Thus compare pure competition with the congestions, market characterizations and regulations of the area price formation.

Bibliography

enl.§1-1. (1990, June 29). Retrieved May 30, 2013, from lovdata.no: http://www.lovdata.no/all/hl-19900629-050.html

Dn. (2002, October 11). Retrieved June 06, 2013, from Dn.no: http://www.dn.no/arkiv/article36557.ece

Dn. (2003, November 03). Retrieved June 06, 2013, from Dn.no: http://www.dn.no/forsiden/energi/article110847.ece

Regjeringen. (2006, March). Retrieved March 10, 2013, from http://www.regjeringen.no/upload/kilde/oed/bro/2006/0003/ddd/pdfv/284610-ev_fakta_06_kap.03_no.pdf

NVE. (2009, January 14). Retrieved April 20, 2013, from nve.no: http://www.nve.no/en/Electricity-market/

Tn. (2009, August 28). Retrieved June 06, 2013, from Tn.no: http://www.tu.no/energi/2009/08/28/-ja-til-hoyere-strompris

Norges Bank. (2011, September 06). Retrieved from http://www.norges-bank.no/en/price-stability/exchange-rates/

SSB. (2011, May). Retrieved April 5, 2013, from http://www.ssb.no/a/publikasjoner/pdf/oa_201105/larsen.pdf

UIO. (2012, November 29). Retrieved April 03, 2013, from jus.uio.no: http://www.jus.uio.no/nifs/forskning/prosjekter/regulering-av-kraftmarkedet/

Nordpoolspot. (2012a). Retrieved June 01, 2013, from Nordpoolspot.com: http://www.nordpoolspot.com/How-does-it-work/The-market-members/Producers/

Nordpoolspot. (2012b). Retrieved 3 12, 2013, from Nordpoolspot.com: http://www.nordpoolspot.com/Global/Download%20Center/Annual-report/Nord-Pool-Spot_Europes-leading-power-markets_Jan2013.pdf

Nasdaqomx. (2013a). Retrieved April 27, 2013, from Nasdaqomx.com: http://www.nasdaqomx.com/commodities/markets/products/power/powerfutures/

Nordpoolspot. (2013a). Retrieved February 17, 2013, from http://www.nordpoolspot.com/About-us/

Yahoo Finance. (2013a, June 02). Retrieved June 02, 2013, from finance.yahoo.com: http://finance.yahoo.com/q/hp?s=GLD&a=10&b=18&c=2008&d=05&e=1&f=2013&g=d

Nasdaqomx. (2013b). Retrieved April 20, 2013, from Nasdaqomx.com: http://www.nasdaqomx.com/commodities/markets/products/power/powerforwards/

Nordpoolspot. (2013b, May 03). Retrieved May 03, 2013, from Nordpoolspot.com: http://www.nordpoolspot.com/How-does-it-work/The-market-members/Producers/

Yahoo Finance. (2013b, June 02). Retrieved June 02, 2013, from finance.yahoo.com: http://finance.yahoo.com/q?s=OIL&ql=1

Nordpoolspot. (2013c). Retrieved June 01, 2013, from Nordpoolspot.com: http://www.nordpoolspot.com/How-does-it-work/

Nordpoolspot. (2013d). Retrieved March 04, 2013, from Nordpoolspot.com: http://www.nordpoolspot.com/Market-data1/Maps/Elspot-Market-Overview/Elspot-Prices/

Nordpoolspot. (2013e). Retrieved February 08, 2013, from Nordpoolspot.com: http://www.nordpoolspot.com/How-does-it-work/Day-ahead-market-Elspot-/

Nordpoolspot. (2013f). Retrieved February 08, 2013, from Nordpoolspot.com: http://www.nordpoolspot.com/How-does-it-work/Day-ahead-market-Elspot-/Price-calculation/

Nordpoolspot. (2013g). Retrieved February 08, 2013, from Nordpoolspot.com: http://www.nordpoolspot.com/How-does-it-work/Intraday-market-Elbas/

Nordpoolspot. (2013h). Retrieved June 10, 2013, from Nordpoolspot.com: http://www.nordpoolspot.com/Market-data1/Power-system-data/Hydro-Reservoir/Hydro-Reservoir/ALL/Hourly/

Berg, L. (2010). *Empirical Studies of Nord Pool's Financial Market.* Bergen: NHH.

Bernseter, K. (2003). *Risikopremien i kraftmarkedet.* Trondheim: NTNU.

Bessembinder, H., & Lemmon, M. L. (2002). Equilibrium Pricing and Optimal Hedging in Electricity Forward Markets. *The Journal of Finance VOL. LVII, No. 3.*

Biørn, E. (2008). *Økonometriske emner.* Oslo: Unipub.

Botterud, A., Kristiansen, T., & Ilic, M. D. (2010). The relationship between spot and futures prices in the Nord Pool electricity market. *Energy Economics*, 967-978.

Burger, M., Graeber, B., & Schindlmayr, G. (2007). *Managing Energy risk: An integrated view on power and other energy markets.* Chichester: Wiley Finance.

Bye, T. (2006, September 12). *Cicero.* Retrieved April 15, 2013, from cicero.no: http://www.cicero.uio.no/fulltext/index_e.aspx?id=4279

Davidson, R., & MacKinnon, J. G. (2004). *Econometric Theory and Methods.* New York: Oxford University Press.

Escribano, A., Pena, J. I., & Villaplanta, P. (2002). *Modeling electricity prices: International Evidence.* Madrid: Universidad Carlos III.

Eydeland, A., & Wolyniec, K. (2003). *Energy and Power Risk Management: New Developments in Modeling, Pricing and Hedging.* New York: John Wiley & Sons.

Fiorenzani, S. (2006). Financial optimisation and risk management in refining activities. *International Journal of Global Energy Issues vol. 26*, 62-82.

Fosso, O. B., Gjelsvik, A., Haugstad, A., Moe, B., & Wangensteen, I. (1999). Generation scheduling in the deregulated system. The Norwegian case. *IEEE Transactios on Power Systems14*, 75-81.

Gjølberg, O., & Brattestad, T.-L. (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.

Hjelset, K., & Monsbakken, L. (2005). *Analyse av områdepriser på NordPool.* Trondheim: NTNU.

Hogan. (1992). Contract Networks for electric power transmission. In W. Hogan, *Journal of Regulatory Economics 4* (pp. 211-242). Springer.

Hull, J. C. (2009). Options, Futures and Other Derivatives 7th. In *Options, Futures and Other Derivatives 7th* (p. 1). Boston: Pearson Prentice Hall.

Hull, J. C. (2009). *Options, Futures, and other Derivatives 7th.* London: Pearson Prentice Hall.

Kennedy, P. (2003). *A guide to Econometrics Fifth Edition.* Oxford: Blackwell Publishing.

Keynes, J. M. (1936). *The Genreal Theory of Employment, Interest and Money.* Cambrigde: Macmillian Cambridge University Press.

Kristiansen, T. (2004). Congestion Management, transmission pricing and area price hedging in the Nordic region. *Eletrical Power and Energy Systems 26*, 685-695.

Lucia, J. J., & Torro, H. (2008, September). Short-term Electricity Futures Prices: Evidence on the time-varying risk premium. Valencia: Department of Financial Economics, University of Valencia.

Madaleno, M., & Pinho, C. (2008). *The hedging effectiveness of electricity futures.* Aveiro: Departmento de Economica Gasao e Engenharia Industrial Universidade de Aveiro.

Marckhoff, J., & Wimschulte, J. (2009). Locational price spreads and the pricing of contracts for difference: Evidence from the Nordic market. *Energy Economics*, 257-268.

McConnell, C. R., Brue, S. L., & Flynn, S. M. (2009). Macroeconomics Eighteenth Edition. In C. R. McConnell, S. L. Brue, & S. M. Flynn. New York: McGraw Hill Irwin.

Newbold, P., Carlson, W. L., & Thorne, B. (2010). *Statistics for Business and Economics seventh edition.* New Jersey: Pearson.

Nome, S. (2010). Retrieved from http://brage.bibsys.no/nhh/bitstream/URN:NBN:no-bibsys_brage_23986/1/Nome%202010.pdf

NordReg. (2011). *Nordic Market Report 2011 Report 3/2011.* Copenhagen: Nordic Energy Regulator.

NVE. (2010). *Annual Report, The Norwegian Energy Regulator.* Oslo: Norwegian Water Resources and Energy Directorate.

NVE. (2011). *Annual Report.* Oslo: The Norwegian Energy Regulator.

OED. (2003). *St.meld nr. 18 - Om forsyningssikkerheten for strøm mv,.* Oslo: Ministry of Petroleum and Energy.

OED. (2013a). *Energi og Vannresurser i Norge.* Oslo: Ministry of Petroleum and Energy.

PÖYRY. (2010). *Wind Energy and Electricity Prices: Exploring the "merit order effect".* The European Wind Energy Association (EWEA).

Studenmund, A. H. (2006). *Using Econometrics A practical guide Fifth Edition.* Los Angeles: Pearson.

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

Walpole, R. E., Myers, R. H., Myers, S. L., & Ye, K. (2012). *Probability and Statistics Ninth edition.* Boston: Pearson.

Appendix

A1 Descriptive Statistics of Spot Prices

Sample 2007-2012	Mean	St.dev.	Min.	Max.	95 % Conf.int	Skewness	Kurtosis	Jarque-Bera	Ljung-Box	n
SYS weekly price (NOK)	321,02	116,07	62,14	714,01	(308 , 334)	0,53	0,38	15,8*	280*	312
SYS weekly price (Ln)	5,700	0,40	4,13	6,57	(5,66 , 5,74)	-0,79	1,47	58*	271*	312
SYS weekly price change	0,0000	0,15	-0,70	1,09	(-0,02 , 0,02)	0,64	12,97	2133*	1,67**	311
Sub-sample 2007-2010										
SYS weekly price (NOK)	299,69	98,64	101,80	570,48	(284 , 315)	0,43	0,03	4,72***	146*	156
SYS weekly price (Ln)	5,65	0,35	4,62	6,35	(5,59 , 5,70)	-0,49	0,15	6,18**	144*	156
SYS weekly price change	0,0014	0,11	-0,50	0,35	(-0,02 , 0,02)	-0,54	4,33	119*	2,66 **	155
N01 weekly price (NOK)	275,04	108,65	30,05	542,18	(258 , 292)	0,04	-0,10	0,16***	149*	156
N01 weekly price (Ln)	5,51	0,53	3,40	6,30	(5,42 , 5,59)	-1,78	4,28	190*	139*	156
N01 weekly price change	0,0146	0,25	-1,32	2,04	(-0,03 , 0,06)	2,96	32,75	6742*	0,79***	156
Sub-sample 2010-2012										
SYS weekly price (NOK)	342,35	128,00	62,14	714,01	(322 , 363)	0,39	0,16	3,93***	138*	156
SYS weekly price (Ln)	5,76	0,43	4,13	6,57	(5,69 , 5,82)	-1,10	2,34	63*	131*	156
SYS weekly price change	-0,0010	0,18	-0,70	1,09	(-0,03 , 0,03)	0,83	10,72	713*	0,70***	156
N01 weekly price (NOK)	339,88	144,27	56,97	922,17	(317 , 363)	0,63	1,15	17,7*	136*	156
N01 weekly price (Ln)	5,72	0,50	4,04	6,83	(5,65 , 5,80)	-1,07	1,83	49*	128*	156
N01 weekly price change	-0,0010	0,22	-1,32	1,17	(-0,03 , 0,03)	-0,19	13,61	1123*	0,11***	156
N02 weekly price (NOK)	328,46	123,73	59,90	615,52	(309 , 348)	0,01	-0,46	1,49***	143*	156
N02 weekly price (Ln)	5,71	0,46	4,09	6,42	(5,63 , 5,79)	-1,23	1,80	57*	128*	156
N02 weekly price change	-0,0030	0,21	-1,32	1,17	(-0,04 , 0,03)	-0,24	17,30	1805*	0,69***	155

*p=0,000, **p<0,05, ***p>0,05, weekly price change given by: $(\ln_x - \ln_{x-1})$

Table 0.1 DESCRIPTIVE STATISTICS OF SPOT PRICES

A2 Descriptive Statistics of Weekly Futures Contract Prices

Sample 2007 - 2012	Mean	St.dev.	Min	Max	Skewness	Kurtosis	Jarque-Bera	Ljung-Box	n
F1 price (NOK)	324,70	116,83	59,84	718,33	0,649	0,637	26*	280*	312
F1 price (Ln)	5,715	0,38	4,09	6,58	-0,559	0,874	25*	277*	312
F1 weekly price change	0,0002	0,13	-0,53	0,60	0,319	4,087	212*	0,16***	311
F4 price (NOK)	334,17	106,49	134,56	694,01	0,511	0,045	13**	287*	312
F4 price (Ln)	5,760	0,33	4,90	6,54	-0,241	-0,484	6,2*	293*	312
F4 weekly price change	-0,0005	0,09	-0,32	0,28	0,264	1,161	19,9*	0,76***	311
F6 price (NOK)	337,89	103,10	149,99	663,12	0,456	-0,110	10,9**	290*	312
F6 price (Ln)	5,775	0,31	5,01	6,50	-0,234	-0,542	6,78*	294*	312
F6 weekly price change	-0,0014	0,08	-0,20	0,26	0,230	0,248	3,37***	2,38***	311
Sub-sample 2007 - 2010									
F1 price (NOK)	303,62	99,51	113,33	574,62	0,498	0,004	6,34**	144*	156
F1 price (Ln)	5,660	0,34	4,73	6,35	-0,346	-0,150	3,27***	144*	156
F1 weekly price change	0,0015	0,10	-0,35	0,32	0,121	1,207	8,62**	0,21***	155
F4 price (NOK)	317,23	99,24	155,26	602,59	0,583	-0,165	8,91**	147*	156
F4 price (Ln)	5,711	0,31	5,05	6,40	-0,059	-0,660	3,08***	148*	156
F4 weekly price change	-0,0007	0,08	-0,21	0,26	0,456	0,818	8,93**	0,10***	155
F6 price (NOK)	322,75	100,76	149,98	606,58	0,602	-0,213	9,62**	146*	156
F6 price (Ln)	5,729	0,31	5,01	6,41	-0,016	-0,675	3,12***	147*	156
F6 weekly price change	-0,0021	0,08	-0,20	0,26	0,317	0,381	3,26***	0,59***	155
Sub-sample 2010 - 2012									
F1 price (NOK)	345,78	128,79	59,84	718,33	0,548	0,446	8,66**	138*	156
F1 price (Ln)	5,770	0,41	4,09	6,58	-0,828	1,622	33*	136*	156
F1 weekly price change	-0,002	0,16	-0,53	0,60	0,372	3,565	79*	0,05***	156
F4 price (NOK)	351,12	111,02	134,56	694,01	0,400	0,164	4,19***	143*	156
F4 price (Ln)	5,808	0,34	4,90	6,54	-0,461	-0,140	5,61***	147*	156
F4 weekly price change	0,000	0,09	-0,32	0,29	0,125	1,370	11,18**	1,27***	156
F6 price (NOK)	353,03	103,50	157,21	663,12	0,333	0,138	2,88***	146*	156
F6 price (Ln)	5,821	0,31	5,06	6,50	-0,469	-0,157	5,84***	148*	156
F6 weekly price change	-0,001	0,08	-0,18	0,25	0,133	0,124	0,50***	1,86***	156

*p=0,0000, **p<0,05, ***p>0,05

Table 0.2 DESCRIPTIVE STATISTICS OF WEEKLY FUTURES CONTRACT PRICES

A3 Proof of Interpretation of Regression Results

The following derivation proofs that the constant can be interpreted as a forecast error with opposite sign:

We use the numbers from Model 8.3 on the one week horizon to show this.

$$(S_T - S_t) = -3{,}708 + 0{,}979\left(F_{t,T} - S_t\right)$$

Say that $F_{t,T} = 200$ and that $S_t = 100$, then:

$$(S_T - S_t) = -3{,}708 + 0{,}979(200 - 100)$$

In this example we replace the beta value by 1 and get:

$$S_T = 96{,}292 + S_t = 96{,}292 + 100 = 196{,}292$$

Then we insert the values in the forecast error equation given by Equation 8.2 and get:

$Forecasting\ error = F_t - S_T = 200 - 196{,}292 = 3{,}708$, hence the alpha value with opposite sign.

The same derivation can be used to show that the forecast error increase with an increasing basis risk if $\beta < 1$.