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DO FUTURES PRICES HELP FORECAST THE SPOT PRICE IN THE NORDIC POWER MARKET?

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Master of Science in Economics and,

Master in Business and Administration

Acknowledgment

This thesis marks the end of our master studies, Master of Business Administration and Master of Science in Economics at the Norwegian University of Life and Sciences. Working on this thesis has been a highly educational, at the same time challenging yet rewarding experience.

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Abstract

This thesis focuses on the Nordic electricity market, mainly the ability of futures contracts to forecast subsequent electricity spot prices in the Nordic power market. Our forecasting horizons are 1 to 4 months. We first analyze the basis and the relative basis to understand the behavior and structure of the market. We then introduce standard models to analyze the relationship between the electricity derivatives and the spot price, we include in these models seasonal effect and market structure - mainly backwardation or contango to further analyze these variables' effect on the spot price. Furthermore, we evaluate our econometric models' performance accuracy at forecasting subsequent spot prices or changes in the spot price by running our results on an out-of-sample and evaluating their subsequent electricity spot price forecast accuracy.

We use monthly electricity spot price data in the Nord pool market for the period November 2003 - March 2021 and monthly electricity futures contracts data for the same period. In addition water reservoir levels, electricity consumption, and production data for Nordic countries are also included. The results show that our models are good at forecasting the subsequent spot prices at least for the shorter term and in some cases, good as unadjusted or naive models. This is more notable in the time before covid 19 in our out-of-sample period. We concluded that the market has become unbiased and more efficient nowadays in a way that futures prices or the basis already incorporate information about spot price to some extent.

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1. Introduction

Our thesis focuses on the Nordic power market, which was the first deregulated power trading market in the world after the Nordic countries deregulated their individual markets and brought them together into a common Nordic market in the early 1990s NordPoolgroup (2021). Today the Nordic power market provides a leading marketplace for buying and selling power in the Nordic regions. It has also brought increased transparency into the electricity market operation and attracted an audience who observe and follow electricity prices and corresponding developments. This has motivated various market activities such as electricity price forecasting.

In general, electricity prices fluctuate heavily, and as a result, forecasting electricity prices is of high importance in many ways. On one side, production companies aim to optimize profit and power generation and help market participants to improve their business strategies. On the other hand, forecasting also helps suppliers and consumers by providing means of hedging against volatile prices, which again minimizes the risk.

Additionally, although the Nordic power market is largely dominated by hydropower and is a flexible production form, hydropower is largely dependent on uncertain hydrological circumstances. The key issues in forecasting electricity prices are often related to understanding market fundamentals and effectively utilizing the market information. Understanding the essentials of hydropower production provides the basis for electricity forecasting, especially for the Nordic power market Javanainen (2005). Although there are several approaches to forecast electricity prices, a classic approach is to look at the futures and spot prices of electricity. Earlier studies by Gjolberg and Brattested (2011), Stan (2012), and Smith-Meyer and Gjolberg (2016) show that futures prices can forecast subsequent spot prices. Based on these studies we continue the research to assert whether these findings are significant.

Different studies have analyzed the performance of futures contracts and their ability to forecast the subsequent spot price. Many studies have found that the market is immature or inefficient by finding a very high-risk premium mostly due to a market dominated by long hedgers. Eventually overshooting the spot price Smith-Meyer and Gjolberg (2016). In this study, we will present an updated study on the futures contracts electricity spot price forecasting performance in the Nordic power market using monthly observations from November 2003 until March 2021. We first estimate the standard models already established in the market before moving to other models that allow studying seasonal effect and market structure, mainly if in backwardation or contango and possible shifts in the risk premium. We eventually evaluate their performance accuracy at forecasting the subsequent spot price or change in the spot price. We assume that futures prices already include information about the future spot price making it an effective tool at forecasting the spot price in the Nordic power market.

Our objective will be to test the futures contracts' ability to forecast the electricity in the spot price with the hypothesis that futures prices already incorporate information about the spot price which can be utilized as a tool to better forecast subsequent spot price.

First, we start by explaining why we need another paper on the forecasting ability of futures contracts and the need for these analyses in a market that is becoming more and more unstable.

Second, we will touch upon the literature already established, the different research papers, and their main findings to put the reader in the context of where are we now and describe our contribution with this paper.

Furthermore, we will dive into the Nordic power market characteristics, organization, different actors, before moving to talk about commodities and fundamental theories that govern this market. This is particularly important as the analysis part will touch upon these theories and will put them to the test.

After we have stated all the necessary information about the past of the Nordic power market. We will start describing the data used in our analyses, including futures contracts data and other variables like water reservoirs. Summaries and comments will be presented to understand the structure of these data before using them in forecasting models.

Now with the analysis part. We will analyse first the basis and relative basis to understand its behavior and the structure of the market. Before moving to the methodological approach where we will introduce how we go about the main analyses of our paper including the forecasting models we use and eventually evaluating their accuracy at forecasting the spot price or the change in the spot price by testing them on an out of sample starting from January 2016 until March 2021.

2. The Nordic Electricity market

The Nord Pool is a leading power market in Europe, covering Norway, Sweden, Denmark, Finland, Estonia, Latvia, and Lithuania. The spot market is traded at the Nord Pool spot where around 70% of electricity consumption is traded at the hourly day-ahead market. Electricity financial derivatives, introduced by Nord Pool in 1995, are traded at NASDAQ OMX, with a market offering a wide range of financial derivatives with maturities ranging from one day to ten years. The contracts are written on both base and peak load power but there is another type of contract written on price differences between different areas and regions, these types of contracts are called Electricity Price Differentials EPADS previously called Contracts for Difference CFDs. In the following two sections, we will have a deep look into the physical market and the financial market.

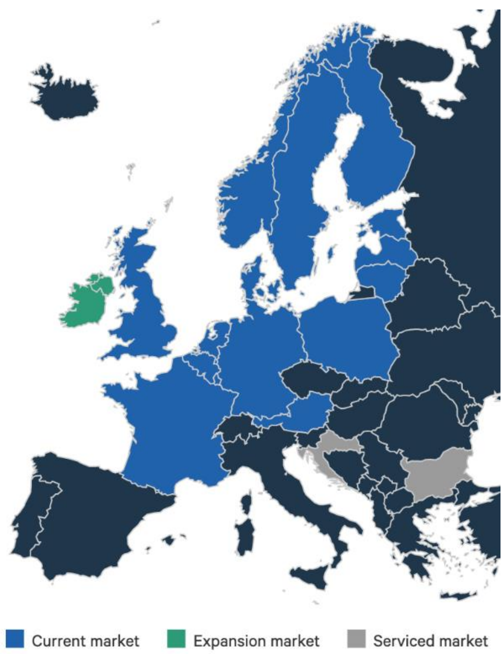

Figure 1: Nord Pool area map, source: NordPoolgroup (2021)

2.1 The physical market

As we mentioned above, the Nordic power market with physical delivery is organized through the Nord Pool spot. This market consists of a day-ahead market or Elspot, and an intraday market or Elbas. Around 85% of the physical power consumption in the Nordic and Baltic states is traded on Elspot while the rest is bilaterally traded. The market has around 360 participants from 20 countries who are typically power producers, suppliers, or traders.

At Nord Pool, buyers and sellers submit bids for next-day delivery. Assuming no transmission restriction, the equilibrium price is found from the aggregated supply and demand curves cross (the system price is set through double auction). The uncertainty of supply and demand predictions from the market participants gives existence to the intraday physical trade where the power can be traded until one hour before delivery. Therefore offering a possibility for buyers and sellers to adjust their hedging position to meet their obligations and the change in the supply and demand.

High electricity demand can make the power production approach the limit capacity, the power plants with a higher marginal cost will generate the requested power amount making the supply curve convex. Thus, a huge increase in the power price can occur. Bessembinder and Lemmon (2002) and Cartea and Villaplana (2008) confirm electricity prices to be increasing in demand and decreasing in supply. They suggest that economic activity and weather conditions are key factors for change in electricity demand.

In competitive markets, the clearing price is equal to the short-run marginal cost of production. This is the case for example for the primary electricity exchange market which is the day-ahead market. A lower bid than the marginal cost by producers will not cover costs while placing a higher bid than the marginal cost may result in them losing the auction. Therefore, according to Huisman et al. (2014). Placing a bid equal to their marginal cost is optimal.

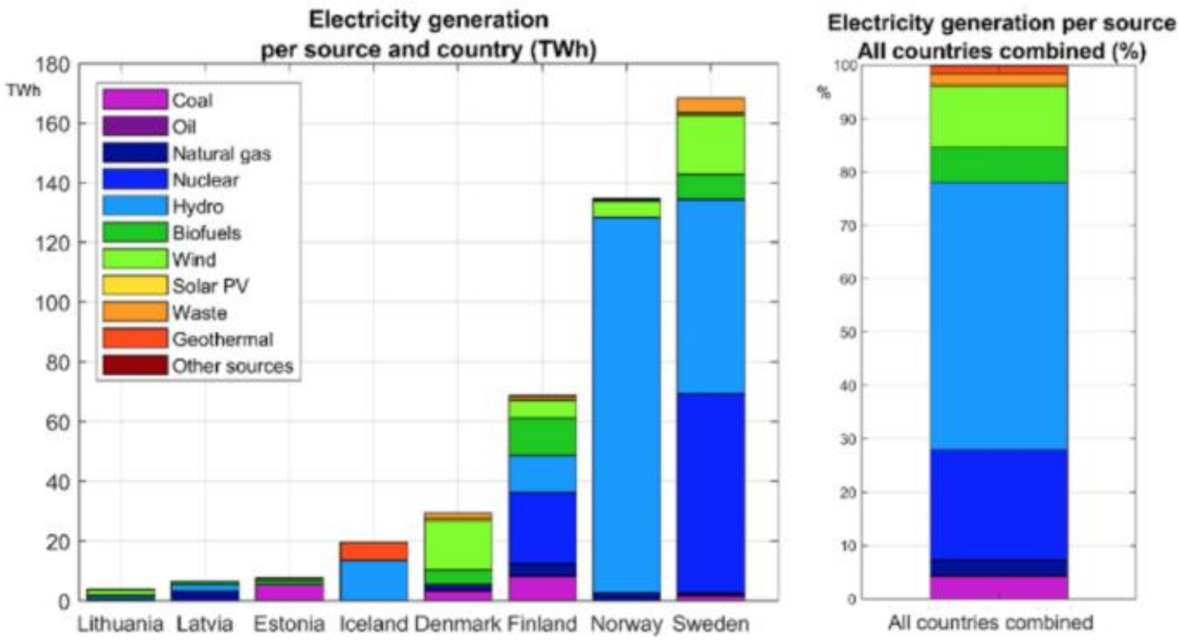

Figure 2 - Electricity generation by source in the Nordic regions, source: Halsnæs et al. (2021)

Figure 2 shows electricity production by source for each country in the Nordic electricity market and total production by source, in which hydro counts for half of the production. Figure 3 on the other hand shows the simplified marginal cost graph in the Nordic electricity market, where the marginal cost is on the y-axis and the total annual production is on the x-axis. Each block represents different generation sources. The width of the blocks reflects the generation capacity, and height means the marginal production costs. As shown in the figure, hydropower and wind combined cover around half of the total power production in the Nord Pool market, and its marginal production cost also very low, shown in the block's height.

When the demand for electricity in the Nordic market exceeds the combined capacity of hydropower, wind, and nuclear, other production methods will be used. when moving from one method to another, the marginal cost of electricity production will also rise. As shown in the figure above, coal-fired production methods have higher marginal costs than nuclear and hydro.

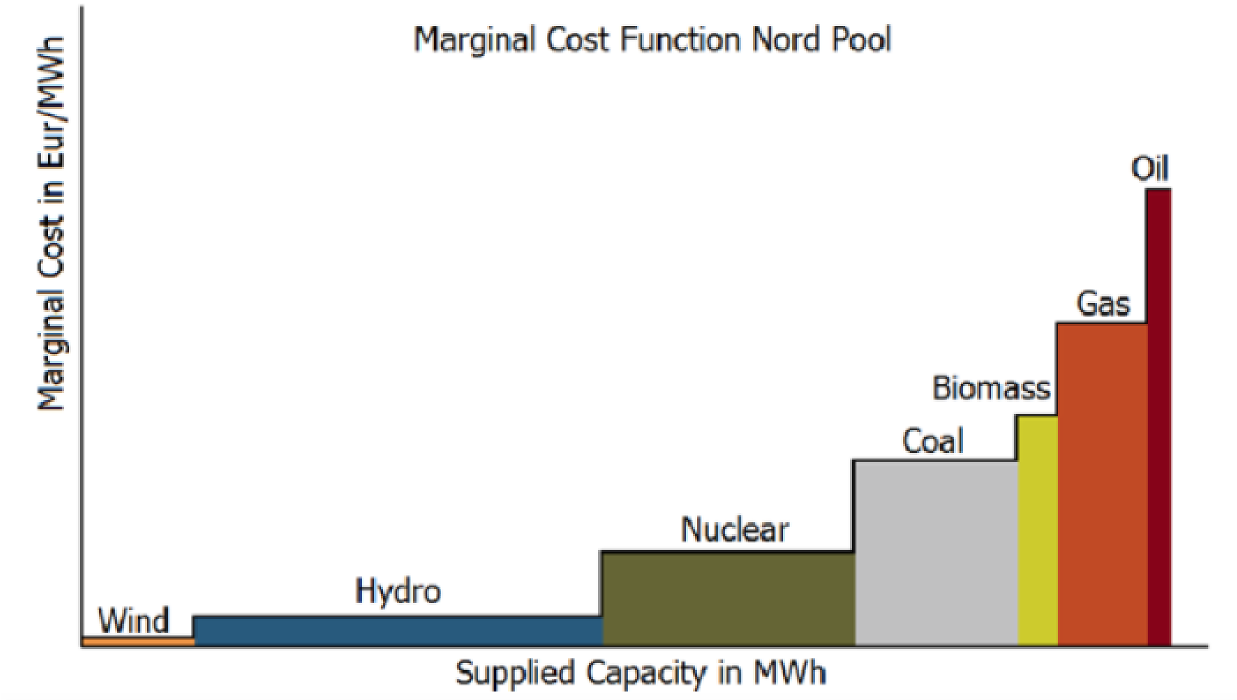

Figure *3 - Marginal cost on the Nord Pool's day-ahead market, source: Huisman et al. (2015)*

2.2 The futures market for electricity

The market for the sale of financial derivatives was acquired by NASDAQ OMX in 2010 and it was renamed NASDAQ OMX Commodities Europe. These derivatives are used by producers, retailers, and end-users as a risk management tool to hedge their needs against the fluctuations of the electricity price.

In the early 2000s, futures contracts were offered with a maturity horizon of up to 3 years. But, after the introduction of cash-settled forward contracts, so-called deferred settlement (DS), the horizon time was decreased to 8-12 months and more changes were made to the structure of futures contracts. Yearly contracts are cascaded into quarters, while quarters are split into months. These kinds of contracts have no settlement during the trading period before the expiry date. Mark to market is aggregated daily through the trading period but not realized until the settlement date. Other contracts for shorter horizon like a week or even day contracts involves both a daily mark to market settlement and a final spot price reference cash settlement after the expiry date.

Commodities futures markets serve two main social roles. First, they give the opportunity of price risk transfer by trading, which is a transfer of performance/ profitability risk due to fluctuations in the price of the commodity that is out of control from the issuing entity since the price is primarily driven by external market forces. Second, they offer a possibility of an unbiased forecasting tool of the future spot price. In this regard, a lot of previous academic research has been conducted to study the relationship between futures and spot prices. Some focused on the futures contracts' price forecasting ability to developing and testing future price models. This kind of research focused empirically on testing market efficiency, functioning, and forward premium to better understand the factors causing deviations from the efficient market state and eventually including these factors in the futures price models to better forecast the spot price. Different commodity markets require different approaches. See, for the general approach, Roache and Reichsfeld (2011) or Gj¯lberg and Johnsen (2001) for more specific on the Nordic electricity market. While other research focused on developing an understanding of the information borne in the futures market and their forecasting ability, and on studying the existence of the futures premium and their variation with different maturities. Fama and French (1987).

A crucial concept in the futures market is the basis, it reflects the difference between the futures price and the spot price of the underlying commodity or asset. We can express the basis mathematically in this way:

$$basis = F_{t,T} - S_t$$

Where $F_{t,T}$ denotes the futures price at time t with delivery at time T of a commodity, while S_t denotes the price of the underlying commodity at time t. it is worth mentioning that the basis can be normalized by dividing it with S_t giving us the following relationship:

$$relative\ basis = \frac{F_{t,T} - S_t}{S_t}$$

The basis serves as an analyzing tool to figure if the market is in contango or backwardation, a positive basis means that the market is in its normal state (contango) with no supply shortage while a negative basis means the market is a premium forward or in backwardation with a supply shortage. See Hecht (2020) for more details.

More specifically, the basis has additional descriptive content, as shown by Gjolberg and Brattested (2011) in the Nordic power market. As the storage of electricity is mostly irrelevant or can be one-sided for the producer since electricity can be stored as water in a dominant hydropower generation. The basis is more dependent on the cost of carry and the convenience yield. A high basis in the Nordic electricity market reflects a high cost of carry while a negative basis may imply a high convenience yield. Also, it is worth mentioning that the expectation hypothesis suggests that the basis includes some information about the expected spot price and risk premium.

As discussed, we can see that the different factors of the basis that is the convenience yield, cost of carry, storage theory, and expectations hypothesis are very important to our research and need to be analyzed deeply in the following subsections. But first, we start by analyzing the spot futures parity in the (hydro) electricity market.

Futures contracts in the electricity market offer a great opportunity for actors to hedge against price volatility and fluctuations in the market, however, they only provide protection against price fluctuation, they cannot fully provide the same benefits of holding physically the actual asset that can protect against unexpected events on a broader range, like production shortages or delivery failures. This gives rise to the convenience yield that represents the benefits of holding the physical commodity such as keeping the production process running or according to Hull (2009), "the convenience yield reflects the market's expectations concerning the futures availability of the commodity". In a Nordic (hydro) electricity market where the storage does not affect much or differs from different commodities. For consumers, the storage of electricity is not an option while for producers, electricity can be stored as water in reservoirs. The convenience yield is very important and reflects the expectations or fears of participants of the availability of electricity during the maturity of the futures contract. Besides, the traditional KaldorWorking-Brennan-Telser hypothesis points out that the expectations are based on participants observing the level of inventories as water availability is the only physical option to base expectations on for electricity availability and production for the maturity period. If water reservoirs are full, then the market will not expect a shortage in the coming months, thus the convenience yield will be low or even zero. On the other hand, low inventories will mean a high shortage risk and thus a high convenience yield. This relationship can be expressed mathematically in the following way:

$$F_{t,T} = S_t(1+r)^T + W - CY$$

Where $F_{t,T}$ denotes the price of the futures contract at time t for delivery at T, S_t is the spot price at t, r is the risk-free interest rate. W represents the cost of carry including all the costs that will be incurred until delivery at time T. A high CY will result in a negative basis since the CY will be higher than the cost of carry which is very small in a hydropower dominant market. Whereas a low or zero CY will give us a positive future spot spread in the limit of W, the cost of carry.

The classical way of pricing future commodities in a no-arbitrage market is referred to as the cost of carry Hull (2009) and Pindyck (2001). The cost of carry reflects the relationship between the spot price of a commodity and the price of the underlying futures contract under no possibility for arbitrage. It dictates that the spot price and futures price are equal if we subtract the cost of holding the commodity (storage cost and cost of capital) from the futures price. Following Hull (2009), this relationship can be expressed as follow:

$$F_0 = S_0 e^{(c-y)T}$$

Where y denotes the convenience yield and c represents the cost of carry which is the sum of the cost of physical storage and the forgone interest as Pindyck (2001) states. However, in the Nordic hydroelectricity power, the concept of physical storage ambiguous or somewhat irrelevant since the electricity can be stored as water as mentioned before, thus the water reservoirs affect the convenience yield that in its turn is the most weighted factor in the expression above.

There is another classical approach to futures pricing which is called the expectation theory. This theory suggests that the futures price equals the expected spot price plus a risk premium which in its turn implies that the futures price has the ability to forecast spot price. See Fama and French (1987), Mork (2006), and Huisman and Kilic (2012). This theory relies on the assumption that the market is efficient and there are no arbitrage opportunities. All available information that could be used to expect the prices are incorporated in the futures price. Thus, this price contains all information about the future changes in the spot price. Hence, the relationship between the futures price, expected future spot price, and risk premium can be expressed as follow:

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

Where $F_{t,T}$ is the futures price at time t for delivery at time T, $E_t(S_t)$ is the expected future spot price S_T at time t and $P_{t,T}$ is the risk premium. Smith-Meyer and Gjolberg (2016), while studying the risk premium in the Nordic power market found out that it depends on the hedging demand. For example, massive net demand for electricity in four to six-week maturity will lead consumers to buy the futures contracts at a higher price than the expected spot price because of fearing a price increase in the near future. So, in a balanced market where hedging demand and supply are matched. The risk premium will be zero and the futures price will simply equal the expected future spot price. While an unbalanced market will cause deviations presented as the risk premium.

Also, according to the same authors, the classical approach to analyze the risk premium was to compare the futures price at time T with the spot price materializes at T and calling the difference a “forecast error”. However, as Smith-Meyer and Gjolberg (2016) continue, the problem is in identifying which part of this forecast error can be considered as a risk premium and which other part can be attributed to nonrational behavior/expectations or market inefficiency. However, the expectations theory is rather controversial among researchers and academics. A lot of academic papers have disagreed with what was presented by this theory. For example, Fama and French (1987) comment that “there is little agreement on whether futures prices contain expected premiums or have the power to forecast spot prices”. They conducted a study on over 21 commodities and found out that only 10 can forecast the spot price. Pointing out that the storage theory is a better fit to explain the spot future parity than the expectation theory. Electricity is different from other physical commodities in two major ways: first, electricity cannot be physically stored as is the case for other commodities. In the Nordic market, it can be stored by filling hydropower reservoir levels from the producer side. But in large quantities, we can say that it is not feasible to store electricity. See Bessembinder and Lemmon (2002), Botterud et al. (2003), Mork (2006), and Huisman and Kilic (2012) for further discussion on electricity storability.

Second, the prices of electricity are highly volatile. since the storability of power is not an option, there are no inventories to smooth shocks in the market. This makes hedging against price fluctuation very important among producers and consumers. The volatility is magnified from the demand side by expectations of the near future production of electricity and prices. As we mentioned and discussed in detail about the convenience yield.

These characteristics of the power market make it difficult to find a suitable approach agreed upon among academics for futures pricing. The cost of carry approach as a traditional way for futures pricing works with physical commodities such as metal, sugar, etc. it simply links the futures price and spot price under a no-arbitrage condition. The same thing cannot be said about electricity that cannot be stored in large quantities. Thus, as Bessembinder and Lemmon (2002) have shown, the spot future parity in the power market does not comply with the cost of carry approach.

As the cost of carry theory cannot be relied on as an approach to futures pricing, some researchers have used the expectations theory as another possible approach. See Huisman and Kilic (2012) and Gjolberg and Brattested (2011). However, this approach presents a problem in the sense that we cannot tell which part is a risk premium and which other part is because of expectations and market inefficiency.

3. Literature on forecasting electricity price

Since the Nordic electricity market became a fully deregulated power market in the early 1990s, there has been conducted a lot of research on electricity pricing. Electricity as a commodity differs from other physical commodities in many ways, most notably that electricity can't be stored in large quantities, from an economic perspective. As produced electricity cannot be stored, the prices of electricity tend to be volatile over time. The unique characteristics of electricity as a non-storable commodity have given interest to many closer studies.

In an early study, Gj¯lberg and Johnsen (2001) analyzed the price relationships in the Nord Pool market. They concluded that futures prices periodically have been biased and poor predictors of subsequent spot prices and do not seem to incorporate available information for prediction. Botterud et al. (2003) study the relationship between electricity spot and futures prices in the Nordic electricity market, using daily observations from 1995 to 2001. Their analysis shows that futures prices on average were above the spot prices during the sample period, implying a contango relationship between electricity futures and spot prices. They emphasise that the study was done in the early 2000s and the validity of the analysis was also limited, because of the relatively short period the Nord Pool market had been in operation.

Botterud et al. (2010) looked at the weekly futures prices with one to six weeks to deliver between 1996 -2006, and they found futures prices to be higher than the spot prices on average. The average convenience yield is also found to be negative. This varies by season and depends on the storage levels in hydro reservoirs. Since electricity is not storable and the Nordic electricity market is primarily dominated by hydropower and water stored in reservoirs, Botterud et al. (2010) argue that convenience yield and storage theory cost are relevant to a hydro-dominated system. They also find a strong statistical relationship between risk premium and deviations from regular inflows and demand during the holding period.

Javanainen (2005) studied the short-term hydropower production and forecasting in the Norwegian electricity market. They found that due to the high flexibility of the production system there is a significantly strong short-term-price dependency in the production. According to their research, the degree of flexibility varies over the time of the year, because reservoir levels have seasonal fluctuations.

Huisman and Kilic (2012) studied the power market in Germany, Netherlands, and France and found that different time series have different average price levels. For example, peak hours correlate with each other and the same applies to hours outside peak. They concluded that the accuracy of forecasting when using time series models can be improved by adding more exogenous variables that can have explanatory power on models, similar to what J´onsson (2008) do in their study, by adding production from wind power as an extra exogenous explanatory variable when forecasting hourly electricity prices in Denmark.

Later studies by Gjolberg and Brattested (2011) looked at the four- and six-week futures prices in the Nordic electricity market from 1995 to 2008. They find that futures prices significantly go above subsequent spot prices and call the difference for "forecast error". They argue that if this forecast is a risk premium, it should follow a seasonal pattern based on the risk expectations. The forecast error varies from 7,4% - 9,3% every month. They argue that this is too large to understand as a risk premium only and conclude this as evidence of market inefficiency. They also find that the forecast error has increased mostly in recent years.

Lucia and Torró (2011) restudied Botterud et al. (2010) and looked at short-term to maturity futures contracts in the period 1998 -2007. They found that risk premium to be positive on average, and it varies throughout the year. Being zero in the summer and positive in the winter and autumn. They also find significant positive risk premiums in the short-term futures prices. Their results come similar to Gjolberg and Brattested (2011). Similarly, Botterud et al. (2003) also found seasonal patterns in the risk premiums. But they argue that the significance and size of premiums vary seasonally over the year, zero in the spring and summer, positive in autumn and winter. This result contradicts the findings of Gjolberg and Brattested (2011) – which finds no significant support for seasonal variation in the risk premiums. However, Stan (2012) studied this relationship between the futures price and spot price in the Nordic market and examined how the storage theory explains electricity basis variation. The result shows a cointegrated relationship between futures and spot prices in the long run, and futures prices do have the power to forecast spot prices.

Comparisons of various ways of producing electricity have also provided important knowledge about the characteristic differences between the electricity markets. Huisman and Kilic (2012) examined the risk premiums in the electricity futures prices from the Dutch and Nord Pool market, basing the analysis on storage theory. They find that electricity prices produced with imperfectly storable fuels such as hydropower in the Nord Pool market or other not perfectly storable powers have the power to forecast the spot prices. Thus, contradicting earlier results by Botterud et al. (2003) and Gjolberg and Brattested (2011).

Weron (2014) mentions that there is earlier research describing statistical models as a tool for creating technical analysis. Such a technical analysis will not try to measure underlying or fundamental values, but only look past patterns and indicators to forecast futures prices. The effectiveness of technical analysis can be discussed, but for forecasting electricity prices, this has proven to be a good method. Because the price of electricity follows a pattern related to seasonal effects. Therefore, statistical time series models will be poor at predicting spikes in electricity prices.

In a more recent paper by Smith-Meyer and Gjolberg (2016), they studied the Nordic futures market to see if forecasts were still unbiased and overshooting subsequent spot prices. They performed the studies with updated data of forecasting performance of Nordic power futures from October 2003 to January 2015. They find that after 2008, Nordic short-term power futures are indeed good indicators and provide more precise forecasts, in addition to being unbiased. Conclusively, the Nordic power futures market might have matured over the years, in which the authors suggested that the physical integration of Nordic and Dutch markets and opening of Nordned in 2018 may have been one of the reasons that contributed to this development.

Haugom et al. (2018) investigated the relationship between weekly futures contracts and spot prices in the Nordic market for 2004-2013. With the holding periods between one and four weeks on the futures contracts, they find that futures prices are biased predictors of the subsequent spot prices. There is a significant forward premium in the Nord Pool market, especially during the winter and autumn. They also found that the average spot prices and deviation of water inflow from the usual level positively impact the forward premium, only for the contracts closest to delivery.

In one of the recent papers, Steinert and Ziel (2019) examine the day-ahead electricity price of the EPEX spot for Germany and Austria and set up a model that incorporates the Phelix futures of EEX for Germany and Austria. They combine econometric autoregressive models in the short run with expectations of market participants reflected in the futures prices for short and mid-run, they find that forecasting performance can be hugely increased while keeping hourly precision. Their forecasting window is 1 to 28 days. Starting from 1.05.2016, which will create a forecast for up to four weeks for every day for one year, implying a total of 365 forecasts. They find that futures data contains relevant price information for future periods of the day-ahead of electricity price. Relying only on deterministic regressors can provide stability for forecast horizons of multiple weeks.

4. Data and descriptive statistics

Our thesis focuses on futures prices ability to forecast the spot price in the Nordic Power Market. For this analysis, we use data collected from Refinitiv DataStream and Montel. The data includes monthly Nord Pool system price and Nasdaq futures contracts in Euro/MWh from November 2003 to March 2021. There are 207 monthly observations in total for spot and futures prices.

Since our analysis is monthly based, we chose the 15th of each month as the base day this is because month contracts are delivered against the average spot price during the delivery month. electricity spot prices are traded seven days a week in the day ahead spot market and the futures prices are traded only on weekdays, to fix this we took the 15th futures price of each month or the closest date in case the 15th is a Saturday or Sunday. Then we matched the spot electricity prices with the futures prices (depending on the forecasting horizon from 1-4 months) creating the time series that will be used in the analyzes.

4.1 Electricity spot price

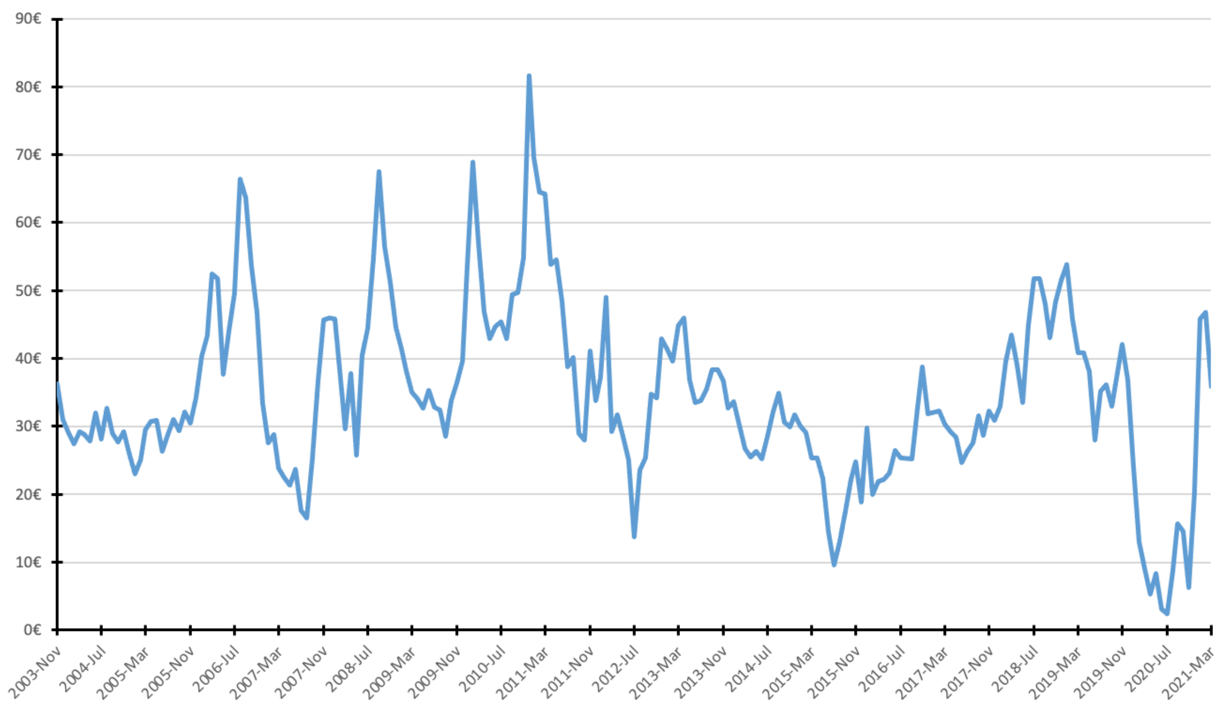

Figure 4 - Monthly Nord Pool system price (Euro/MWh) November 2003 - March 2021.

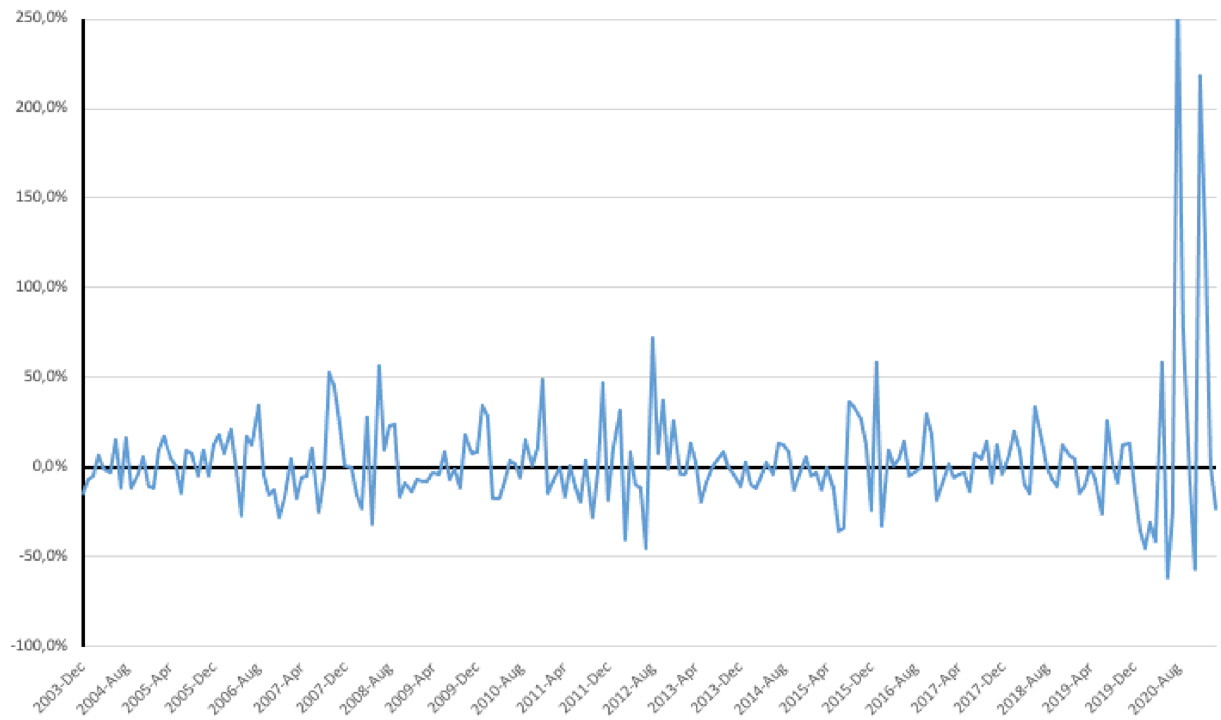

Figure 5 - Monthly percentage change in Nord Pool system price, December 2003 - March 2021.

Figure 4 shows the monthly Nord Pool system prices development between 2003 -2021. Prices ranging from under 10€/MWh to over 80€/MWh and are highly volatile. In Figure 5 monthly percentage changes in the electricity system price are shown in the same period. As it appears percentage price changes vary largely from 50%, -50% in the same period except in 2020 price fluctuations were extremely high. The reason for electricity prices in 2020 was fluctuating highly and was at lowest since 2002, because of the large hydrological surplus and warmer summer Aanensen (2021). Otherwise, the price fluctuation is more frequent at the start of the year. During the winter months, prices rise and fall in the spring/summer months. This pattern is notable when observing monthly averaged spot prices over the year, as shown in figure 6.

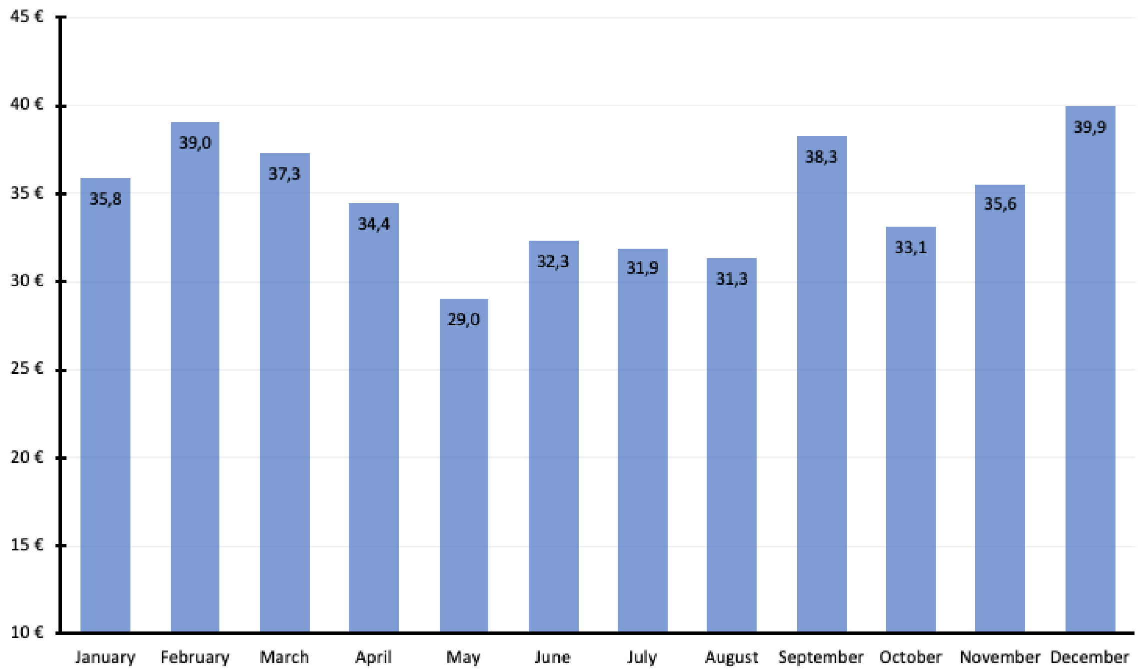

Figure 6 - Nord Pool averaged system price by month (Euro/MWh), November 2003 - March 2021.

As shown in figure 6, electricity prices vary widely from month to month. The prices range from under 30€/MWh at the lowest to over 40€/MWh at the highest. As mentioned earlier, it is high during the winter months (December, January, February) when the electricity demand is high and low in the summer months (June, July, August) when demand is low. Although prices fluctuate throughout the year, it is important to consider the effect of hydropower, because most electricity in the Nordic regions is produced by hydropower. Hydropower is usually saved in the reservoirs for later use and therefore its capacity level will influence electricity prices. However, we will exclude the hydropower data from our analysis since our interest is mainly in the futures prices and their accuracy as a tool for forecasting the electricity spot price.

4.2 Futures contracts prices

Descriptive Statistics / Variables	Futures contracts period (month)	Mean	Standard deviation	Coefficient of Variation (CV)	Minium	Maximum
Spot price (€/MWh)	-	34,6	12,8	0,37	2,4	81,7
Monthly futures (€/MWh)	(F1)	35,7	12,6	0,35	6,6	72,8
	(F2)	36,2	12,5	0,34	5,5	75,4
	(F3)	36,6	12,4	0,34	5,6	80,3
	(F4)	37,1	12,3	0,33	8,9	81

Table 1: Descriptive statistics for averaged monthly spot and futures prices (Euro/MWh). November 2003 – March 2021.

The electricity spot and futures prices in the Nord Pool electricity market are very volatile - which is a major characteristic of electricity prices. As shown in Table 1 above, the electricity spot price in the Nord Pool electricity market was on average 34,6 €/MWh during the period 2003 – 2021. The standard deviation was 12,8 €/MWh for the same period. For the futures prices, on the other hand, the average prices were between 35,7 - 37,1 €/MWh in the same period. Standard deviation was lower with time to maturity.

The same applies to monthly futures contracts with different maturities as shown in the same table. The spread between minimum and maximum prices on the spot and futures are extremely large and descriptive statistics prove once again electricity prices are very volatile.

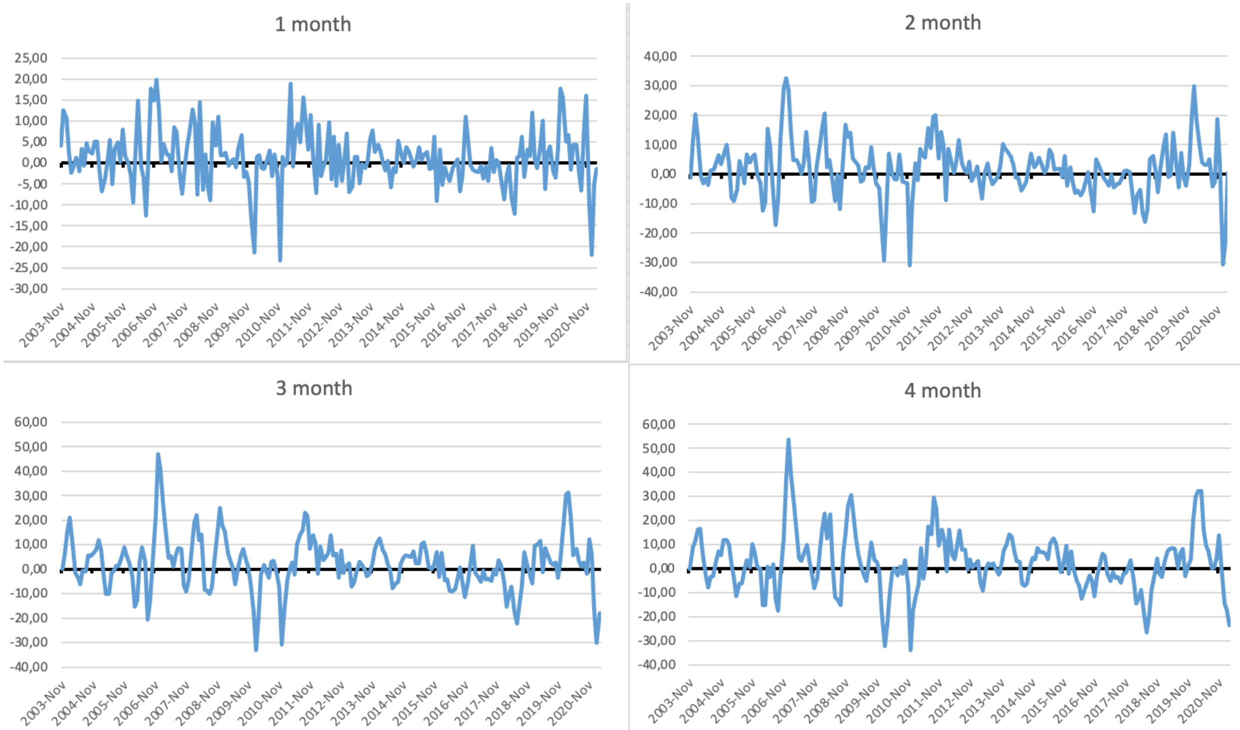

Figure 7 - Basis for futures contracts with different maturities 1 to 4 months. November 2003 - March 2021.

Figure 7 shows that the basis mainly has been in contango, and the smaller horizon for maturity, the greater the fluctuations in the basis. Fluctuations increased with as the basis in unstable and more difficult to predict as in the first year in the graph where it had relatively low fluctuations pattern, which creates a need for forecasting the basis and eventually the spot price to minimize risk against these changes in the forward premium.

4.3 Water reservoir levels, electricity production, and consumption in the Nordic countries

The data for water reservoir levels are reported monthly from February 2002 to March 2021. The data is monthly average water reservoir filling levels and is provided as a percentage of the maximum water reservoir capacity in four Nordic countries (Norway, Sweden, Denmark, and Finland). Figure 8 below presents the historical monthly median water reservoir levels as a percentage of maximum reservoir capacity.

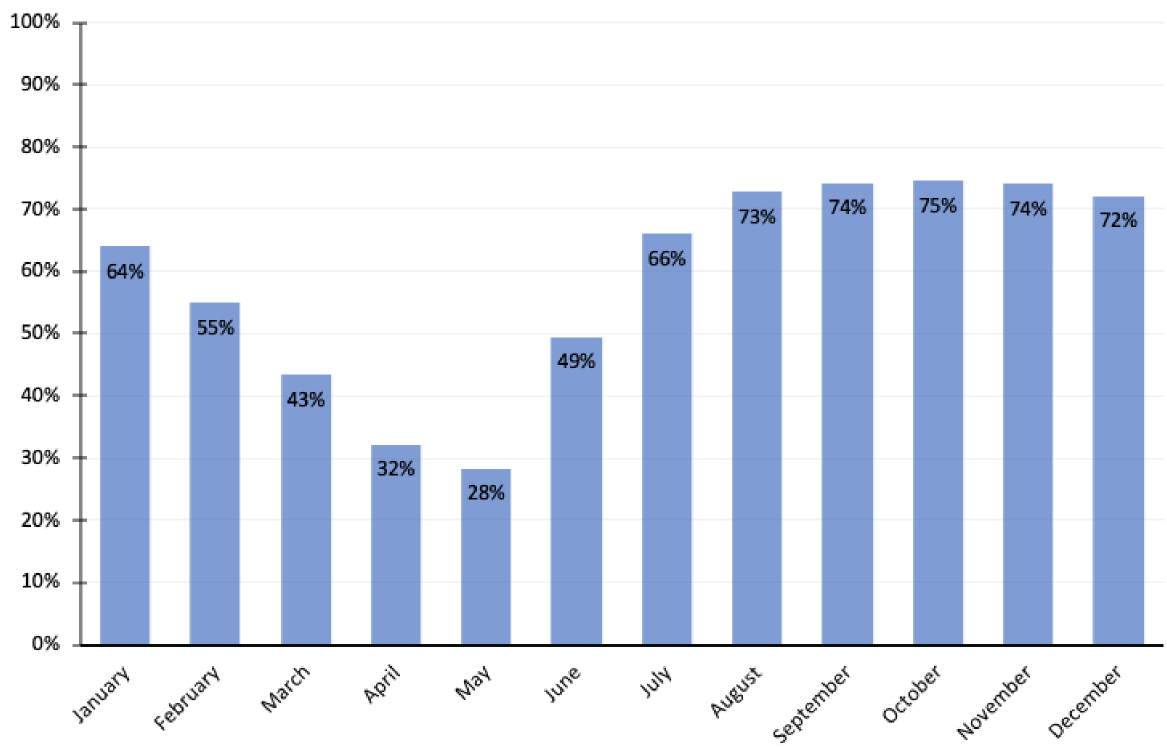

Figure 8 - Monthly averaged water reservoir levels as a percentage of maximum water reservoir capacity for all Nordic countries. February 2002 - March 2021.

As appears from figure 8 the water reservoir levels follow seasonal patterns and reach the lowest levels of maximum capacity during the spring months, particularly in May. The highest levels of maximum capacity are seen during the autumn months, particularly in October, after which the precipitation and melting snow from spring and summer fill the reservoirs again. On average, the lowest level is registered in May just under 30%, and the highest level in October around 75%.

Data for electricity consumption (demand) and production is collected from Montel and Refinitiv DataStream. The electricity demand - monthly electricity consumption and electricity production data consist of 194 monthly observations each. All data are from January 2005 to March 2021.

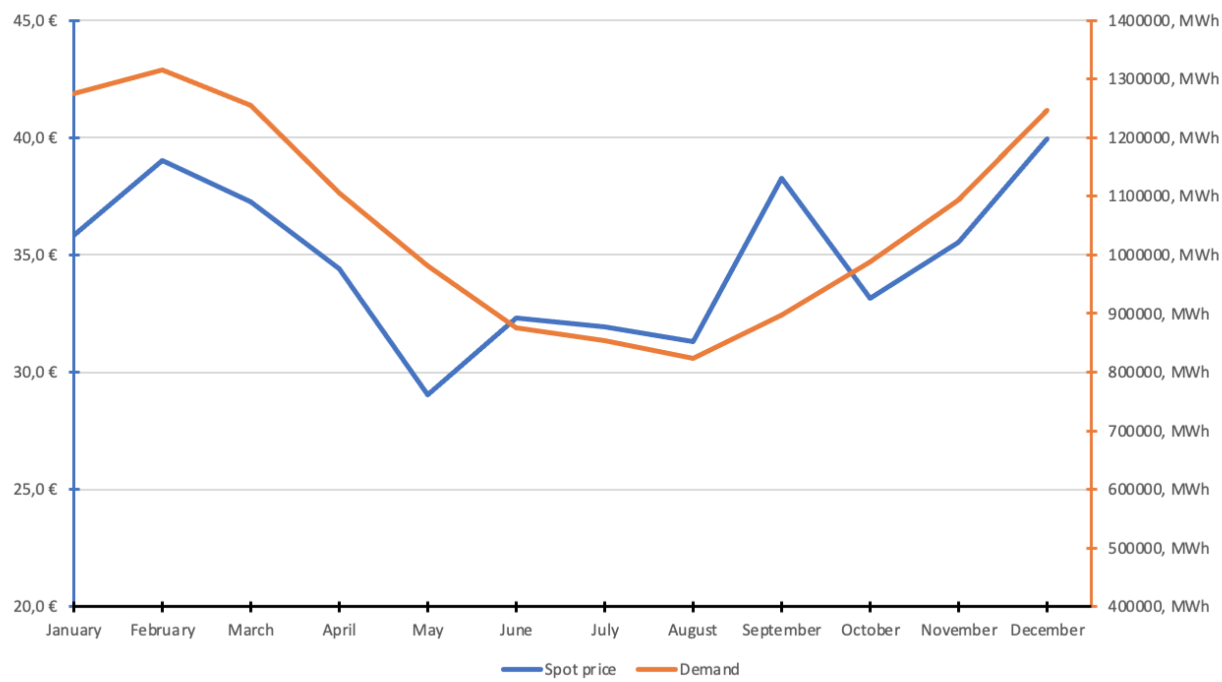

Figure 9 - Average electricity system price (Euro/MWh) and electricity consumption (MWh) in the Nord Pool area by months. January 2005 - March 2021.

The graph above highlights the relationship between the monthly average spot price and monthly average electricity demand. There is a positive correlation between the spot price and demand curve, as both follow similar patterns. Both the electricity spot price and electricity demand reach their lowest levels in the summer months and are highest during the winter months, which illustrates the seasonality both in electricity demand and spot prices.

As a comparison, the average monthly electricity production and average monthly water reservoir levels of maximum capacity in the Nordic regions are highlighted in figure 10 below. Because electricity production mostly comes from hydropower in the Nordic regions, the relationship between these two factors seems to have a relatively positive correlation as well. As shown in figure 10, electricity production is higher in the winter months and lower in the summer months. Water reservoir capacity is moderate during the winter months and higher during the late summer months. Although hydropower is the primary source for electricity production in the Nordic regions, there are also other sources like nuclear power, wind power, and thermal power. NordREG (2020).

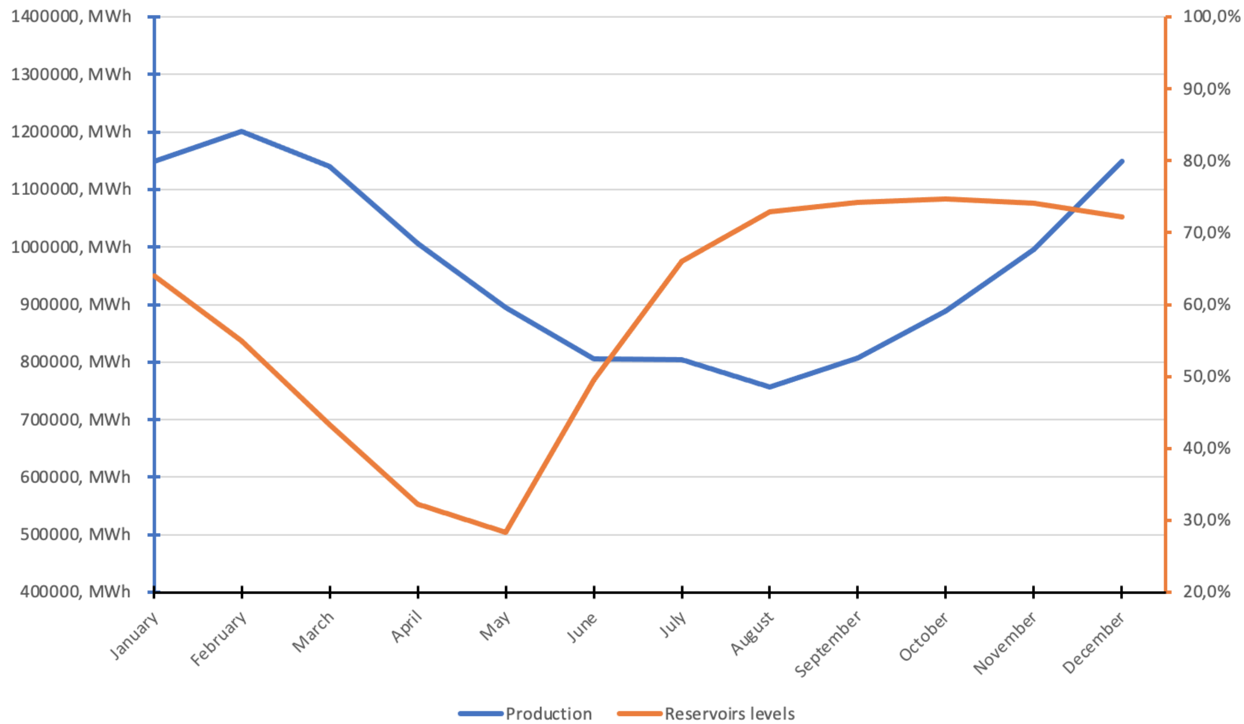

Figure 10 - Average monthly electricity production (Euro/MWh) and average monthly water reservoir levels (in the percentage of maximum capacity) in the Nordic regions. January 2005 - March 2021.

5. Futures contracts prices and their ability to forecast the spot price

5.1 Methodological approach

When it comes to analyzing the forecasting performance of the futures prices. We find two standard popular models. The first one is the expectations hypothesis approach that we will start with postulating that the expected future spot price simply equals the current futures price at time T.

$$lnS_T = \alpha + \beta\, lnF_{t,T} + \varepsilon_t. \qquad (1)$$

where S_T is the observed future price at time T, $F_{t,T}$ is the futures price for delivery at time t+T and ε_t is the risk premium. When we deduct the spot price S_T from both sides of the equation, we get a second model:

$$(lnS_T - lnS_t) = \alpha + \beta\, (lnF_{t,T} - lnS_t) + \varepsilon_t. \qquad (2)$$

α can be explained as the constant component of the risk premium. If the basis is an unbiased forecast of the expected spot price, then α will equal 0 and β will equal 1 while the error term or the risk premium will have a conditional mean of zero. This should hold if we assume that the market expectations are rational and that the futures prices hold information about the futures prices and the risk premium.

However, the risk premium and consequently, the forecasting ability of the futures contracts can be affected by the structure of the forward curve, whether the market is in contango or backwardation. The first is explained as the current futures price is higher than the spot prices while the latter is the fact that the current futures price is below the spot price. Following the same steps, Smith-Meyer and Gjolberg (2016) took. We will allow this in our analyzes by including a dummy variable called $BACK_t$, which is equal to 1 when $tF_{t,T} - S_t) < 0$ and equal to 0 otherwise. This will help us understand how the structure of the forward curve affects the basis (δ) and the change in the slope (θ) allowing for a change in the bias if the market is in backwardation:

$$(lnS_T - lnS_t) = \alpha + \beta\,(lnF_{t,T} - lnS_t) + \delta\, BACK_t$$

$$+\theta\,[\,BACK_t * (lnF_{t,T} - lnS_t)]\; + \varepsilon_t. \qquad (3)$$

Multiple studies found a seasonal effect in the power market. A widely known example is seasonality in temperature which affects production and demand. Spot price seasonality was documented by Weron (2008) and Botterud et al (2010), although at a decreasing rate from the mid-1990s to the mid2000s. using the same data, Torró (2009), also found seasonality in the futures-spot spread (the basis). Seasonal patterns were found also by Lucia and Schwartz (2002) and they documented that it was crucial for explaining the shape of the futures and forward curve. Also, Weron and Zator (2014) found that part of this seasonality in the case of Nord Pool could be explained by seasonal variations in reservoir levels.

To incorporate seasonal change in our analysis and its effect on the forecasting performance of the Nordic power market as Smith-Meyer and Gjolberg (2016) did. We will analyze the following model.

$$lnS_T = \alpha + \beta\, lnF_{t,T} + \sum_{i=1}^{11} MD_i + \varepsilon_t. \qquad (4)$$

Where $\sum_{i=1}^{11} MD_i$ is a vector for dummy variables of monthly dummies for the first eleven months of the year.

After getting the estimates for each model we will analyze next how good the models are at forecasting the subsequent spot price and the basis for 4 different horizons (1 to 4 months). We have above 4 models, models 1 and 4 are used to forecast the spot price, thus the evaluation of their performance will be conducted simultaneously to see which model is best at forecasting the spot price. We will do the same for models 2 and 3 to evaluate the best at forecasting the change in the spot price.

As a benchmark we will use two models, first, we have the naïve model which states that the spot price or the basis will be the same as last month. the second model is what we call the model of unadjusted futures. It states that the price of electricity at time T is the price of futures contracts at time t with delivery at T. for example, the price of electricity in February 2021 will be the price of futures contracts in January 2021 with one-month delivery. This is a one-month forecast. Increasing the horizon of the forecast will change the futures contract used in the forecast. If we take the same example but for 4 months horizon. The subsequent spot price for February 2021 will be the futures contract price in October 2020 with delivery in February. The same logic applies for 2 months forecast and 3 months forecast. This will help us benchmark these 2 models (unadjusted futures and naïve models) against our econometric models which is the adjusted futures (futures multiplied by beta plus alpha) to see how good they are at forecasting.

Our out-of-sample data goes until March 2021. Including around one year since the Covid19 crisis hit Norway and most of the European countries since March 2019. This can affect our results of forecasting accuracy of the spot electricity price in the out of sample since the market was in crisis and our models are not made to predict the spot price while the market is going through a crisis such as the Covid19. So we will be first using all of the out-of-sample data in our analysis as a start. And then comparing it to a smaller out sample from January 2016 until February 2019 excluding the Covid period and analyzing any changes compared to what we got with the full data set.

To evaluate the results of each model we will use three key performance indicators (KPIs). The Mean Absolute Error (MAE) is a very good KPI to measure forecast accuracy. As the name implies, it is the mean of the absolute error. The issue with this indicator is that it is not scaled to the average, if MAE equals 10 for example, you cannot know if it is good or bad cause it depends on the average of the variable in question. Also, we will use the Mean absolute percentage error known as MAPE and the mean squared error known as MSE. The first instrument is one of the most widely used measures of forecast accuracy. It measures the absolute size of each error in percentage terms before giving the average of all percentages. This tool is typically not ideal for low volume data as being off by a few units can skew the final results significantly. The MAPE output can be interpreted as being off by the percentage you got. On the other hand, the MSE measures the average squared difference between the forecast and actual values. This tells the reader how close the model was to get the actual value and the higher the value of MSE the worse the model as a forecasting instrument. Squaring the errors can make the errors looks larger especially if the data in question is noisy. We will also represent the root of the mean square error or RMSE, this simply takes the square root of the MSE. The purpose of originally squaring the errors was done so that negative errors did not cancel out positive errors. the results can be interpreted as the absolute distance between the line of best fit and the data point.

5.2 Futures premium in the Nordic electricity market

As we talked about before, the basis or the forward premium which is the difference between the futures price and the spot price reflects a balance between buyers and sellers in the Nordic electricity market. We will test the expected hypothesis that the basis is not perfectly matched in the market which dictates that a nonzero futures premium exists in the Nordic power market.

In addition, we would like to measure the size of the basis along with its economic significance, we do this by calculating the basis using the equation stated before where $Basis = F_{t,T} + S_t$. Furthermore, the economic significance will be analyzed using the relative basis which relates the basis to the spot price to get an idea of how much the basis contributes to the overall spot price level, the equation used already stated before is $relative\ basis = \frac{F_{t,T} - S_t}{S_t}$

In addition to these two tests and based on previous literature by Botterud et al. (2002), Mork (2006), Botterud et al. (2010), and Gjolberg and Brattested (2011), we expect the market to be in contango on average meaning that the basis will be positive. If proven right this will mean that in the electricity market the buyers are confronted with greater pressure to hedge their electricity need against price volatility than the producers.

Descriptive Statistics / Variables	Mean	Standard Deviation	Coefficient of variation	Kurtosis	Skewness	Minimum	Maximum	positive values %
1 month basis	0,63	8,08	12,8	3,67	-0,46	-36,77	31,33	53,62%
2-month basis	1,17	10,42	8,9	3,24	-0,22	-44,32	34,93	53,62%
3-month basis	1,57	11,87	7,6	2,70	0,17	-44,27	46,05	56,04%
4-month basis	2,03	13,08	6,4	2,49	0,35	-47,37	55,37	55,56%

Table 2: Descriptive statistics for the basis in (Euro/MWh) for different monthly futures contracts. November 2003 - March 2021.

Descriptive Statistics / Variables	Mean	Standard Deviation	Coefficient of variation	Kurtosis	Skewness	Minimum	Maximum	Positive values%
1-month relative basis	0,02	0,23	11,5	3,67	-0,46	-1,03	0,88	53,62%
2-month relative basis	0,03	0,29	9,7	3,24	-0,22	-1,24	0,98	53,62%
3-month relative basis	0,04	0,33	8,3	2,70	0,17	-1,24	1,29	56,04%
4-month relative basis	0,06	0,37	6,2	2,49	0,35	-1,32	1,55	55,56%

Table 3: Descriptive statistics for the relative basis in (Euro/MWh) for different monthly futures contracts. November 2003 - March 2021. Source: Refinitiv Datastream

We can see from the two tables above that the standard deviation is high and the spread between the minimum and maximum values for the basis and the relative basis for different futures contracts are also high indicating high volatility in the price of electricity in the Nordic power market. The percentage of positive values range from 53% for one month basis to 56% for 4 months basis which does not show a strong clustering of observations on either side and the fact that there is an imbalance in the distribution between positive and negative values with the lowest equals to 3.62% for 1 month basis confirms that most of the basis observations in our data are non-zero which confirms the first hypothesis that nonzero futures exist in the Nordic electricity market.

Furthermore, the existence of more positive values in all our data on average provides support to the hypothesis already proven by previous studies cited before in this section that the basis is positive in the electricity market on average proving that there is more need to hedge electricity need by consumers than by producers which proves that the hedging balance between buyer and seller is not perfectly matched.

In this analysis we would direct the attention to analyzing the relative basis which is not susceptible to changes in the overall price of electricity as the basis is making the observations for the relative basis comparable over time. However, when the price of electricity price is high, a small relative basis can be documented as a high difference between the futures prices and spot prices, and vice versa, a high basis in times of low electricity prices can be taken as a small basis which can make my interpretation biased, to solve this I still presented the results for the basis in the first table for the reader to have an idea about the basis in Euros per megawatt/h. but the coming analyzes will focus on the relative basis.

The mean for the relative basis is very close to zero, ranging from 0.02 for a one-month relative basis to 0.06 for a four-month relative basis while the proportion for positive values varies from 53% to 56% for the same instruments. The standard deviation follows an increasing pattern is, small for one-month maturity with a value of 0.23 compared to 4 months maturity with 0.37. The same increasing pattern applies for minimum and maximum values and the spread also increases with the increase of the maturity date for the futures contract, but on average weighted toward positive values showing a contango relationship. These results underline the extremely high volatility found in the Nordic electricity market.

6. Econometric results

In this part of the paper, we present the econometric results from analyzing the ability of futures contracts to forecast the spot price in the Nordic electricity market. We used monthly data by picking the price of a different futures month and spot price at the 15^{th} of each month or the closest date to it in case the 15^{th} is not available (i.e. happens to be on a weekend). Also, used the closing price as the main price in our analysis. The analysis period is from 15^{th} of November 2003 until 15^{th} March 2021 while excluding two dates (15^{th} august 2016 &15^{th} January 1017) because we were not able to retrieve the futures prices data at these dates.

Variable/ coefficient	α	β	Adj R²
ln F1	0,15 (0,19)	0,94 (0,05)	0,60
ln F2	0,34 (0,23)	0,89 (0,07)	0,47
ln F3	0,52 (0,27)	0,83 (0,07)	0,37
ln F4	0,84 (0,3)	0,74 (0,08)	0,27

Table 4: Estimation results from the model (1), SE in parentheses. F1 – F4 indicates the maturity time of futures contracts in months. November 2003 - March 2021.

Table 4 represents results for estimating the standard model (1). The model includes the 4 futures contracts with maturity varying from 1 month (F1) to 4 months (F4). We see from the table that beta is not different from unity for F1, F2, and F3 with $\frac{1-\beta}{SE}$ equals respectively 1.5, 1.57, and 2.42. As for F4, the beta is significant from zero. All the futures contracts have a decreasing pattern for betas and an increasing pattern for alpha the more the maturity date increases. For F1 we found Beta equals 0.94 and it decreases until it reaches 0.74 for F4. We can document the same pattern for alpha with 0.15 for F1 and 0.84 for F4. Finally, the explained variance (Adj R^2) remains relatively low (0.6 for F1 and 0.27 for F4) indicating that there are more variables not included in the model affecting the change of the spot price.

As for the estimations of model 2 reported in Table 5. We can see that the beta for the one-month contract is significantly different from unity, its numerical value is very close to 1 while the standard error is 0.1. Also, we can document the same decreasing pattern found before but only for betas as the increase in the horizon decreases the coefficient and the adjusted R^2. As for the constant term, which might be interpreted as a risk premium seems to be relatively small and around the same numeric values for all the different futures contracts showing that the due date does not affect the constant term.

Variable/ coefficient	α	β	Adj R^2
ln F1	0,04 (0,02)	1,07 (0,1)	0,35
ln F2	0,04 (0,02)	0,59 (0,07)	0,24
ln F3	0,04 (0,03)	0,48 (0,06)	0,21
ln F4	0,04 (0,03)	0,39 (0,06)	0,16

Table 5: Estimation results from the model(2), (SE in parentheses). F1 – F4 indicates the maturity time of futures contracts in months. November 2003 - March 2021. Source: Refinitiv Datastream.

Variable/ coefficient	α	B	δ	θ	Adj R^2
F1	0,14 (0,03)	1,41 (0,14)	0,15 (0,06)	-0,51 (0,33)	0,57
F2	0,15 (0,04)	0,84 (0,10)	0,13 (0,06)	-0,51 (0,22)	0,29
F3	0,16 (0,04)	0,73 (0,09)	0,13 (0,06)	-0,52 (0,20)	0,26
F4	0,15 (0,04)	0,61 (0,09)	0,09 (0,07)	-0,58 (0,20)	0,2

Table 6: Estimation results from the model (3), SE in parentheses. F1 – F4 indicates the maturity time of futures contracts in months. November 2003 - March 2021. Source: Refinitiv Datastream.

Table 6 represents results from estimating model 3 in which we include a shift and an interaction dummy for those months where the market has been in backwardation. The betas and alphas are almost the same as the results for model 3, all of the numeric values increased but none of them are close to unity. for the backwardation (δ), the dummy variable is not significant either in terms of numeric values or the standard error. Also, the change in the slope (θ) is medium for all types of contracts with a large standard error showing that the coefficient is not significant.

	F1		F2		F3		F4	
	coefficient value	SE	coefficient value	SE	coefficient value	SE	coefficient value	SE
α	0.08	0.16	0.02	0.22	0.25	0.27	0.59	0.32
β	1.00	0.04	0.97	0.06	0.90	0.07	0.80	0.08
D_jan	0.03	0.08	0.05	0.10	0.01	0.12	-0.01	0.13
D_feb	0.02	0.08	0.03	0.10	-0.01	0.12	-0.04	0.13
D_mar	0.07	0.08	0.05	0.10	0.03	0.12	-0.02	0.13
D_apr	0.05	0.08	0.10	0.10	0.04	0.12	-0.03	0.13
D_may	0.04	0.08	0.11	0.10	0.10	0.12	0.02	0.14
D_jun	0.01	0.08	0.05	0.10	0.04	0.12	0.02	0.14
D_jul	0.01	0.08	0.05	0.10	0.02	0.12	-0.01	0.14
D_aug	0.07	0.08	0.09	0.11	0.08	0.12	0.06	0.14
D_sep	0.05	0.08	0.08	0.10	0.06	0.12	0.06	0.13
D_oct	0.02	0.08	0.09	0.10	0.08	0.12	0.07	0.13
D_nov	-0.03	0.08	0.02	0.10	0.02	0.12	0.01	0.13
Adj R2	0.32		0.60		0.45		0.32	

Table 7: Estimation results from the model (4), (SE in parentheses). F1 – F4 indicates the maturity time of futures contracts in months. November 2003 - March 2021. Source: Refinitiv Datastream.

The table above represents the results from model 4 which takes seasonality into account. We see the results do not differ from earlier. The betas are significant and very close to unity for F1, F2, F3, and F4 while the seasonal variables are generally insignificant in terms of their ability to forecast the spot price changes. This means that the futures price already incorporates information about seasonality, which is normal in a market with rational and informed actors. The risk premium which is the forecast error term is insignificant for all the types of contracts in our analyzes. The futures prices and the spot price seem to be an unbiased forecast of the subsequent spot price and spot price change. However, this forecasting ability is somewhat lost the more the maturity date increases and it is strong the more the due date is very close.

6.1 Evaluating the electricity spot price forecast Accuracy

As we mentioned before, we will start by testing our models on the out-of-sample that we have from January 2016 until March 2021as to see which one is the fittest at forecasting the subsequent electricity spot price or the change in the spot price (the basis). We will start by evaluating the performance of models 1 & 4 at forecasting the spot price at different horizons (1-4 months).

Models 1 & 4 are meant to forecast the subsequent spot price. Thus, a comparison between the two is permitted to find the best one at forecasting. We used the price of electricity 1-4 months before (Naïve), unadjusted futures, and adjusted futures (multiplied by beta + alpha) as independent variables in model 1 to benchmark with the models we have established (model 1 & 4).

Horizon	1-month			
Model/ kpi	model 1			Model 4
	Adjusted Futures	Naive	Unadjusted Futures	Adjusted Futures
MAE	6,78	6,82	6,37	**6,34**
MSE	83,59	84,51	**81,05**	81,3
RMSE	9,14	9,19	**9,00**	9,02
MAPE	41%	41%	**41%**	41%

Table 8: One-month spot price forecast KPIs, January 2016 - March 2021

Horizon	2-month			
Model/ kpi	model 1			Model 4
	Adjusted Futures	Naive	Unadjusted Futures	Adjusted Futures
MAE	8,95	8,99	**8,03**	8,17
MSE	135,45	156,85	**127,9**	129,26
RMSE	11,64	12,52	**11,31**	11,37
MAPE	**52%**	56%	53%	53%

Table 9: Two-month spot price forecast KPIs, January 2016 - March 2021

Horizon	3-month			
Model/ kpi	model 1			Model 4
	Adjusted Futures	Naive	Unadjusted Futures	Adjusted Futures
MAE	10,05	**9,01**	9,07	9,16
MSE	167,85	161,82	148,7	**145,36**
RMSE	12,96	12,72	12,19	**12,06**
MAPE	54%	**45%**	57%	54%

Table 10: Three-month spot price forecast KPIs, January 2016 – March 2021

Horizon	4-month			
Model/ kpi	model 1			Model 4
	Adjusted futures	Naive	Unadjusted futures	Adjusted futures
MAE	12,9	9,82	**9,58**	10,99
MSE	209,9	183,3	**166,6**	181,25
RMSE	14,49	13,54	**12,89**	13,46
MAPE	62%	**52%**	66%	61%

Table 11: Four-month spot price forecast KPIs, January 2016 - March 2021

Looking at 1 monthly forecast key performance indicator for model 1, we see how unadjusted futures did a good job forecasting the subsequent spot price for all the key performance indicators (MSE, RMSE, and MAPE) except MAE. This can be explained by the fact that for short-term forecasts, the futures prices already incorporate information about the spot price and the market structure which makes it a good forecast instrument and thus show the ability of futures to forecast the electricity spot price. Moreover, the forecast of model 4 has slightly the same results as the futures independent variables because it includes seasonality variables that have a significant effect on the spot price in the Nordic market since most of the production is based on hydropower. This also confirms the forecasting ability of futures contracts at forecasting the spot price.

The same can be said for 2 months forecast evaluation both for the 1st and 4th model as the unadjusted futures are the best at forecasting with a slightly good performance from model 1 when looking at MAPE indicator with 52% which is the lowest. For 3 months forecast, the Naïve variable had the lowest error for MAE and MAPE while the adjusted futures for model 4 had the lowest errors when looking at MSE and RMSE. Finally, for the 4-month forecasts, we can see that the unadjusted futures still have the lowest error when looking at MAE, MSE, and RMSE. While MAPE indicates that the Naïve is the fittest for forecasting the electricity spot price. These results indicate that the futures contracts prices already incorporate information about the electricity spot price that can be utilized to forecast the latter, especially in the short run.

Next, we move to evaluate models 2 & 3 performance at forecasting the change in the spot price for all 4 horizons (1-4 months) and thus, the subsequent spot price. We have also used the spot price change (1-4) months before (Naïve), unadjusted basis, and adjusted basis (multiplied by beta + alpha) as independent variables in model 1 to benchmark with the models we have established (model 1 & 4).

Horizon	1-month			
Model/ kpi	model 2			Model 3
	Adjusted basis	Naive	Unadjusted Basis	Adjusted basis
MAE	6,47	10,06	**6,37**	6,44
MSE	83,13	180,31	**81,05**	82,44
RMSE	9,12	13,43	**9,00**	9,08
MAPE	209,8%	367,5%	**199,9%**	203%

Table 12: One-month spot price change forecast KPIs, January 2016 - March 2021

Horizon	2-month			
Model/ kpi	model 2			Model 3
	Adjusted basis	Naive	Unadjusted Basis	Adjusted basis
MAE	6,91	12,24	8,03	**6,61**
MSE	89,63	234,6	127,9	**88,06**
RMSE	9,47	15,32	11,31	**9,38**
MAPE	225%	573%	345,5%	**184%**

Table 13: Two-month spot price change forecast KPIs, January 2016 - March 2021

Horizon	3-month			
Model/ kpi	model 2			Model 3
	Adjusted basis	Naive	Unadjusted Basis	Adjusted basis
MAE	**7,0**	9,08	9,07	6,44
MSE	**82,3**	143,06	148,7	83,71
RMSE	**9,07**	11,96	12,19	9,15
MAPE	217%	392%	412,7%	**171%**

Table 14: Three-month spot price change forecast KPIs, January 2016 - March 2021

Horizon	4-month			
Model/ kpi	model 2			Model 3
	Adjusted basis	Naive	Unadjusted Basis	Adjusted basis
MAE	6,95	7,63	9,58	**6,91**
MSE	**83,65**	116,3	166,05	89,95
RMSE	**9,15**	10,78	12,89	9,48
MAPE	189,2%	253%	413,4%	**131%**

Table 15: Four-month spot price change forecast KPIs, January 2016 - March 2021

Looking first at the 1-month evaluation. We can see that the unadjusted Basis has the lowest forecasting errors for 4 indicators making it the best fit for eventually forecasting the spot price for a 1-month horizon. These results confirm more the capability of the risk premium at forecasting the spot price change in the short run. As for the other forecast horizons (2-4 month), we can see that the adjusted basis in model 2 and 3 had the lowest errors compared to the benchmarks we added stating that forecasting the change in the spot price is more difficult and the two models have a relatively low error and can be used as a forecast model or can be approved upon to get lower errors.

Next, we will follow the same logic of our evaluation method. However, this time we will shorten the out of sample to exclude the Covid19 period. The new out-of-sample will be from January 2016 until February 2020. The results for the analysis are presented below:

Horizon	1-month			
Model/ kpi	model 1			Model 4
	Adjusted Futures	Naive	Unadjusted Futures	Adjusted Futures
MAE	5,73	5,86	5,3	**5,06**
MSE	54,3	56,3	53,8	**48,97**
RMSE	7,37	7,5	7,34	**7**
MAPE	19,0%	20%	**18%**	**18%**

Table 16: One-month spot price forecast KPIs, January 2016 - February 2020

Horizon	2-month			
Model/ kpi	model 1			Model 4
	Adjusted Futures	Naive	Unadjusted Futures	Adjusted Futures
MAE	7,77	7,35	6,69	**6,35**
MSE	91,4	91,86	84,46	**66,95**
RMSE	9,56	9,58	9,19	**8,18**
MAPE	26%	25%	**24%**	**24%**

Table 17: Two-month spot price forecast KPIs, January 2016 - February 2020

Horizon	3-month			
Model/ kpi	model 1			Model 4
	Adjusted Futures	Naive	Unadjusted Futures	Adjusted Futures
MAE	8,8	**7,3**	7,56	7,63
MSE	119,6	**88,4**	95,8	89,65
RMSE	10,94	**9,4**	9,79	9,47
MAPE	28%	**25%**	26%	27%

Table 18: Three-month spot price forecast KPIs, January 2016 - February 2020

Horizon	4-month			
Model/ kpi	model 1			Model 4
	Adjusted Futures	Naive	Unadjusted Futures	Adjusted Futures
MAE	11,1	**7,5**	7,8	9,88
MSE	169,5	**94,5**	108	143,94
RMSE	13,02	**9,72**	10,39	12
MAPE	34%	**26%**	27%	32%

Table 19: Four-month spot price forecast KPIs, January 2016 - February 2020

Looking at the results for all the horizons for forecasting the electricity spot price, we can see that the errors are lower than the one we got with the out-of-sample going all the way to 2021. This is due to the increased price volatility while the market was going through a crisis because of the Covid19 making the forecasts even much harder to implement with good accuracy.

We can see some changes in which model is best fit to forecast the spot price compared with the results before. For the 1- and 2-month forecast, the adjusted futures for model 4 had the lowest errors for all the key performance indicators. However, for the 3- and 4-month horizon, the Naïve was the best fit for forecasting since it got lower errors than the models we established.

Now we will present results for forecasting the electricity spot price change on the out-of-sample from January 2016 to February 2020.

Horizon	1-month			
Model/ kpi	model 2			Model 3
	Adjusted basis	Naive	Unadjusted Basis	Adjusted basis
MAE	5,4	8,82	**5,3**	5,43
MSE	55,6	128,4	**53,81**	59,8
RMSE	7,46	11,33	**7,34**	7,8
MAPE	225,9%	396,6%	215,2%	**212,9%**

Table 20: One-month spot price change forecast KPIs, January 2016 - February 2020

Horizon	2-month			
Model/ kpi	model 2			Model 3
	Adjusted basis	Naive	Unadjusted Basis	Adjusted basis
MAE	5,86	10,06	6,7	**5,7**
MSE	**60,3**	138,7	84,5	65,75
RMSE	**7,76**	11,78	9,19	8,11
MAPE	240,7%	626,8%	370,6%	**188%**

Table 21: Two-month spot price change forecast KPIs, January 2016 - February 2020

Horizon	3-month			
Model/ kpi	model 2			Model 3
	Adjusted basis	Naive	Unadjusted Basis	Adjusted basis
MAE	6,0	7,68	7,56	**5,5**
MSE	**58**	91,97	95,8	61
RMSE	**7,62**	9,59	9,79	7,8
MAPE	230%	437,2%	438,4%	**170%**

Table 22: Three-month spot price change forecast KPIs, January 2016 - February 2020

Horizon	4-month			
Model/ kpi	model 2			Model 3
	Adjusted basis	Naive	Unadjusted Basis	Adjusted basis
MAE	5,92	7,19	7,8	**5,7**
MSE	**59,01**	108,7	108	61,2
RMSE	**7,68**	10,43	10,39	7,87
MAPE	194,8%	280,3%	424,8%	**110%**

Table 23: Four-month spot price change forecast KPIs, January 2016 - February 2020

As for forecasting the change in the spot price. We see that the unadjusted basis has the lowest errors for the 1-month horizon. While for 1-, 2- and 3-month horizon, adjusted basis for model 3 had the best accuracy according to MAPE and MAE, while the adjusted basis for model 2 had the lowest errors when looking at MSE and RMSE making the established models that can give better forecasting results than the benchmark variables (naïve & unadjusted basis)

6.2 Main findings

The purpose of this master thesis has been to analyze the futures price ability to forecast subsequent spot prices and price changes in the Nordic electricity market. Analyzes of basis and relative basis show that the market has been Contango on average. Estimating models 1 and 4, when forecasting the spot price shows that our models have a lower explanatory effect by observing the Adj R^2 values. The optimal Adj R^2 values of 0,6 are seen for the one-month forecasting horizon, in which we observe decreasing values for longer horizons. Similarly, for models 2 and 3, there is an indication that more variables outside of our models potentially affect the forecasting ability of spot prices and spot price changes.

Furthermore, when evaluating models 1 and 4 we see differences in forecasting accuracies as well. In the short term for 1 and 2 months, there are minor variations between our adjusted, naive, and unadjusted futures. However, for longer forecasting horizons, the differences increase, particularly for MAPE values. The gap between the lowest MAPE value for one-month and four-month forecasts is 11%. For models 2 and 3, however, there are more notable differences in MAPE values across all time horizons, compared to models 1 and 4. However, the lowest MAPE values on an adjusted basis for model 3 decrease with increasing forecasting horizons, across all time horizons.

Additionally, when excluding the Covid-19 period, there are significant changes in the results. All values are lower than the period with Covid-19. For models 1 and 4, Naive comes best out with lower MAPE values with 25% and 26% for 3 and 4-month forecasts, respectively. Model 2 and 3 follow the same pattern and results are challenging to interpret because there are too many variations in the result.

Conclusively, our models are good at forecasting the spot price in the short term, and some cases, good as unadjusted or naive models. This can be explained by the fact that futures prices already incorporate information about the future spot prices to some extent. For further studies, additional variables can be included in our models to develop more robust models. For instance, temperature data, wind, coal, nuclear power production data, etc.

7. Conclusion

The result presented in this thesis documented the existence, on average, of a nonzero positive basis in the Nordic power market. The longer the maturity date the higher percentage of positive monthly basis in the market. This is following the previous findings by Botterud et al. (2003), Mork (2006), Botterud et al. (2010), Gjolberg and Brattested (2011), Lucia and Torró (2011), and Huisman and Kilic (2012). These results imply that the hedging needs in the market are unbalanced between buyers and sellers and it suggests that the pressure is on buyers that are willing to pay a risk premium to electricity producers to fix electricity prices in the future.

As for the futures prices ability to forecast the electricity spot price. Future price-based forecasts are hard to beat and they were statistically significant in most of the results, including both the unadjusted futures and adjusted futures for this thesis. They perform at least as well as a naïve model and in some cases, they do significantly better. The fact that the unadjusted futures or basis outperformed the adjusted futures or basis can be explained by the fact that the futures or the basis already incorporate information about the spot price making it an effective tool to forecast the electricity spot price in the Nordic power market. This aligns with Smith-Meyer and Gjolberg (2016) findings that the futures prices and the basis have become unbiased and more precise and capable of forecasting the subsequent spot price. Thus, the market is more efficient nowadays compared to previous studies where the Nord pool futures prices were biased forecasts of the electricity spot price in the Nordic power market.

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