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Analyzing Market Efficiency and Price Dynamics in the Nordic Electricity Futures Market

Master Thesis

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Geir Høidal Bjønnes

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Abstract

This paper examines the relationship between monthly spot and futures prices in the Nord Pool electricity market, exploring long and short-term equilibrium dynamics. Using various models, including error correction models, we analyze futures contracts with holding periods from one to four months. Findings reveal an unbiased long-term relationship between spot and future prices, indicating a tendency toward market equilibrium. However, short-term biases are observed due to temporary shocks, market inefficiencies, or other factors affecting price dynamics. The analysis reveals no significant forward premium, indicating the absence of systematic mispricing. Factors impacting the forward premium include consumption deviations, wind production, and spot price variance. Seasonal variables have limited significance in forecasting spot price changes or explaining variations in the forward premium.

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1. Introduction

Efficient pricing is a fundamental requirement for well-functioning markets, as it provides accurate information to investors and enables effective capital allocation. In the Nordic electricity market context, where spot and future prices are crucial for electricity contract trading, understanding the dynamics of market efficiency, biasedness, and forward premium is of utmost importance. This master thesis aims to investigate the extent to which futures prices in the Nordic electricity market predict spot prices and explain variation in the forward premium using fundamental factors. We approximate the forward premium using the difference between the futures price in the first trading month and the realized spot price at the time of delivery. By examining these relationships, this master thesis aims to provide valuable insights into the dynamics of spot and future prices and their implications for market participants and policymakers.

Nord Pool, initially established in 1996 as a cooperative Norwegian-Swedish power exchange, has undergone subsequent expansions over the year (Nordpool history, 2021). The Nordic countries are divided into several bidding areas, with Norway having five, Sweden having four, Denmark having two, and Finland having one. The Baltic nations and the UK each have one bidding area (Nordpool bidding areas, 2021). This has inspired a variety of market activities, including the forecasting of electricity prices. Accurate electricity price forecasts are crucial due to the significant fluctuations typically observed in electricity markets. The financial market provides essential opportunities for risk management, hedging, and speculation in a volatile physical market, through derivatives such as futures and forward contracts.

Predicting power prices is often challenging and requires a deep understanding of market fundamentals and effective utilization of market data. In the Nordic market, where hydropower generation plays a significant role, electricity forecasting is particularly important and highly competitive (Javanainen, 2005). While various methods exist to forecast energy prices, one traditional approach involves analyzing futures and spot prices. Previous studies have examined futures contracts' effectiveness and capacity to predict the ensuing spot price. For a long time, research showed nearby future prices in the Nordic market to be biased forecast, overshooting the subsequent spot price. However, more studies by Smith-Meyer and Gjolberg (2016) show the market has become more mature and efficient. There may be several reasons for this, but they highlighted the opening of the NORNed cable in 2008 as one possible explanation. With new power cables to England (Nord Sea Link) and Germany (NordLink), combined with the energy crisis and volatility in the market, we will test if this still holds.

Our thesis will contribute to the literature on the relationship between spot- and futures prices in the Nord Pool electricity market. We extend the study performed by Smith-Meyer and Gjolberg (2016) using a more recent data sample (2004-2022) on futures prices with holding periods between one and four months. The analysis incorporates various econometric models, including error correction models and those incorporating seasonal effects and market structure - mainly backwardation or contango to test whether futures prices are unbiased predictors of future spot prices. These methodological choices enhance the robustness and accuracy of the investigation, allowing for a deeper understanding of the dynamics in the Nordic electricity market. The prices of all contracts are collected at three different points, enabling us to investigate how the timing influences the spot and future relationship. In addition, using more recent data (2004-2020), monthly observation, and temperature data, we apply a similar study by Haugom et al. (2018), looking at the variation in the forward premium. We assume that futures prices already include information about the future spot price, which makes it an effective tool for forecasting the spot price in the Nordic power market. Also, we make the widespread assumption that the forecast error in the future spot prices is zero on average, i.e., we assume that the expected spot equals the released spot. Thus, approximate the expected premium using the realized premium.

The findings reveal an unbiased long-term relationship between spot and future prices, indicating a tendency toward market equilibrium. However, short-term biases are observed, which can be attributed to temporary shocks, market inefficiencies, or other factors affecting price dynamics. The analysis reveals no significant forward premium, indicating the absence of systematic mispricing. When exploring factors impacting the forward premium, we observe significant effects of deviations in consumption and wind production for contracts with longer delivery periods. A positive impact is also seen for the variable measuring the variance of the spot price, but only for the contract closest to delivery. Seasonal variables generally have limited significance in forecasting spot price changes or explaining variations in the forward premium. The implications of this research are valuable for market participants and policymakers. Understanding the dynamics of spot and futures prices in the Nord Pool electricity market provides crucial insights for decision-making and risk management. The findings emphasize the importance of monitoring market conditions and implementing regulations for efficiency and minimizing distortions. Market participants can benefit from exploiting or correcting short-term biases based on the insights gained from this study.

This paper is organized as follows. First, we discuss the established literature and their findings in Section 2 before moving on to the relationship between spot and futures prices in Section 3. Section 4 discusses the data and statistics of the parameters we use in our models. We will begin by outlining the data that went into our calculations, including information from futures contracts and other factors like water reservoirs, consumption, wind, and temperature. Section 5 discusses futures contract prices and their ability to forecast the spot price. We specify a set of econometric models that consider various dynamics, such as long and short-term dynamics, market contango/backwardation and seasonal explanatory variables. After presenting the results from estimating these models, Section 6 presents the regression model and econometric results employed to analyze the variation in the ex-post forward premium. Finally, Section 7 concludes with a summary of the main results and findings.

2. Literature review

Accurate pricing and reliable forecasting in the Nordic electricity market are crucial for optimal capital allocation and risk mitigation. This section provides an overview of previous studies conducted in this field, highlighting the key findings and identifying areas of agreement and disagreement.

From an economic standpoint, one of the main ways electricity differs from other physical commodities is that it cannot be stored in significant quantities, making electricity prices prone to fluctuation over time. However, when hydropower dominates the market and can be stored, things change, and the theory of storage might apply (Botterud et al.,2010). According to the research of Linkenheil & Göss (2017) and Hirth (2018), increasing the amount of renewable energy produced will increase price volatility. This is because renewable energy sources are more vulnerable to exogenous factors like weather changes. Compared to nuclear power we will typically see more considerable price differences. Halsnæs et al. (2021) argue there is still a potential for improving the management of existing resources in the Nord pool market. They exemplify that one could ensure short-term demand better, despite the high volatility of wind.

Studies on cointegration between spot and futures prices have been conducted. Ghosh (1993) tested for cointegration and employed error correction models (ECM) to analyze electricity futures. Their findings suggest that error correction models (ECM) outperform price change regression and that this statistical approach can be very valuable in the commodity-futures market, of which electricity is a part. Lence and Falk (2005) conducted extensive research on cointegrated prices, market efficiency, and market integration. Their study revealed that efficient markets could exhibit cointegrated prices, challenging the notion that cointegration implies market inefficiency. They emphasized that the error in the cointegrated relationship does not necessarily need to be white noise, indicating that asset prices can be cointegrated even when markets are not perfectly efficient. Fridolfsson & Tangerås (2009) found no evidence of market power in the Nordpool market, while Stan (2012) identified a long-term cointegrated link between futures and spot prices, suggesting that futures prices can be useful in predicting spot prices.

Gjolberg & Johnsen (2001) investigated price correlations in the Nord Pool market and found that futures prices occasionally exhibited bias, were poor predictors of subsequent spot prices, and did not fully consider available information for forecasting. Building on this, Botterud *et al.* (2002) explored the relationship between spot and futures pricing in the Nordic power market using daily observations from 1995 to 2001. They observed that futures prices were, on average, higher than spot prices, indicating a contango link between electricity futures and spot prices. Between 1996-2006 Botterud *et al.* (2010) examined the weekly futures prices with one to six weeks to delivery and discovered the same result.

Botterud *et al.* (2010) also discovered a significant statistical connection between risk premiums and variations from expected inflows and demand over the holding period. However, Weron & Zator (2014) challenged some of Botterud *et al.* (2010) conclusions, demonstrating that their analysis did not support the alleged negative relationship between risk premiums and water reservoir levels. They further show that the coefficients obtained by Botterud *et al.* (2010) can only be comprehended when the ex-post risk premium is considered as opposed to the ex-ante one.

Javanainen (2005) discovered that hydropower production has a strong short-term price dependency because of the high degree of flexibility of the production system. According to their research, this is due to the seasonal variations in reservoir levels. Lucia & Torró (2011) finds that a below-average level of water leads to a lower risk premium, whereas Weron & Zator (2014) reports a positive relationship between the risk premium and the reservoir level.

Gjolberg & Brattested (2011) examined the Nordic energy market's four- and six-week futures prices from 1995 to 2008. They find a contango relationship between spot- and future prices. The authors argue that if this prediction is a risk premium, it should exhibit a seasonal pattern. The average inaccuracy lies around 8% every month, which implies it is too significant to be understood as a simple risk premium and therefore concludes market inefficiency. Lucia & Torró (2011) further explored short-term futures contracts and discovered significant positive risk premiums in their prices, supporting the findings of Gjolberg & Brattested (2011).

In more recent research, Smith-Meyer and Gjolberg (2016) assessed the forecasting performance of Nordic power futures. Their study spanned from October 2003 to January 2015, utilizing the most up-to-date forecasting performance data for Nordic power futures. They found that Nordic short-term power futures became reliable indicators after 2008, offering more accurate and unbiased predictions. The authors suggested that the physical integration of the Nordic and Dutch markets, facilitated by the opening of the NORNed cable in 2008, might have contributed to the development of an unbiased Nordic power market.

Haugom *et al.* (2018) examined the Nordic market's weekly futures contracts and spot prices from 2004 to 2013. They discover that futures prices are unreliable predictors of subsequent spot prices when the holding periods for the futures contracts are between one and four weeks. They found that the forward premium is favorably influenced by average spot prices and the variance of the water inflow from its typical level. A positive impact is also seen for the variable measuring the variance of the spot price, but only for the contract closest to delivery.

Our thesis adds new insights to the existing literature on the Nordic electricity market. We incorporate additional variables, a more recent dataset, various definitions of the future price, and employ error correction models. Unlike previous studies, we analyze monthly futures contracts instead of weekly, providing a comprehensive understanding of long-term equilibrium dynamics and the forward premium.

3. The relationship between spot and futures prices

This section will provide a brief introduction to the theory of futures pricing for commodities, with an emphasis on electricity. Relevant definitions and assumptions applied in the further analysis are presented and discussed. Fama and French (1987) detailed two popular views of commodity futures prices. The *first* model is known as the theory of storage, while the *second* model explains the futures price as the sum of the expected spot price and a risk premium.

The theory of storage

The storage theory is based on the argument of *no arbitrage* and explains the difference between spot and futures prices (the basis) in terms of interest forgone in storing a commodity, warehousing cost, and convenience yield on the inventory (Fama & French, 1987). This theory predicts that the return from purchasing the commodity at t and selling it for delivery at T, $F_{t,t+T} - S_t$, equals the interest forgone $S_t R_{(t+T)}$, plus the marginal storage cost W, less the marginal convince yield from additional unit of storage, CY:

$$F_{t,t+T} - S_t = S_t R_{(t+T)} + W - CY \qquad (3.1)$$

We can express the basis and relative basis mathematically in this way:

$$basis = F_{t,t+T} - S_t \text{ and } relativ\ basis = \frac{F_{t,t+T} - S_t}{S_t}.$$

Where $F_{t,t+T}$ denotes the futures price at time t with delivery at time t+T of a commodity, while S_t represents the price of the underlying commodity at time t. The basis is an analytical tool to determine whether the market is in a state of contango or backwardation. A positive basis indicates that the market is in its normal state of contango. Conversely, a negative basis represents a state of backwardation.

A classical way of pricing future commodities in a no-arbitrage market is referred to as the *cost of carry*. Following Hull (2018), this relationship can be expressed as follow:

$$F_0 = S_0^{(c-y)T} \qquad (3.2)$$

Where the cost of carry, c, measures the storage cost plus the interest paid to finance the asset less the income earned on the asset. The convenience yield, y, reflects the market expectations concerning the future availability of the commodity. For the electricity market, these expectations are based on participants observing the level of water availability for the relevant maturity. If water reservoirs are full, there is very little chance of shortages soon, and the convenience yield tends to be low. However, shortages are more likely if reservoir levels are low, and the convenience yield is usually higher.

Following equation (3.1), the interest foregone and storage costs increase the basis, which makes it more advantageous to hold a futures contract instead of the actual commodity. On the other hand, convenience yield reduces the basis and makes it more attractive to hold the commodity itself. As mentioned, the convenience yield can be exemplified by the water stored in reservoirs. Producers can utilize the stored water during unexpected electricity demands, thus taking advantage of elevated electricity prices. Meanwhile, the storage cost can be seen as the cost of water overflow. Since consumers are unable to store electricity, the general consensus is that cost-of-carry relationships between spot and futures prices do not exist. As a result, the second model is the most applied when pricing futures contracts on electricity.

Futures price as expected spot price and a risk premium

In the second model, Fama and French (1987) view the difference between the future price and the current spot price as the sum of a forward premium and expected change in the spot price:

$$F_{t,t+T} - S_t = FP_{t+T}^{ea} + E_t[S_{t+T} - S_t]. \qquad (3.3)$$

Where $F_{t,t+T}$ is the future price at time t, S_t the spot price at time t and S_{t+T} is the spot price in the delivery week t+T. The expected ex-ante forward premium is defined as the bias of the future price as a forecast of the future price, $FP_{t+T}^{ea} = F_{t,t+T} - E_t[S_{t+T}]$.

Since the expected spot price is not directly observable, and the results would depend on the model applied, researchers often choose to investigate the ex-post forward premium (Botterud et al., 2010; Fama & French, 1987; Gjolberg & Brattested, 2011; Haugom, Hoff, Mortensen, et al., 2018; Haugom & Ullrich, 2012; J. J. Lucia & Torró, 2011; Weron & Zator, 2014). We will use the definition of the realized or ex-post forward premium in our thesis:

$$FP_{t+T}^{ep} = F_{t,t+T} - S_{t+T} \qquad (3.4)$$

Where $F_{t,t+T}$ is the future price at time t, and S_{t+T} the observed or actual spot price in the delivery week t+T. We will consider three definitions of the futures price: the first closing future price for month, t, the average closing futures price for month t, and the last closing futures price for month, t. The different alternatives will be assessed later in Section 4. For robustness, we will examine the log ex-post forward premium LFP_{t+T}^{ep} defined as:

$$LFP_{t+T}^{ep} = \ln F_{t,t+T} - \ln S_{t+T} \qquad (3.5)$$

The ex-post forward premium can be decomposed into the sum of the ex-ante forward premium plus a forecast error,

$$\begin{aligned} FP_{t+T}^{ep} &= FP_{t+T}^{ea} + E_t[S_{t+T}] - S_{t+T} \\ &= FP_{t+T}^{ea} + FE_{t+T} \qquad (3.6) \end{aligned}$$

where $FE_{t+T} = E_t[S_{t+T}] - S_{t+T}$ is the forecast error. In common practice, the forecast error is assumed to be random noise. The noise term is assumed to be white noise which is uncorrelated to information known at time t and zero on average[1]:

$$FP_{t+T}^{ep} = F_{t,t+T} - S_{t+T} = FP_{t+T}^{ea} + \varepsilon_{t+T} \qquad (3.7)$$

Hence, the ex-post forward premium is a good proxy for the ex-ante forward premium.

[1] In previous research when the realized forward premium is used. it is assumed that the difference between the expected spot price and realized spot price (the forecast error) act as random noise (Botterud et al., 2010; Gjolberg & Brattested, 2011; Guttorm & Mortensen, 2014; Haugom & Ullrich, 2012; J. J. Lucia & Torró, 2011; Weron & Zator, 2014).

4. Data and descriptive statistics

This section will introduce the data used in this paper together with summary statistics for the most relevant variables. Table 1 summarizes the data and the sources they are obtained from. A more detailed analysis of the variables follows later.

Table 1: The table provides the source of data, time period and frequency.

Data	Source	Time period	Frequency
Spot	(Montel, 2023)	Jan 2004- Dec 2022	Daily
Futures	(Montel, 2023)	Jan 2004- Dec 2022	Daily
Consumption	(Statnett, 2023)	Jan 2004- Dec 2022	Hourly
Export	(Statnett, 2023)	Jan 2019- Dec 2022	Hourly
Inflow	Nord Pool FTP server	Jan 2004- Dec 2020	Weekly
Reservoir level	Nord Pool FTP server	Jan 2004- Dec 2020	Weekly
Wind production	(Energistyrelsen, 2023)	Jan 2004- Dec 2020	Monthly
Temperature	(Norsk Klima Service Senter, 2023)	Jan 2004- Dec 2020	Monthly

We calculate three different monthly future prices for each future contract and the monthly average spot price[2]. Then we match the spot price at delivery month $t+T$ with the different future prices at time t (depending on the forecasting horizon from 1-4 months) to create the ex-post forward premiums used in this analysis. Consequently, the spot price at t is the average spot price for the month we observe the future price. In contrast, the price against which we create the forward premium and evaluate the future forecasting performance is the average spot price $t+T$ through the delivery month. Considering the future price as a forecast implies a forecasting horizon of roughly one to four months.

Spot price

The monthly Nord Pool spot or system price is collected from the information provider Montel. A time series of monthly prices was generated using the arithmetic average of daily base spot prices for each month[3]. Previous literature has also calculated the spot price using arithmetic averages (Weron & Zator, 2014; Botterud *et al.*, 2010; Lucia & Torró, 2011).

[2] We consider three definitions of the futures price: the first closing future price for month, t, the average closing futures price for month t, and the last closing futures price for month, t.
[3] Period 2004-2022, some contracts were quotes in Euro. We use the monthly exchange rates from Norges Bank: https://www.norges-bank.no/tema/Statistikk/Valutakurser/?tab=currency&id=EUR to convert the future prices to NOK.

Norway and the Nordic region are closely interconnected with the European power market through interconnectors, making them susceptible to its electricity pricing dynamics. As the EU area (including the UK) experiences a growing share of unstable power production, particularly from wind sources, more instability in prices is expected (i.e., not just higher prices). According to Statnett, the new interconnectors to England (Nord Sea Link) and Germany (NordLink) will further enhance the value of Norwegian hydropower through increased exports and the utilization of renewable energy sources. Based on their report from 2018 on how the power market would be without trading, NVE[4] claims that during normal times the electricity price would be two to three times higher than without the interconnectors in wintertime due to the volatility of rain and possible scarce magazines (NVE, 2020).

Now let's turn our attention to Figure 1. Hydropower is typically stored in reservoirs for later use, and the capacity level will impact electricity costs. This pattern is notable when observing monthly averaged spot prices over the year. Electricity prices vary significantly from month to month, from 313 kr/MWh at the lowest price to 507 kr/MWh at the highest. It is high in the winter (December, January, and February), when there is a high demand for power, and low in the summer (May, June, and July), when there is a low demand.

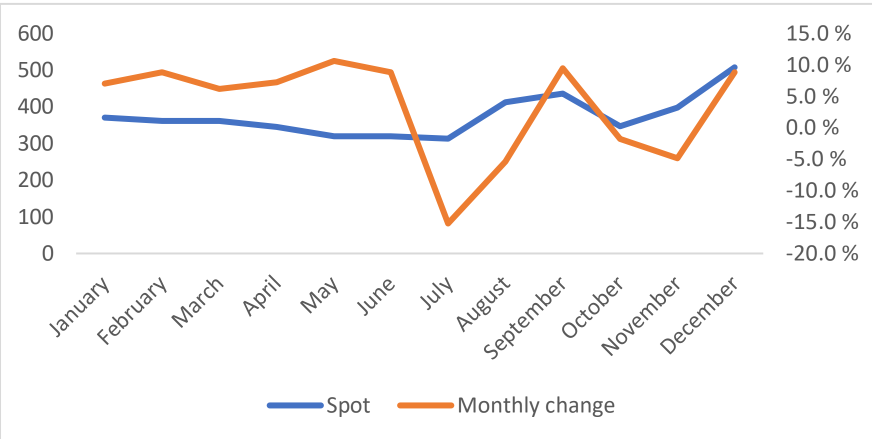

Figure 1*: The figure shows the average monthly spot and the average monthly change in the Nord Pool area from January 2004 to December 2022. All data is given in NOK/MWh. The left axis shows the spot price and the right axis show the percentage change.*

[4] NVE, short for Norges vassdrag- og energidirektorat, is responsible for regulating various aspects of the energy sector in Norway, including the oversight of Statnett.

On the other hand, there are arguments against the notion that interconnectors positively impact spot prices. One prominent critic is Kjell Erik Eilertsen, who asserts that the cables were used to transport excessive electricity production, depleting energy reserves to unprecedented low levels (Eilertsen, 2023). Similar views are shared by others such as Andersen and Birkelund (2014), Heldahl (2022) and Eilertsen (2019). Additionally, Myrvoll & Undeli (2022) found that Nordlink had a price-reducing effect on electricity prices in Germany, but an increasing effect in Norway (NO2).

After 2005, a rise in the level of spot prices is seen in Figure 2. According to Sijm et al. (2006) & Åhman et al. (2008), a significant portion of this rise in spot prices can be attributed to the implementation of ETS[5]. Also, in 2010, spot prices on the market were elevated. This year, maintenance was carried out on several Sweden nuclear power facilities to prevent unplanned output stoppage. The plants' downtime caused high spot prices. In 2011, the spot price fell to a low level due to very warm temperatures, significant precipitation, and a high level of wind power generation in Denmark (Haugom et al., 2018).

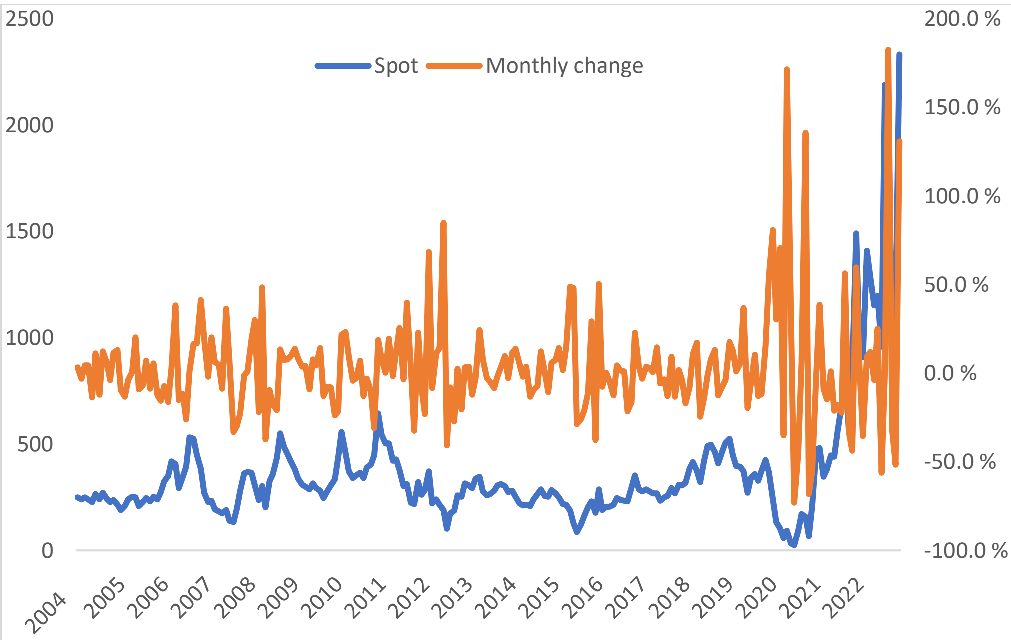

Figure 2: *The figure shows the monthly development in spot prices and the accompanied monthly change from January 2004- December 2022 in the Nordpool area. The left axis shows spot prices in NOK/MWh, whereas the right axis shows the percentage change.*

[5] ETS refers to the "emission trading system." First Launched in 2005 for EU to meet the Kyoto targets. (*Development of EU ETS (2005-2020)*, n.d.)

In the same period, the monthly percentage changes in electricity spot prices exhibit significant variation, ranging from 50% to -50%. However, a shift occurred in 2020 when price fluctuations intensified. Aanensen (2021) notes that electricity prices experienced remarkable volatility during that year, reaching their lowest level since 2002. This decline can be attributed to a surplus in hydrological conditions and a warmer summer (Yohanathan & Guelzim, 2021).

In recent years, Norway has experienced a significant price surge driven by various factors. This includes the ongoing conflict between Russia and Europe, resulting in higher energy prices, and the unusually dry conditions in Southern and Eastern Norway in 2021, which have impacted power generation. Additionally, maintenance issues and drought-related challenges have affected the operational capacity of French nuclear plants and disrupted coal transportation in Europe. These circumstances have collectively contributed to a decrease in energy output and supply constraints (Fornybarnorge, 2022).

Table 2 provides descriptive statistics for the monthly average spot price from January 2004 to December 2022. For the entire sample, the mean spot price is 366,89 NOK/MWh. Furthermore, we divided the spot price by seasonality, as the climate in the Nordpool area changes a lot during the year. Table 2 below shows the descriptive statistics we have visually seen from Figures 1 and 2.

Table 2: The table shows descriptive statistics for the monthly spot price. Winter is defined from months 12 to 2, and the other seasons are defined by the subsequent 3-month periods. All prices are in NOK/MWh. ***,**, and * indicate rejection of the null hypothesis stating normal distribution at a 1%, 5% and 10% level, respectively.

	Prices				
	All	Winter	Spring	Summer	Fall
Mean	366.89	403.30	384.26	343.60	336.43
Std. error	19.96	44.27	39.93	41.62	32.2
Std. deviation	301.45	334.22	301.43	314.19	243.10
Minimum	25.04	132.51	67.87	25.04	59.63
Median	287.11	305.54	301.14	271.92	276.38
Maximum	2331.7	2331.7	2158.72	2190.93	1409.44
Skewness	3.97	4.17	4.04	4.09	3.21
Excess Kurtosis	19.54	20.52	20.94	21.21	11.14
Jarque-Bera	4051.93***	983.34***	1008.91***	1034.21***	334.30***

High excess kurtosis and a right-skewed distribution suggest a volatile market subject to frequent spikes in the spot price. The Jarque-Bera test statistic rejects the null hypothesis of a normal distribution for all samples. The whole sample is tested for stationarity using the ADF unit root test (Dickey & Fuller, 1979). The null hypothesis of non-stationarity is rejected at a 5% significance level for log prices but fails to reject for raw prices[6].

Future prices

We use monthly future contracts with a time to delivery of between one and four months[7]. Montel provides the monthly futures prices and covers the period corresponding to the spot price data, i.e., Jan 2004- Dec 2022. The choice of monthly futures has two main advantages. The monthly futures data sample size is sufficient to draw valid and persistent conclusions. In addition, there exists high liquidity of contracts with long holding periods compared to weekly futures contracts. Futures prices are collected at three different points in time:
(1) The first closing price of the month (hereinafter called *first closing price*), (2) the average closing price during the month (hereinafter called *average price*) and (3) the last closing price of the month (hereinafter called *last closing price*).

Descriptive statistics for the different future prices are provided, cf. Table 3. We also report the summary statistic for the log last closing price. The statistics for log first closing and log average prices are similar and are not reported due to space considerations. The contracts' mean value and standard deviation increase with the holding period. The Jarque-Bera test statistic rejects the null hypothesis of a normal distribution for all contracts. The null hypothesis of non-stationarity cannot be rejected for all futures and log futures prices using an ADF unit root test. Looking at the time series below (Figure 3-4), this may be explained by the volatile and upward trend in the last couple of years. According to an ADF unit root test, removing the last two years will make most future prices stationary[8]. Statistically, it can be challenging to reject the null hypothesis due to temporary shocks common in energy prices.

[6] See footnote 7
[7] Hereupon, we will refer to a future contract with one month to delivery as F1, a futures contract with two months to delivery as F2, and so on.
[8] See Table 15-16 for Unit root tests and The Limitations of ADF and KPSS Tests in Analyzing Energy Prices in appendix

Table 3: The table shows descriptive statistics for the monthly future contracts. The mean and standard deviation are given in NOK/MWh. The columns reflect holding periods of one, two, three and four months. ***,**, and * indicate rejection of the null hypothesis stating normal distribution at a 1%, 5% and 10% level, respectively.

	F1	**F2**	**F3**	**F4**
First closing prices				
Mean	382.45	391.63	400.84	401.63
Std. deviation	360.65	409.61	467.68	484.23
Skewness	5.42	5.58	5.79	6.20
Excess Kurtosis	36.80	35.14	35.91	42.06
Jarque-Bera	13391.9***	12375.3***	12960.9***	17504.6***
Average prices				
Mean	380.11	389.15	397.66	402.81
Std. deviation	329.66	373.74	432.03	468.72
Skewness	4.30	4.85	5.50	6.03
Excess Kurtosis	21.79	25.93	33.01	40.72
Jarque-Bera	4998.53***	6979.01***	11024.2***	16413***
Last closing prices				
Mean	384.81	396.94	401.99	407.01
Std. deviation	364.54	412.84	441.16	459.99
Skewness	5.10	5.34	5.58	5.86
Excess Kurtosis	33.58	31.91	34.68	38.42
Jarque-Bera	11206.7***	10309***	12079***	14687.5***
Log last closing prices				
Mean	5.754	5.788	5.792	5.806
Std. deviation	0.567	0.529	0.531	0.523
Skewness	0.665	1.404	1.539	1.720
Excess Kurtosis	3.934	5.762	6.250	6.892
Jarque-Bera	155.38***	372.91***	440.90***	539.32***

To test the ex-post forward premium, we perform the following regressions:

$$FP_{t+T} = \gamma \quad \text{and} \quad LFP_{t+T} = \alpha \qquad (4)$$

Consequently, these regression models test the null hypothesis that the forward premium (γ) and the log forward premium (α) are equal to zero. The significance level is based on the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator. Table 4 presents descriptive statistics for both the forward and logarithmic forward premiums. The forward premiums are not significantly different from zero in most cases. Longer time horizons are related to more uncertainty, and in most cases the standard deviation and absolute value of the mean increase with time-to-delivery.

Table 4: The table shows the descriptive statistics for the forward premium (FP) and logarithmic forward premium (log FP) based on the various methods for calculating the futures price.

	FP				Log FP			
	F1	F2	F3	F4	F1	F2	F3	F4
Calculated from first closing prices								
Mean	0.73	-1.86	-7.01	-18.83	0.034	0.036	0.033	0.026
Std. dev	177.40	204.95	245.23	233.94	0.274	0.332	0.398	0.45
Skewness	2.05	1.22	1.02	-1.99	0.70	0.77	0.63	0.48
Kurtosis	30.68	19.47	19.87	12.51	3.63	2.43	1.80	2.14
Calculated from average prices								
Mean	2.36	0.50	-3.752	-12.51	0.032	0.039	0.037	0.032
Std. dev	150.28	203.24	239.75	235.73	0.233	0.309	0.373	0.426
Skewness	1.87	2.24	1.59	-0.76	1.18	0.67	0.64	0.55
Kurtosis	33.80	29.09	23.68	14.34	5.13	2.68	1.99	2.15
Calculated from last closing prices								
Mean	11.84	10.61	3.70	24.76	0.026**	0.050	0.043	0.063
Std. dev	138.15	230.60	237.26	336.88	0.174	0.314	0.352	0.410
Skewness	3.84	4.63	2.65	6.10	1.13	0.93	0.68	0.70
Kurtosis	36.71	44.72	25.85	57.30	5.05	3.52	2.06	3.28

The columns reflect holding periods of one, two, three and four months. ***, **, and * indicate significance at a 1%, 5%, and 10% level, respectively, based on the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator.

Figure 3 compares the spot price to the F1 and F4 average price. As seen from the figure, the contract price follows the spot price closely throughout the entire sample. By visually inspecting Figures 3 and 4, we observe that futures contracts with longer holding periods react slower to changes in the spot price compared to futures with shorter holding periods. As the forecasts are made months in advance, the futures prices will not be able to capture sudden and unexpected spikes or drops in the spot price. Thus, as the spot price reverts to normal levels, the futures prices still incorporate the previous price level.

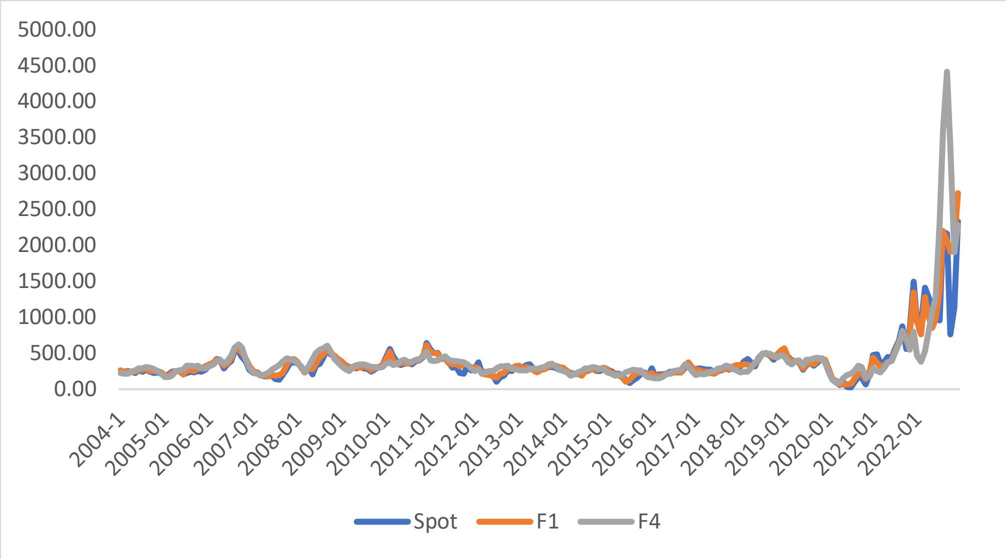

Figure 3: *The figure shows the average monthly Nord Pool spot price and the averaged F1 and F4 closing price in the period January 2004-December 2022. All data is given in NOK/MWh*

Figure 4 demonstrates that the basis has primarily been in contango, and that basis volatility has massively increased in the last couple of years. We can see that the basis for the F1 contract is smaller than the F4 contract, as expected. This is due to more uncertainty on longer horizons. Hedging could be an alternative to reduce risk from these changes in the forward premium (Yohanathan & Guelzim, 2021)

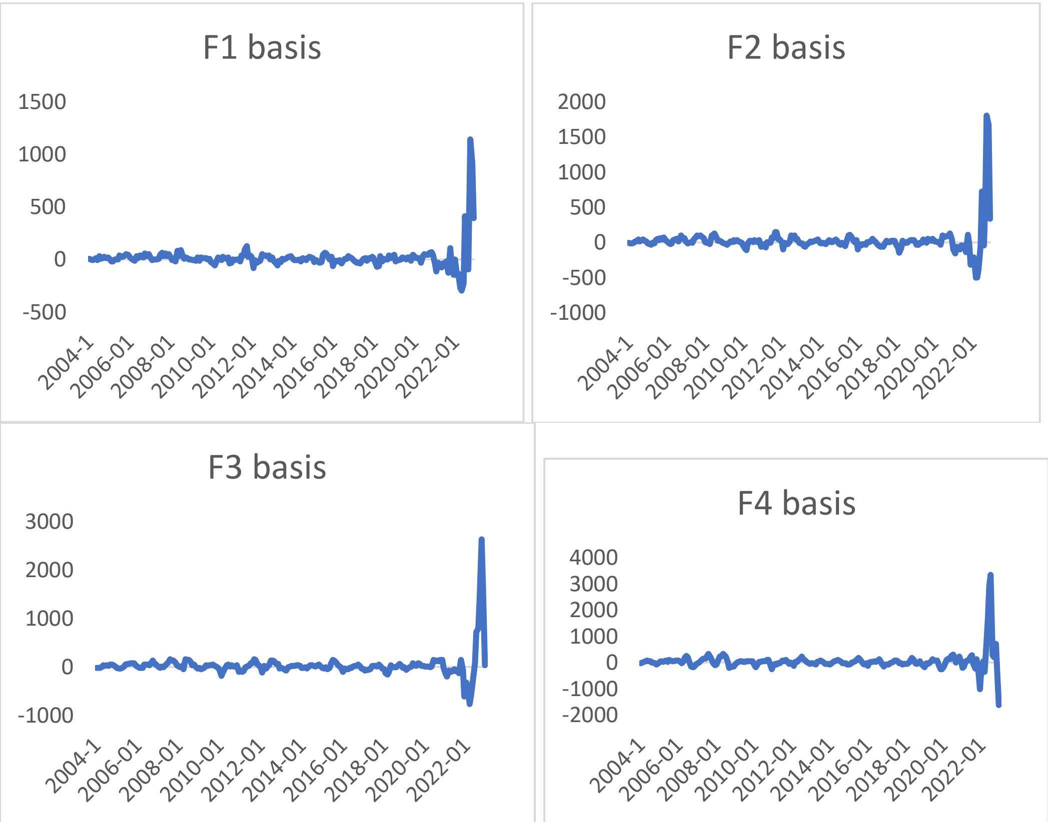

Figure 4: *Basis for futures contracts with different maturities of 1 to 4 months using averaged future prices. January 2004 – December 2022. The left axis shows the future price given in NOK/MWh.*

Physical Variables

In previous literature, physical conditions are found to have an essential impact on spot and futures prices. The Nordic climate is characterized by cold winters and relatively warm summers. The appendix contains all the mentioned figures.

Figure 5 illustrates the temperature, inflow, and consumption trends from January 2004 to December 2020. Inflow represents the total inflow in Norway, Sweden, and Finland, while consumption denotes the total consumption in Norway. Temperature approximates the mean temperature in Norway, calculated as the average of five geographically spread Norwegian areas. A negative correlation between temperature and consumption is observed, while a positive correlation exists between temperature and inflow. These patterns align with previous findings, indicating reduced electricity demand for heating during warmer temperatures and increased inflow due to precipitation and spring snowmelt. Haugom et al. (2018) similarly reported these associations in their study using data from 2004-2013.

Figure 6 displays the historical monthly median water reservoir levels as a percentage of maximum capacity. Seasonal patterns are evident, with the lowest levels in April and the highest level in October.

Figure 7 depicts the relationship between the monthly average spot price and monthly average electricity demand. The electricity demand and production data consist of hourly data and observations depending on the length of the month. January is for instance, based on 744 monthly observations (31*24). A positive correlation is evident for the most part, with both the spot price and demand reaching their lowest points during the summer months and peaking in the winter months, highlighting the presence of seasonality.

Figure 8 showcases the seasonality of electricity production, which tends to be higher in winter and lower in summer. Correspondingly, water reservoir capacity exhibits a moderate level during winter and a higher level in late summer. Comparing Figures 7 and 8 reveals consistent seasonality patterns with a U-shape for all variables, confirming findings consistent with Yohanathan & Guelzim (2021).

Lastly, Figure 9 examines the relationship between wind production in Denmark and the spot price, demonstrating a negative dependence between the two variables.

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

Methodology

Two common standard models exist for analyzing the forecasting performance of future prices. The first one, the unbiased forward rate hypothesis (UFH), is based on a weak-form efficient market view, where all historical spot price information is included in the futures prices. It estimates the spot price level as a function of the previous future price level:

$$\ln S_T = \alpha + \beta lnF_{t,T} + \varepsilon_t \qquad (5.1\ a)$$

To further look at the cointegration relationship between spot and future, we run an error correction model on equation (5.1a) to get more information about the adjustment:

$$\Delta\ln S_T = \alpha + \Delta\, \beta lnF_{t,T} + \gamma_1 U_{t-1} + \varepsilon_t \qquad (5.1\ b)$$

By employing cointegration and error correction model (ECM), researchers can analyze the long and short-term dynamics of variables, providing insights into the efficiency of financial markets and the speed of adjustment towards equilibrium. The Efficient Market Hypothesis (EMH) posits that financial markets are efficient, reflecting all available information in asset prices (Fama, 1970). Malkiel (2003) supports the EMH, emphasizing the challenges of consistently achieving arbitrage profits over time. However, short-term deviations from the long-term equilibrium can occur due to various factors such as seasonal variations, temporary shocks, or market inefficiencies. These deviations may present opportunities for market participants to capitalize on mispricing or take advantage of short-term inefficiencies potentially. Shiller (2003) argues that market inefficiencies and anomalies exist, challenging the assumptions of the EMH. He suggests incorporating these anomalies into financial paradigms can lead to a more comprehensive understanding of market dynamics.

Cointegration, introduced by Granger and Engle (1987), refers to a statistical property that implies a long-run equilibrium relationship among non-stationary variables. Cointegration analysis allows for the identification of variables that move together in the long term, despite exhibiting individual trends. The concept of cointegration has been extensively cited in empirical studies across various fields, such as economics, finance, and environmental sciences (Engle & Granger, 1991; Johansen, 1988; Phillips & Ouliaris, 1990).

The ECM, a dynamic model derived from cointegration analysis, incorporates short-term dynamics and the speed of adjustment toward the long-run equilibrium. The coefficient estimates of the ECM capture the short-term dynamics and how deviations from the long-term equilibrium are corrected over time (Enders, 2014; Engle & Granger, 1987; Phillips, 1991). The significance and magnitude of these coefficients can shed light on market efficiency and the speed at which it incorporates new information.

In the second model, we deduct the spot price S_t from both sides of the equation, and the spot price change is modeled as a function of the previous future-spot differences (the basis):

$$(\ln S_T - \ln S_t) = \alpha + \beta(lnF_{t,T} - lnS_t) + \varepsilon_t \qquad (5.2)$$

Where, S_T is the observed future price at time T, $F_{t,T}$ is the futures price for delivery at time t+T. Following Haugom and Ullrich (2012), if we assume that future prices are unbiased forecasts of future spot prices, then α will equal 0 and β will equal 1, while the uncorrelated residuals will have a mean value of zero. As a result, we interpret an alpha significantly different from zero as evidence of a systematic forward premium and a beta significantly different from one as evidence of futures prices being biased predictions of the subsequent spot prices.

However, the risk premium and, consequently, the forecasting ability of the future price may depend on the shape of the forward curve. Specifically, whether the market is in contango or backwardation, i.e., whether the current futures price is above or below the current spot price. Following previous research by Smith-Meyer and Gjolberg (2016), we allow for this by including a term-structure dummy $(BACK_t)$, which is equal to 1 whenever $(F_t^T - S_t) < 0$ and equal to 0 otherwise. The additional term enables both a shift in the constant or the risk premium (δ_1) and a change in the slope (δ_2), allowing for a change in the bias if the market is in backwardation:

$$(\ln S_T - \ln S_t) = \alpha + \beta(lnF_{t,T} - lnS_t) + \delta_1 BACK_t + \delta_2[BACK_t \,\mathrm{x}\, (\ln F_{t,T} - \ln S_t)] + \varepsilon_t \qquad (5.3)$$

Several studies have found a seasonal effect in the power market. A well-known factor is temperature seasonality, which affects demand and production. Spot price seasonality was documented by Weron (2008) and Botterud *et al.* (2010), although at a decreasing rate from the mid-1990s to the mid-2000s. Torró (2009) used the same data to find seasonality in future prices and a significant seasonality in the future-spot spread (the basis). Lucia and Schwartz (2002) found a seasonal pattern in power prices crucial in explaining the shape of the future and forward curves. In addition, Lucia and Torró (2008) and Botterud *et al.* (2010) found a seasonal pattern in the risk premium. Furthermore, Fleten *et al.* (2011) found significant monthly patterns at Nord Pool using data from 2003-2009. Weron and Zator (2014) found that seasonal variations in reservoir levels could explain part of this seasonality at Nord Pool.

To incorporate possible seasonal effects on the forecasting performance of Nordic electricity futures, we will follow Smith-Meyer and Gjolberg (2016) framework with monthly dummy variables:

$$ln\, S_T = \alpha + \beta lnF_{t,T} + \sum_{t=1}^{11} MD_i + \varepsilon_t \qquad (5.4)$$

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

Rolling estimation

Rolling estimation is performed on the entire sample using a window size corresponding to five years of data, i.e., 60 observations. The window size is kept constant and moves one month at a time, which allows us to investigate the coefficient estimates in a short-term picture. Figure 10 plots the results from the regression on Equation (5.1a) with a rolling estimation of the parameters. The average futures prices are used, and the contracts have one- and two-month holding periods.

The plots reveal time-varying coefficients throughout the entire period. The number of observations in the rolling window is too small to produce stable short-term estimates of the coefficients. However, the rolling estimation still provides insights into potential seasonal patterns and long-term trends. Wider confidence intervals and more volatile estimates are observed for the M2 contract, which coincides with a higher risk premium for more extended holding period contracts. We can see parameters with wide confidence bands and increased volatility from 2020-2023. We believe the variation in this period is caused by extremely high spot prices, cf. Section 4.

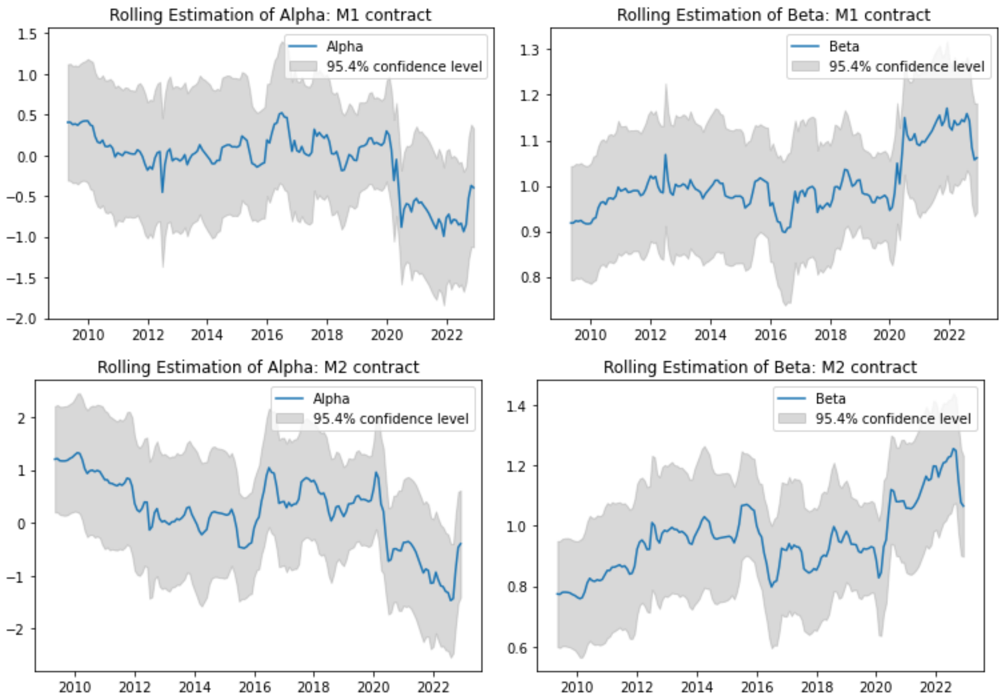

Figure 10: Rolling estimation on: $ln\, S_T = \alpha + \beta ln F_{t,T} + \varepsilon_t$ (5.1 a) using OLS regression with a rolling estimation of the coefficients. The holding period for the futures contracts on the top row is one month, while the bottom row reports a holding period of two months. The window size is five years, i.e., 60 observations. The standard errors are based on Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator. The confidence bands reflect a confidence level of 95.4%. Alpha is reported in the left column, while beta is reported in the right column. The sample period is from Jan 2004 to Dec 2022.

Recursive estimation

The recursive estimation starts with a window size of one year, i.e., 12 observations. The window size increases with one month for each iteration and let us investigate the long-term coefficient estimates. Figure 11 plots the results from the recursive estimation of Equation (5.1a) using average futures prices with holding periods of one and two months.

All figures show volatile coefficient properties during the first couple of years. Overall, the decreasing alpha and increasing beta values imply that the futures prices have become less biased and more accurate in reflecting the spot prices over time. It suggests an improvement in market efficiency and the convergence of futures and spot prices. However, it is important to note that a spike in volatility has been observed since 2020, and the confidence intervals have not significantly reduced over time. This suggests uncertainty in the coefficient estimates and potential bias in futures prices. More data is needed to draw conclusions.

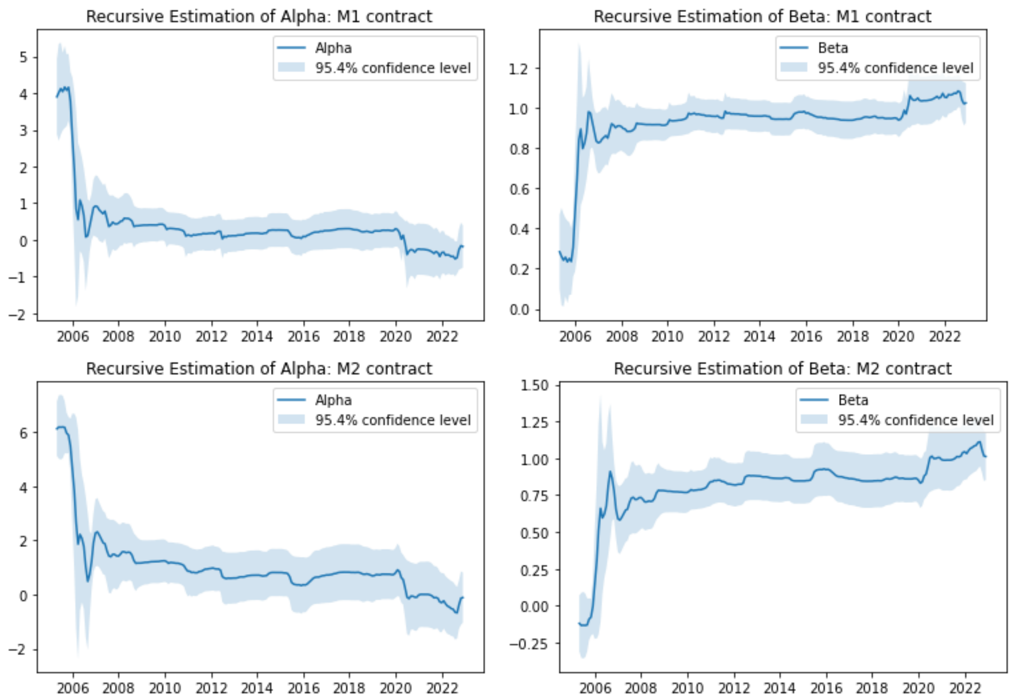

Figure 11: Recursive estimation on: $ln\, S_T = \alpha + \beta ln F_{t,T} + \varepsilon_t$ (5.1 a) using OLS regression with a recursive estimation of the coefficients. The holding period for the futures contracts on the top row is one month, while the bottom row reports a holding period of two months. The window size starts with one year, i.e., 12 observations, and increases with one month for each iteration. The standard errors are based on Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator. The confidence bands reflect a confidence level of 95.4%. Alpha is reported in the left column, while beta is reported in the right column. The sample period is from Jan 2004 to Dec 2022.

Comparison of Regression Models: Exploring Different Approaches to Analyzing the Spot and Future Price Relationship

In this section, we present the econometric results from analyzing the future forecasting performance in the Nordic electricity market. We use monthly data with 1–4-month maturity and consider three definitions of the futures price: the first closing future price for month, t, the average closing futures price for month t, and the last closing futures price for month, t. The analysis period is from Jan 2004 until Dec 2022.

Table 5 reports the results from estimating the standard model (5.1a). This model focuses on the long-term relationship between spot and forward prices without explicitly considering short-term dynamics or adjustments. The presence of non-stationarity can affect the interpretation and reliability of the coefficient estimates. However, the cointegration between the spot and future prices can say something about the long-term relationship[9].

We can see from the table that beta is not different from unity. This aligns with the findings of Smith-Meyer and Gjolberg (2016), who found future prices to be unbiased forecasts of the subsequent spot price. All future contracts have a decreasing pattern for beta, and interpreting the beta estimate as a forecast error, this finding provides evidence of increased difficulties related to the prediction of the spot price far from delivery. Alpha, representing the systematic forward premium, increases with time to maturity. However, the alpha parameter is not significantly different from zero for all prices and maturities, which aligns with Smith-Meyer and Gjolberg (2016), who found the constant term to no longer be significant after 2008. However, our findings differ from Haugom et al. (2018), who found the futures prices to be biased predictors of future spot prices. Also, Haugom et al. (2018) reported significant forward premiums for all examined contracts, but our results did not show the same significance level.

As expected, the last closing prices have the highest explained variance ($Adj\ R^2$), with decreasing values for longer maturities. Focusing on the average prices, the explained variance is 0.840 for F1 and 0.465 for F4, indicating that the model

[9] See Table 17 in appendix for Cointegration test (Engle-Granger two-step method).

performs best for short-term maturities. With longer maturities, more uncertainty exists, and the explained variance remains relatively low. Indicating that there are more variables not included in the model affecting the change in the spot price.

Table 5: $\boldsymbol{ln\,S_T = \alpha + \beta lnF_{t,T} + \varepsilon_t}$ (5.1 a): Test of unbiased forward rate hypothesis on logarithmic prices, defined in Equation (5.1a). The sample period is from January 2004 to Dec 2022. The columns reflect holding periods from one to four months. ***, **, and * indicate significance at a 1%, 5%, and 10% level, respectively, based on the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator. The null hypothesis states that $\alpha = 0$ and $\beta = 1$.

	Log first closing prices			
	1	2	3	4
α	-0.0776	-0.0138	0.2571	0.5673
β	1.0076	0.9962	0.9495	0.8969
Adj R^2	0.777	0.674	0.533	0.399
	Log average prices			
	1	2	3	4
α	-0.1830	-0.1102	0.1063	0.3497
β	1.0263	1.0124	0.9752	0.9336
Adj R^2	0.840	0.718	0.589	0.465
	Log last closing prices			
	1	2	3	4
α	0.0317	0.0400	0.1403	0.8727
β	0.9899	0.9844	0.9682	0.8384*
Adj R^2	0.911	0.708	0.634	0.522

Looking at the error correction model in Table 6 below, we see that short-term dynamics cause spot and futures prices to deviate from the long-term relationship. Engle-Granger's two-step method shows evidence of cointegration between the variables; it suggests the presence of a long-term equilibrium relationship among the variables[10]. This means the variables move together in the long run, despite exhibiting individual trends or short-term deviations from the equilibrium. These deviations could be due to factors such as transaction costs, risk premiums, or other market frictions. Our results concur with Stan (2012), who found a long-term cointegrated link between futures and spot prices in the Nordpool market, and that futures prices can predict spot prices.

The non-significance of alpha suggests that the systematic forward premium, or

[10] See Table 17 in appendix for Cointegration test (Engle-Granger two-step method)

the average expected deviation between spot and future prices, is not significantly different from zero. The coefficients β and γ reflect the short-term relationship and speed of adjustment towards the long-run equilibrium, respectively. The magnitude of the γ coefficient represents the speed of adjustment or the strength of the correction mechanism. Larger absolute values indicate a faster adjustment process, while smaller absolute values suggest a slower adjustment. The beta values are generally significantly different from unity and decreasing, indicating a biased short-term relationship between the changes in spot and future prices. These values indicate that the short-term relationship between the variables is not fully capturing the long-term equilibrium, suggesting the presence of market inefficiencies or temporary shocks.

The negative signs on all γ values are expected as they indicate that any deviations from the equilibrium relationship are being corrected over time. The error correction term (γ) is generally between -1 and 0, and ECT is statistically significant, indicating the presence of a long-run causal relationship. However, the adjustment back to equilibrium is slow, particularly for longer maturities. Focusing on average prices, we have (γ) values of -0.8228 and -0.1632 for M1 and M4 contracts, respectively. Suggesting that almost 82% of the discrepancy between the long and the short run is corrected within a month for M1, and nearly 16% of the discrepancy is corrected within a month for M4. In the case of the (γ) coefficient being below -1, it suggests an over-correction or an overshooting effect. This may imply a relatively strong tendency for the variables to correct towards equilibrium in the short term, potentially resulting in slight over-corrections. Since ECM is expressed in difference form, the R-squared values will be significantly lower than those of the level form regressions. Overall, the results suggest that there may be evidence of deviations from short-term market efficiency and a cointegrating relationship.

Table 6: $\Delta \boldsymbol{ln\,S_T} = \boldsymbol{\alpha} + \Delta\, \boldsymbol{\beta lnF_{t,T}} + \boldsymbol{\gamma_1 U_{t-1}} + \boldsymbol{\varepsilon_t}$ **(5.1 b):** Error correction model defined in Equation (5.1b). The sample period is from January 2004 to Dec 2022. The columns reflect holding periods from one to four months. ***, **, and * indicate significance at a 1%, 5%, and 10% level, respectively, based on the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator. The null hypothesis states that $\alpha = 0$, $\beta = 1\ and\ \gamma = 0$.

	Log first closing prices			
	1	2	3	4
α	0.0047	0.0035	0.0030	0.0061
β	0.5633**	0.6090**	0.6074***	0.3595***
γ	-0.4969***	-0.2893***	-0.1866***	-0.1338***
Adj R^2	0.158	0.161	0.139	0.053
	Log average prices			
	1	2	3	4
α	0.0000	0.0043	0.0033	0.0034
β	1.0292	0.5795**	0.5942***	0.5763***
γ	-0.8228***	-0.3567***	-0.2230***	-0.1632***
Adj R^2	0.301	0.150	0.140	0.117
	Log last closing prices			
	1	2	3	4
α	0.0003	0.0068	0.0052	0.0072
β	0.9569	0.3400***	0.4443***	0.2940***
γ	-1.0103***	-0.3796***	-0.2581***	-0.1740**
Adj R^2	0.598	0.164	0.120	0.059

Looking at Table 7 and Equation (5.2). The results vary slightly depending on which futures prices are used. Still, most beta values are significantly different from unity with volatile numerical values, suggesting that futures prices are biased predictors of the subsequent spot price change. By focusing on the changes in the variables, Model (5.2) allows us to study the short-term relationship between spot and forward prices, considering any temporary discrepancies or inefficiencies that may arise. As for the constant term, none of the forward premiums are significantly different from zero at the 5% level. The numeric values seem to be small and around the same value for the different future contracts and maturities. This result, combined with the ECM above, contradicts the findings of Smith-Meyer and Gjolberg (2016), who found future-spot difference (the basis) to be an unbiased forecast of the subsequent spot price change.

Table 7: $(\boldsymbol{ln\, S_T - ln\, S_t}) = \boldsymbol{\alpha + \beta(lnF_{t,T} - lnS_t) + \varepsilon_t}$ **(5.2):** Test of unbiased forward rate hypothesis on logarithmic prices, defined in Equation (5.2). The sample period is from January 2004 to Dec 2022. The columns reflect holding periods from one to four months. ***, **, and * indicate significance at a 1%, 5%, and 10% level, respectively, based on the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator. The null hypothesis states that $\alpha = 0$ and $\beta = 1$.

	Log first closing prices			
	1	2	3	4
α	-0.0119	-0.0211	-0.0099	0.0017
β	0.5027***	0.7248**	0.5747**	0.5221***
Adj R^2	0.160	0.287	0.201	0.172
	Log average prices			
	1	2	3	4
α	-0.0252	-0.0314	-0.0184	-0.0077
β	0.8462**	0.8778	0.6875*	0.6167***
Adj R^2	0.288	0.354	0.251	0.223
	Log last closing prices			
	1	2	3	4
α	-0.0251*	-0.0301	-0.0265	-0.0296
β	0.9688	0.7112***	0.7467*	0.6509**
Adj R^2	0.599	0.386	0.324	0.281

Table 8 reports the results from estimating model (5.3), in which we include a shift and an interaction dummy for the months the market has been in backwardation. As before, the results vary depending on which future prices are used, but the overall finding findings suggest that futures prices are unbiased predictors of the subsequent spot price change. On average, the constant term is generally not significantly different from zero at the 5% level.

Table 8: $(\boldsymbol{ln\, S_T - ln\, S_t}) = \boldsymbol{\alpha + \beta(lnF_{t,T} - lnS_t) + \delta_1 BACK_t + \delta_2[BACK_t\, x\, (ln\, F_{t,T} - ln\, S_t)] + \varepsilon_t}$ **(5.3):** Test of unbiased forward rate hypothesis on logarithmic prices, defined in Equation (5.3). The sample period is from January 2004 to Dec 2022. The columns reflect holding periods from one to four months. ***, **, and * indicate significance at a 1%, 5%, and 10% level, respectively, based on the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator. The null hypothesis states that $\alpha = 0$, $\beta = 1$, $\delta_1 = 0$ and $\delta_2 = 0$.

	Log first closing prices			
	1	2	3	4
α	-0.0516**	0.1260***	-0.0141	-0.1477**
β	0.6563***	1.0140	0.8224	0.9583
δ_1	0.0301	0.1370**	-0.1797***	0.0194
δ_2	-0.4120	-0.5116**	-1.1924***	-1.2304***
Adj R^2	0.169	0.329	0.353	0.286

	Log average prices			
	1	2	3	4
α	-0.0330	-0.1157**	-0.0027	-0.1031*
β	0.8664	1.1164	0.8299	0.9252
δ_1	0.0270	0.1054	-0.2195***	-0.0714
δ_2	0.1121	-0.5071	-1.2475***	-1.2597***
Adj R^2	0.283	0.381	0.368	0.310
	Log last closing prices			
	1	2	3	4
α	-0.0204	-0.1183***	0.0223	-0.0313
β	0.9371	0.9205	0.7724*	0.7252*
δ_1	0.0079	0.0701	-0.2060***	-0.1913**
δ_2	0.1404	-0.5632***	-0.7638***	-0.9188***
Adj R^2	0.597	0.416	0.390	0.325

Including calendar dummies supports the findings from the first model with the estimation of model (5.4) in Table 9. The estimated slope parameters are not significantly different from unity and are numerically close to 1 for (F1-F3) contracts. As seen below, alpha, representing the systematic forward premium, generally increases with time to maturity. The alpha parameter is not significantly different from zero at the 5% level for all prices and maturities. At the same time, the seasonal variables are generally insignificant in terms of forecasting spot prices. These results align with the finding of Smith-Meyer and Gjolberg (2016). However, monthly dummies for April-Jun are significant for short-term maturities when focusing on the last closing prices. This supports that, on average, the future price already incorporates seasonal information, which is expected in a market with rational and informed participants.

Table 9: $\boldsymbol{ln\, S_T = \alpha + \beta ln F_{t,T} + \sum_{t=1}^{11} MD_i + \varepsilon_t}$ **(5.4):** *Test of unbiased forward rate hypothesis on logarithmic prices, defined in Equation (5.4). The sample period is from January 2004 to Dec 2022. The columns reflect holding periods from one to four months. ***, **, and * indicate significance at a 1%, 5%, and 10% level, respectively, based on the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator. The null hypothesis states that α=0, β=1 and* $D_{month} = 0$.

	Log first closing prices			
	1	2	3	4
α	-0.1936	-0.2701	-0.1296	0.1861
β	1.0303	1.0338	1.0039	0.9577
D_{Jan}	-0.0526	-0.0008	0.0166	-0.0500
D_{Feb}	-0.0660	-0.0396	-0.0105	-0.0774
D_{Mar}	0.0021	0.0373	0.0342	-0.0081
D_{Apr}	0.0282	0.0576	0.0597	-0.0136

D_{May}	0.0710	0.1212	0.1368	0.0600
D_{Jun}	0.0258	0.0991	0.1391	0.0695
D_{Jul}	-0.0142	0.0788	0.1467	0.0947
D_{Aug}	0.0373	0.1268	0.2061*	0.1957
D_{Sep}	0.0217	0.0763	0.1329	0.1230
D_{Oct}	-0.1322	-0.0005	0.0339	0.0168
D_{Nov}	-0.0948	-0.0899	-0.0222	-0.0455
Adj R^2	0.776	0.669	0.524	0.385
	Log average prices			
	1	2	3	4
α	-0.2523	-0.3098	-0.2074	-0.0121
β	1.0410	1.0425	1.0196	0.9882
D_{Jan}	-0.0440	-0.0017	0.0014	-0.0249
D_{Feb}	-0.0511	-0.0396	-0.0233	-0.0625
D_{Mar}	0.0210	0.0268	0.0335	0.0169
D_{Apr}	0.0231	0.0780	0.0569	0.0141
D_{May}	0.0322	0.1052	0.1469	0.0867
D_{Jun}	0.0097	0.0658	0.1101	0.1117
D_{Jul}	-0.0193	0.0477	0.0989	0.1081
D_{Aug}	0.0534	0.1007	0.1689	0.1815
D_{Sep}	-0.0153	0.0673	0.1145	0.1261
D_{Oct}	-0.0957	-0.0522	0.0263	0.0346
D_{Nov}	-0.0956	-0.0855	-0.0494	-0.0318
Adj R^2	0.838	0.714	0.580	0.452
	Log last closing prices			
	1	2	3	4
α	-0.0915	-0.3270	-0.1106	0.8757*
β	1.0033	1.0396	1.0054	0.8461*
D_{Jan}	0.0016	0.0360	0.0103	-0.0563
D_{Feb}	0.0229	0.1126	-0.0327	-0.0626
D_{Mar}	0.0795	0.1432**	0.0137	-0.0122
D_{Apr}	0.0938***	0.1851**	0.0614	-0.0401
D_{May}	0.0901***	0.1688**	0.1098	-0.0273
D_{Jun}	0.0776**	0.1764**	0.0917	-0.0625
D_{Jul}	0.0204	-0.0532	0.0793	-0.0608
D_{Aug}	0.1276***	0.0195	0.1285	0.0118
D_{Sep}	0.0049	0.0120	0.0846	-0.0146
D_{Oct}	-0.0014	-0.1154	-0.0329	-0.1135
D_{Nov}	0.0371	-0.091	-0.0837	-0.1354
Adj R^2	0.912	0.723	0.627	0.503

6. Factors Contributing to Variations in the Forward Premium

This section presents the model applied to describe the variation in the forward premium in the Nordic electricity market, using fundamental factors observable in the first trading month of the futures contracts. As mentioned above, we will focus on the ex-post forward premium. The regression variables used in Equation (6.1) are chosen based on previous studies on the forward premium and seasonality in the Nordic market. The model is formulated to make the analysis comparable to prior studies, with the log forward premium as the dependent variable. Following a similar model used by Haugom *et al.* (2018), we include additional temperature data:

$$LFP_{t+T} = \alpha + \beta_1 CONSD_t + \beta_2 INFD_t + \beta_3 WINDP_t + \beta_4 RESM_t + \beta_5 RESD_t + \beta_6 TEMP_t + \beta_7 VAR_t + \beta_8 S_t + \varepsilon_t \quad (6.1)$$

where,

LFP_{t+T}	Realized log forward premium in month *t* + *T*, using average prices
$CONSD_t$	Total deviation in actual electricity consumption in Norway, from average (2004-2020) in month t [MWh]
$INFD_t$	Total deviation in actual inflow in Norway, Sweden, and Finland from average (2004-2020), in month t [MWh]
$WINDP_t$	Wind production in Denmark in month *t* [GWh]
$RESM_t$	Median reservoir level in Norway, Sweden, and Finland (2004-2020) in month *t* [%]
$RESD_t$	Deviation in actual reservoir level in Norway, Sweden, and Finland from the median ($RESM_t$) in month t [%]
$TEMP_t$	Total average temperature in Norway, from normal (1991-2020) in month *t* [°C]
VAR_t	Variance of hourly spot prices in month *t*
S_t	Spot price in month t [NOK/MWh]
ε_t	Regression error term

The timing of observations is essential. Previous literature uses explanatory variables from the actual trading week/month, delivery week/month, or time between when investigating the forward premium. In accordance with Haugom *et al.* (2018), we focus on the risk factors the market participants face when futures contracts are traded. Using information known at the time of trading allows us to assume that all market participants have the same information. By only including variables from the trading month, we can construct a model describing how fundamental factors affect the ex-post forward premium; we do not intend to approximate forecasts with this model. Before the models were estimated, the stationarity was tested for using the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests (Kwiatkowski et al., 1992) and the ADF unit root test. The null hypothesis of unit root is rejected for all time series except for CONSD and WIND[11]. Figure 12 in the appendix shows a visual inspection of time series data for CONSD and WIND, where the series shows an upward trend which implies that these variables are increasing over time. The decision to proceed with non-stationary data was made to maintain comparability with previous studies and to capture the inherent dynamics in the data that could be lost through differencing or detrending.

Following Haugom *et al.* (2018), we apply a method from Weron (2006) to reduce the effect of spikes in the time series. Previous research finds that *Damped* methods perform the best (Haugom & Ullrich, 2012; Weron, 2006). We set an upper and lower limit for the log premium. If LFP_{t+T} is outside the interval the premium is set to:

$$LFP_{t+T} = T + T \times log_{10} \frac{LFP_{t+T}}{T} \qquad (6.2)$$

The upper and lower limits are

$$T = \mu + N \times \sigma \text{ and } T = \mu - N \times \sigma,$$

respectively, where μ is the mean log forward premium and σ is the standard deviation. N is the number of standard deviations; the lower the number, the stricter the premium damping. We will calculate the limits using one, two and three standard deviations. Hereafter, the models with damped spikes will be referred to as Model 1 ($N = 1$), Model 2 ($N = 2$) and Model 3 ($N = 3$). See Table 12-13 in the appendix for Model 0, without damped methods.

[11] See Table 15-16 in appendix for Unit root tests

Table 10: *Regression results from Model 1, Model 2 and Model 3. The sample period is from Jan 2004 to December 2020. ***, **, and * indicate significance at a 1%, 5%, and 10% level, respectively, based on the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator. CONSD is the total deviation in actual electricity consumption in Norway, from the average (2003–2020), in month t [MWh], INFD is the deviation in actual inflow in Norway, Sweden and Finland from the average (2003–2020), in month t [MWh], WINDP is the wind production in Denmark, in month t [GWh], RESM is the median reservoir level in Norway, Sweden and Finland (2003-2020) in month t [%], RESD is the deviation in actual reservoir level in Norway, Sweden and Finland from median (RESM) in month t [%], TEMP is the total average temperature in Norway, from normal (1991-2020) in month* t *[℃], VAR is the variance of monthly spot prices in month t, S is the spot price in month t [NOK/MWh], C the constant term.*

		CONSD ($\times 10^8$)	**INFD** ($\times 10^9$)	**WINDP** ($\times 10^5$)	**RESM**	**RESD**	**TEMP**	**VAR**	**S** ($\times 10^5$)	**C**	R^2	**Adj** R^2
a	LRP1	-5.187***	2.790	7*	0.0792	-0.3490	0.0008	0.0005***	1.65	-0.0937**	0.098	0.061
	LRP2	-7.030**	-0.794	10**	0.1060	-0.3023	0.0016	0.0004**	2.07	-0.1295	0.070	0.031
	LRP3	-10.210**	-2.003	10**	0.1204	-0.0372	0.0031	0.0003	30.00	-0.2207*	0.079	0.040
M1	LRP4	-12.410**	1.180	20**	0.1435	-0.0287	0.0068	0.0002	60.00	-0.3644***	0.126	0.090
	LRP1	-5.157***	2.737*	7	0.0807	-0.3627**	0.0007	0.0005***		-0.0895***	0.098	0.066
	LRP2	-6.991**	-0.860	10**	0.1079	-0.3194	0.0015	0.0005*		-0.1242**	0.070	0.036
b	LRP3	-9.701**	-2.888	10*	0.1467	-0.2611	0.0022	0.0005		-0.1517*	0.071	0.037
	LRP4	-11.320*	-0.673	20**	0.1992	-0.4965	0.0050	0.0004		-0.2200**	0.100	0.067
a	LRP1	-5.642***	3.627*	9	0.0636	-0.3950	0.0019	0.0006***	-1.72	-0.0926*	0.086	0.049
	LRP2	-8.312**	-2.317	20**	0.0971	-0.3485	0.0028	0.0006*	-3.80	-0.1458	0.069	0.030
	LRP3	-11.650**	-2.945	20*	0.1337	-0.0597	0.0040	0.0004	30.00	-0.2554*	0.070	0.031
M2	LRP4	-15.220**	1.373	30**	0.1562	-0.0740	0.0086**	0.0002	60.00	-0.4493***	0.126	0.089
	LRP1	-5.674***	3.683*	9	0.0620	-0.3808**	0.0019	0.0005***		-0.0970**	0.086	0.053
	LRP2	-8.383**	-2.196	20**	0.0935	-0.3172	0.0029	0.0005***		-0.1554**	0.069	0.035
b	LRP3	-11.170**	-3.782	20*	0.1586	-0.2712	0.0032	0.0005		-0.1902*	0.065	0.031
	LRP4	-13.990**	-0.713	20**	0.2191	-0.6009	0.0065	0.0005		-0.2866**	0.104	0.072
a	LRP1	-5.269**	4.057*	10	0.0611	-0.4391	0.0021	0.0006***	-7.30	-0.0812	0.083	0.046
	LRP2	-8.768**	-2.749	20**	0.0978	-0.3727	0.0032	0.0006*	-7.39	-0.1576	0.076	0.038
	LRP3	-11.630*	-3.317	20*	0.1433	-0.0634	0.0004	0.0004	20.00	-0.2700*	0.067	0.028
M3	LRP4	-14.900**	1.149	30**	0.1719	-0.0746	0.0087*	0.0001	60.00	-0.4740***	0.118	0.081
	LRP1	-5.405**	4.294**	10	0.0543	-0.3784**	0.0024	0.0005***		-0.0998**	0.082	0.050
	LRP2	-8.905**	-2.513	20*	0.0908	-0.3119	0.0034	0.0006*		-0.1763**	0.075	0.042
b	LRP3	-11.190*	-4.099	20*	0.1666	-0.2612	0.0033	0.0005		-0.2091*	0.064	0.030
	LRP4	-13.700*	-0.091	30*	0.2338	-0.5945	0.0066	0.0004		-0.3135**	0.100	0.067

Table 11: *Regression results from Model 1, Model 2 and Model 3, based on standardized explanatory variables. The sample period is from Jan 2004 to December 2020. ***, **, and * indicate significance at a 1%, 5%, and 10% level, respectively, based on the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator. CONSD is the total deviation in actual electricity consumption in Norway, from the average (2003–2020), in month t [MWh], INFD is the deviation in actual inflow in Norway, Sweden and Finland from the average (2003–2020), in month t [MWh], WINDP is the wind production in Denmark, in month t [GWh], RESM is the median reservoir level in Norway, Sweden and Finland (2003-2020) in month t [%], RESD is the deviation in actual reservoir level in Norway, Sweden and Finland from median (RESM) in month t [%], TEMP is the total average temperature in Norway, from normal (1991-2020) in month t [°C], VAR is the variance of monthly spot prices in month t, S is the spot price in month t [NOK/MWh], C the constant term.*

		CONSD	INFD	WINDP	RESM	RESD	TEMP	VAR	S	C	R^2	Adj R^2
a	LRP1	-0.0312***	0.0151	0.0283*	0.0154	-0.0260	0.0053	0.0221***	0.0000	0.0311	0.098	0.061
	LRP2	-0.0424**	-0.0043	0.0457**	0.0205	-0.0222	0.0110	0.0186	0.0000	0.0507	0.070	0.031
	LRP3	-0.0616**	-0.0108	0.0504**	0.0232	-0.0027	0.0214	0.0143	0.0003	-0.0113	0.079	0.040
M1	LRP4	-0.0748**	0.0064	0.0740**	0.0275**	-0.0021	0.0473	0.0074	0.0006	-0.0938	0.126	0.090
	LRP1	-0.0310***	0.0148*	0.0281	0.0157	-0.0270**	0.0049	0.0224***		0.0359***	0.098	0.066
	LRP2	-0.0421**	-0.0046	0.0455**	0.0209	-0.0235	0.0106	0.0190*		0.0568**	0.070	0.036
b	LRP3	-0.0585**	-0.0156	0.0520*	0.0282	-0.0191	0.0153	0.0193		0.0694**	0.071	0.037
	LRP4	-0.0683**	-0.0036	0.0690**	0.0382	-0.0361	0.0344	0.0180		0.0758**	0.100	0.067
a	LRP1	-0.0339***	0.0197*	0.0375	0.0124	-0.0294	0.0130	0.0231***	0.0000	0.0458	0.086	0.049
	LRP2	-0.0501**	-0.0125	0.0637**	0.0188	-0.0256	0.0256	0.0236	0.0000	0.0744	0.069	0.030
	LRP3	-0.0703**	-0.0159	0.0695*	0.0257	-0.0044	0.0280	0.0170	0.0003	-0.0007	0.070	-0.031
M2	LRP4	-0.0917**	0.0074	0.1018**	0.0299**	-0.0054	0.0598**	0.0078	0.0060	-0.1052	0.126	0.089
	LRP1	-0.0341***	0.0200*	0.0376	0.0121	-0.0284	0.0134	0.0228***		0.0408**	0.086	0.053
	LRP2	-0.0505**	-0.0118	0.0641**	0.0181	-0.0233	0.0203	0.0203*		0.0632**	0.069	0.035
b	LRP3	-0.0674**	-0.0204	0.0672*	0.0305	-0.0198	0.0221	0.0217		0.0755**	0.065	0.031
	LRP4	-0.0843**	-0.0039	0.0962**	-0.0436	-0.0436	0.0453	0.0197		0.0858**	0.104	0.072
a	LRP1	-0.0317**	0.0220*	0.0419	0.0119	-0.0327	0.0146	0.0232***	0.0001	0.0660	0.083	0.046
	LRP2	-0.0529**	-0.0148	0.0751**	0.0189	-0.0274	0.0221	0.0253*	0.0001	0.0900	0.076	0.038
	LRP3	-0.0702*	-0.0179	0.0788*	0.0276	-0.0046	0.0285	0.0162	0.0002	0.0112	0.067	0.028
M3	LRP4	-0.0898*	0.0062	0.1142**	0.0329	-0.0054	0.0601*	0.0047	0.0006	-0.0945	0.118	0.081
	LRP1	-0.0325**	0.0233*	0.0426	0.0106	-0.0282**	0.0163	0.0219***		0.0446**	0.082	0.050
	LRP2	-0.0537***	-0.0135	0.0758*	0.0176	-0.0229	0.0237	0.0240*		0.0682*	0.075	0.042
b	LRP3	-0.0675**	-0.0221	0.0767*	0.0321	-0.0191	0.0231	0.0206		0.0825**	0.064	0.030
	LRP4	-0.0826*	-0.0049	0.1087*	0.0448	-0.0432	0.0457	0.0165		0.0939*	0.100	0.067

Regression Analysis Findings: Impact of Variables on Forward Premium

Tables 10 and 11 present the results obtained from the regression analysis in Equation (6.1). Table 11 explicitly displays the standardized coefficients, allowing us to assess each variable's relative impact on the forward premium. Panel b in the table illustrates the outcomes when the spot price is excluded. Removal of the spot will let us investigate a possible presence of simultaneity bias and multicollinearity caused by the spot price[12]. R2 is low for all maturities, meaning that the overall fit of the regression model is poor.

CONSD emerges as the sole parameter with consistent statistical significance across all contracts and maturities, although its significance diminishes for longer maturities. Notably, Haugom et al. (2018) did not find significant evidence for CONSD when using weekly contracts, contrasting our findings. In a separate study, Weron and Zator (2014) observed significance for CONSD in a 6-week contract but not in a 3-week contract. Furthermore, they reported a positive coefficient for CONSD when it was significant, which contradicts our findings based on monthly contracts. These disparities highlight the complexities of interpreting the relationship between CONSD and the forward premium and emphasize the importance of considering contract duration and frequency in future research.

In previous studies, such as Botterud et al. (2010) and Weron and Zator (2014) focusing on weekly contracts, it was found that INFD exhibits significance when it is negative. Botterud et al. (2010) observed this effect for 1- and 6-week contracts, while Weron and Zator (2014) found it for weeks 1 and 3. This indicates that higher inflow deviation corresponds to a lower forward premium. Interestingly, our findings contradict this pattern, as INFD is only significant when it is positive. However, Haugom et al. (2018) reported in their model that deviation in inflow, with a positive sign, is the most influential factor in determining the forward premium in the Nordic power market. Their findings also indicated a decreasing significance for shorter-term contracts, which aligns with our observation of 10% significance at the 1-month contract duration. This

[12] Multicollinearity may be present for variables in Equation (6.1), see correlation measures between the explanatory variables in the regression, cf. Table 14.

discrepancy is noteworthy and could be attributed to our newer dataset's increased volatility, which may have altered the relationship between INFD and the forward premium. It is essential to highlight that most electricity production in Norway relies on hydropower, which led us to expect that inflow would significantly explain the forward premium.

In contrast to Haugom (2018), our findings indicate that WINDP exhibits significance for more extended delivery periods. RESM and RESD only show significance for a limited number of contracts and maturities. Despite the significance of the change in reservoir level observed in previous studies by Weron and Zator (2014) and Lucia and Torró (2011), our analysis does not find it a significant factor in explaining the variation in the forward premium. These findings align with the research conducted by Haugom (2018), who also reported no evidence of reservoir level deviation as an explanatory factor. Using RESM as a seasonal component finds seasonal variables insignificant in describing the variation in the forward premium for monthly contracts. On the other hand, VAR demonstrates general significance for the first two months, indicating that higher variance positively influences the forward premium for shorter maturities.
The coefficient of spot price exhibits a slightly increasing trend with maturity. Still, it does not reach statistical significance for any contract, consistent with the findings of Weron and Zator (2014), who observed significance only for 1-week contracts. However, Haugom (2018) found stronger evidence of the significance of spot price. The significance of TEMP is weak, as it is only significant in a few sporadic instances.

The significant effects of CONSD, WIND, and VAR imply that these parameters explain a portion of the variance in the forward premium, providing evidence that market risks may impact the forward premium. The negative coefficient for CONSD raises interest and highlights the model's susceptibility to input variables. The discrepancies in findings compared to previous studies may be attributed to the utilization of monthly observations and more up-to-date data. However, it is crucial to consider the non-stationarity of the data when interpreting these findings. Moreover, it is possible that the variables do not describe variation in the premium but capture the effects of other variables included or not included in the model.

7. Conclusion

This master thesis contributes to the understanding of market efficiency, biasedness, and forward premium in the Nordic electricity market. Our objective was to analyze the relationship between spot and futures prices and explain variations in the forward premium using fundamental factors.

Analyzing a dataset from January 2004 to December 2022, we employed various econometric models, including error correction models and those incorporating seasonal effects and market structure. The results reveal an unbiased long-term relationship between spot and future prices and support the notion of market efficiency, as prices reflect relevant information and adjust over time. However, we identified the presence of short-term biases, which contradicts the findings of Smith-Meyer and Gjolberg (2016), who found future-spot difference (the basis) to be an unbiased forecast of the subsequent spot price change. These biases suggest the influence of temporary shocks, imperfections in market functioning, or other factors affecting price dynamics.

Moreover, our analysis supports a cointegration relationship between spot and future prices in the Nordic electricity market. The adjustment back to equilibrium is slow, particularly for longer maturities. Seasonal variables demonstrated limited significance in forecasting spot price changes based on dummy variables, implying that future prices already incorporate seasonal information.

The systematic forward premium, represented by alpha, is generally not significantly different from zero. This indicates that deviations from the equilibrium tend to be transitory and not driven by a consistent over- or underpricing of future spot prices. However, predicting spot prices far from the delivery date remains challenging, as future prices explain only a small portion of the variance in the spot price as the maturity date extends. For robustness, we consider various definitions of the future price and find that multiple definitions generally result in consistent conclusions.

The difference in beta values between models highlights the importance of addressing non-stationarity and incorporating the error correction mechanism for reliable and accurate estimates. While the long-term relationship suggests market efficiency and equilibrium tendencies, short-term biases underscore the significance of monitoring market conditions and implementing appropriate regulations to ensure efficiency and minimize distortions. These insights can be valuable for market participants and researchers seeking to exploit or correct these inefficiencies for potential profit opportunities.

Deviations in consumption and wind production are key factors in determining the forward premium in our model. CONSD consistently exhibits statistical significance across all contracts and maturities, while wind production demonstrates significance for longer delivery periods. Higher deviations from consumption correspond to lower forward premiums, whereas increased wind production levels result in higher forward premiums. These findings differ from those of Weron and Zator (2014), who observed positive and significant effects for deviations in consumption. The negative coefficient for CONSD raises interest and highlights the model's susceptibility to input variables. Additionally, a higher variance in spot prices leads to a higher forward premium for contracts with shorter maturities of 1-2 months. However, the role of inflow levels in explaining the premium is limited, with significance observed only for the shortest one-month maturity period at a 10% level. The significance of seasonal variables in describing the variation in the forward premium based on RESM is generally insignificant. Notably, our regression model explains only a tiny portion of the variation in the forward premium, indicating the presence of other factors influencing the premium that the model does not capture. This limitation may be attributed to multicollinearity between variables and the non-linear nature of the model's sensitivity to input variables.

Acknowledging the challenges associated with interpreting coefficients and statistical significance when dealing with non-stationary variables is essential. Energy prices exhibit unique characteristics such as seasonality, temporary shocks, and market inefficiencies, which can introduce non-stationarity in the short term. As a result, caution should be exercised when interpreting the estimates of the model, as spurious regression results can occur. Nevertheless, the decision to work with non-stationary data was justified to capture the inherent dynamics of the market and maintain comparability with previous studies.

In future research, it would be beneficial to delve deeper into the factors contributing to short-term biasedness and investigate the underlying reasons for the differences in findings regarding the variations in the forward premium. This could involve exploring additional variables or refining the model specifications to capture the electricity market's complexities better. By addressing these aspects, a more comprehensive understanding of the dynamics of the forward premium and its determinants can be achieved.

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Appendix

Physical Variables

(i) Figure 5

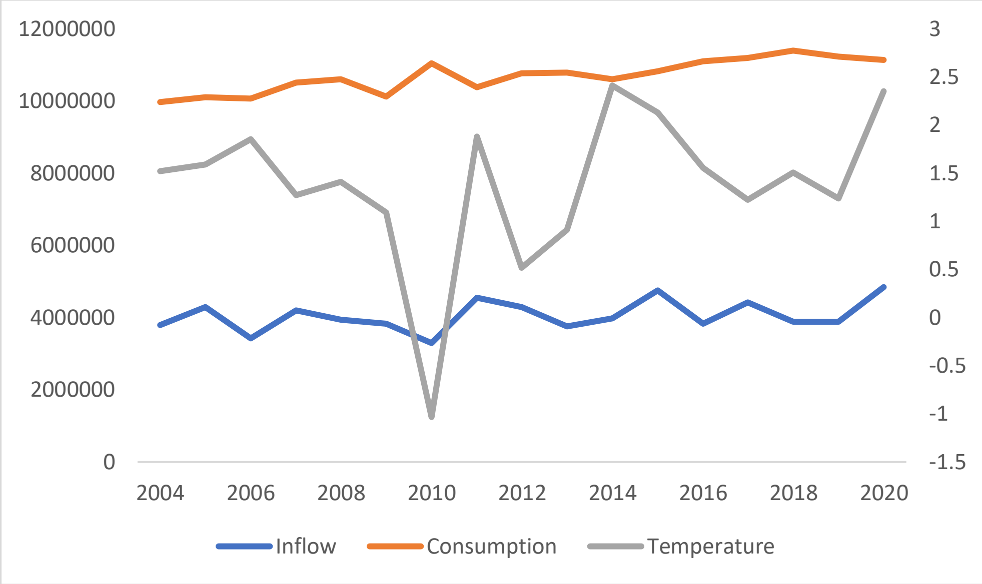


Figure 5: *Plots temperature, inflow and consumption in the period 2004-2020. The temperature is an approximation of the mean temperature in Norway. Inflow is the total inflow in Norway, Finland and Sweden. Consumption is the total consumption in Norway, Sweden, Denmark and Finland. Inflow and consumption($\times 10-3$) are measured on the left axis and given in MWh. The temperature is measured on the right axis and given in ◦C.*

(ii) Figure 6

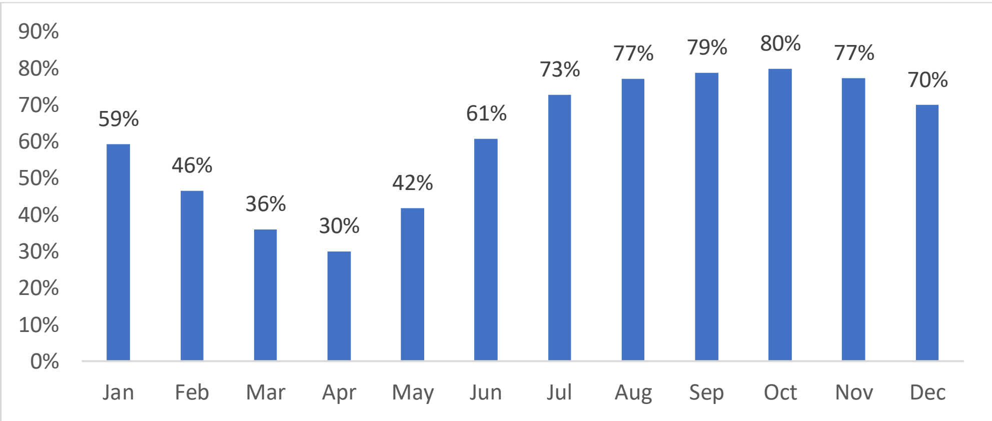


Figure 6: *Monthly averaged water reservoir levels for all Nordic countries as a percentage of maximum water reservoir capacity. January 2004 – December 2022.*

(iii) [*Figure 7*]

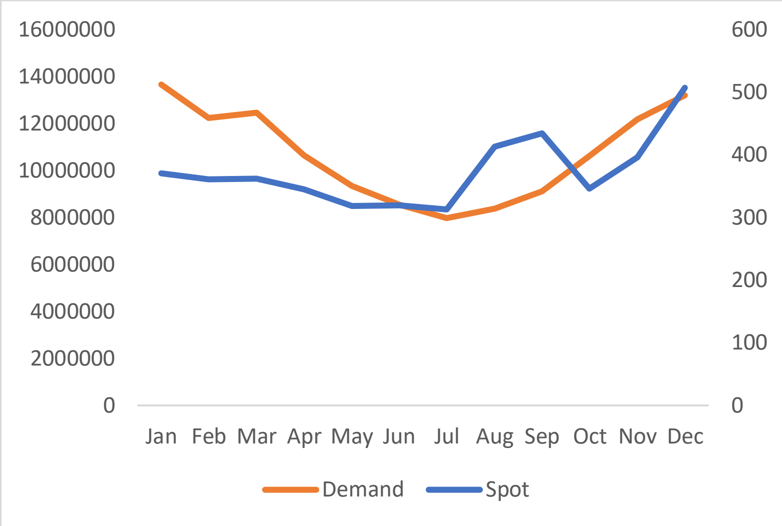


Figure 7: *Average electricity spot price (NOK/MWh) is shown on the right axis, and electricity consumption (MWh) is shown on the left axis in Norway by months. January 2004 – December 2022.*

(iv) [*Figure 8*]

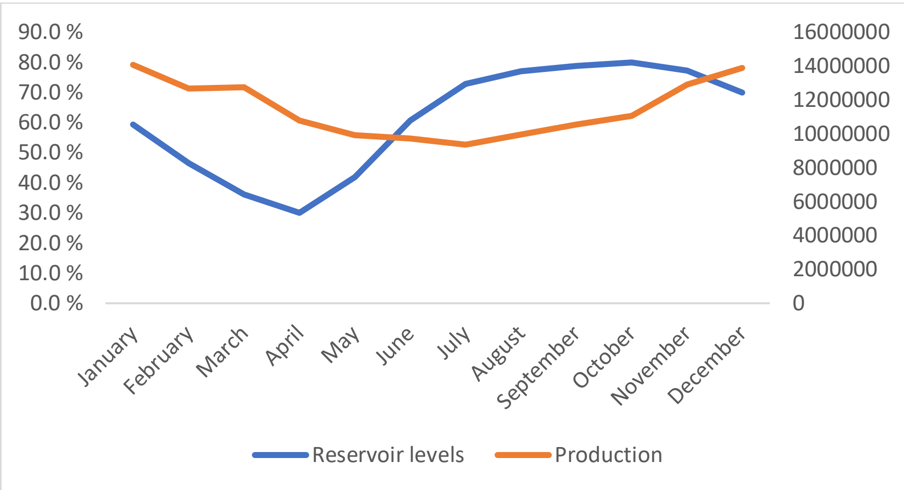


Figure 8: *Average monthly electricity production (NOK/MWh) on the right axis and average monthly water reservoir levels (in the percentage of maximum capacity) on the left axis in the Nordic regions. January 2004 – December 2022.*

(v) [*Figure 9*]

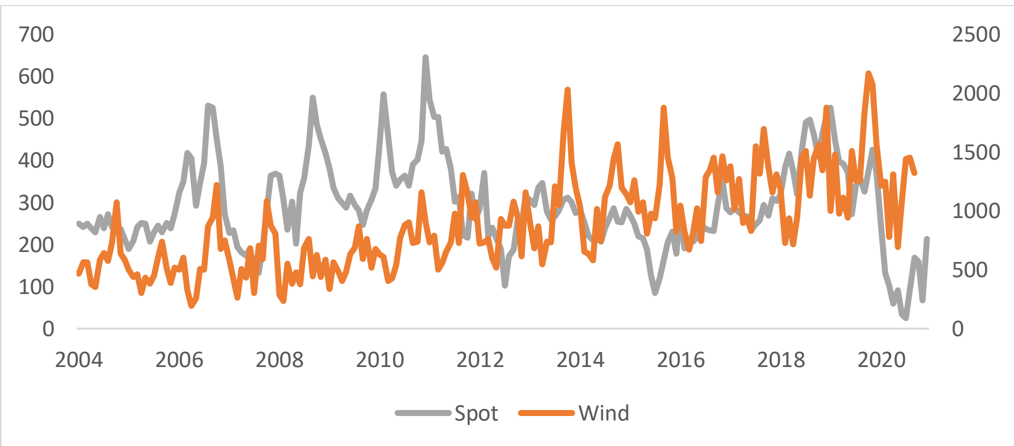
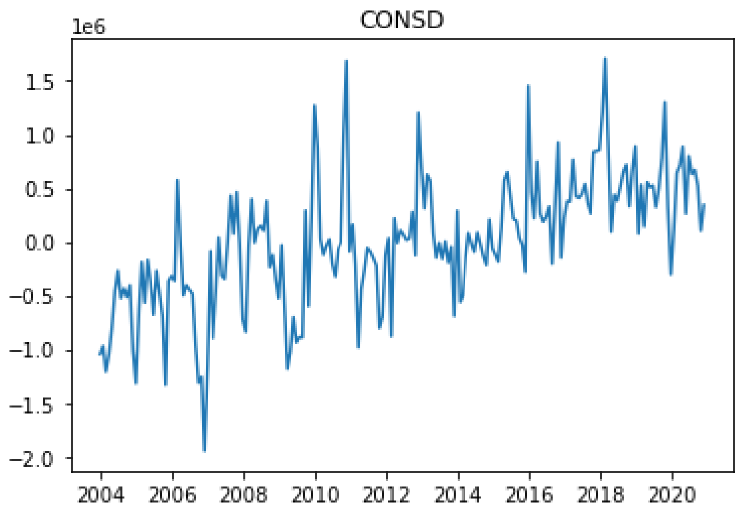


Figure 9: The figure plots the actual produced wind power in Denmark, and the spot price, in the period January 2004 – December 2020. The wind power is measured on the right axis and given in GWh, while the spot price is measured on the left axis and given in NOK/MWh

Time series data



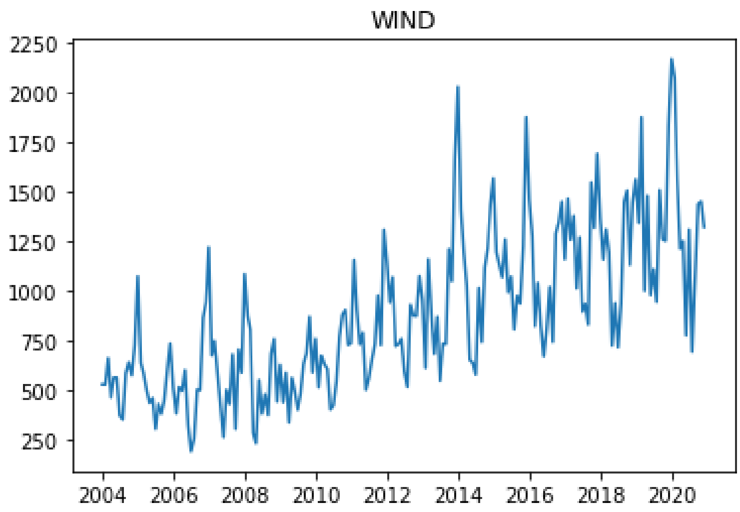


Figure 12*:* Time series data for CONSD and WIND.

Table 12-13

Table 12: *Regression results from Model 0. The sample period is from Jan 2004 to December 2020. ***, **, and * indicate significance at a 1%, 5%, and 10% level, respectively, based on the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator. CONSD is the total deviation in actual electricity consumption in Norway, from the average (2003–2020), in month t [MWh], INFD is the deviation in actual inflow in Norway, Sweden and Finland from the average (2003–2020), in month t [MWh], WINDP is the wind production in Denmark, in month t [GWh], RESM is the median reservoir level in Norway, Sweden and Finland (2003-2020) in month t [%], RESD is the deviation in actual reservoir level in Norway, Sweden and Finland from median (RESM) in month t [%], TEMP is the total average temperature in Norway, from normal (1991-2020) in month* t [℃] *VAR is the variance of monthly spot prices in month t, S is the spot price in month t [NOK/MWh], C the constant term.*

		CONSD ($\times 10^8$)	INFD ($\times 10^9$)	WINDP ($\times 10^5$)	RESM	RESD	TEMP	VAR	S ($\times 10^5$)	C	R^2	Adj R^2
a	LRP1	-4.731*	4.946*	10	0.0728	-0.4613	0.0022	0.0006***	-10	-0.0765	0.081	0.043
	LRP2	-8.648**	-2.759	20**	0.1077	-0.3591	0.0033	0.0006*	-8	-0.1687	0.075	0.036
	LRP3	11.810**	-3.387	20*	0.1484	-0.0575	0.0042	0.0004	20	-0.2875	0.069	0.030
M0	LRP4	14.960*	0.9316	30**	0.1792	-0.0736	0.0086	0	70	-0.4963	0.119	0.082
	LRP1	-4.937**	5.304*	10	0.0626	-0.3698**	0.0026	0.0005***		-0.1046	0.079	0.046
	LRP2	8.790**	-2.515	20*	0.1005	-0.2963	-0.0036	0.0006*		0.1881**	0.074	0.041
b	LRP3	-11.350*	-4.179	20*	0.1719	-0.2578	0.0034	0.0005		0.2257*	0.066	0.032
	LRP4	-13.720*	-1.190	30*	0.2431	-0.6095	-0.0065	0.0004		-0.3309**	0.100	0.068

Table 13: *Regression results from Model 0, based on standardized explanatory variables. The sample period is from Jan 2004 to December 2020. ***, **, and * indicate significance at a 1%, 5%, and 10% level, respectively, based on the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator. CONSD is the total deviation in actual electricity consumption in Norway, from the average (2003–2020), in month t [MWh], INFD is the deviation in actual inflow in Norway, Sweden and Finland from the average (2003–2020), in month t [MWh], WINDP is the wind production in Denmark, in month t [GWh], RESM is the median reservoir level in Norway, Sweden and Finland (2003-2020) in month t [%], RESD is the deviation in actual reservoir level in Norway, Sweden and Finland from median (RESM) in month t [%], TEMP is the total average temperature in Norway, from normal (1991-2020) in month* t [℃]*, VAR is the variance of monthly spot prices in month t, S is the spot price in month t [NOK/MWh], C the constant term.*

		CONSD	INFD	WINDP	RESM	RESD	TEMP	VAR	S	C	R^2	Adj R^2
a	LRP1	-0.0284*	0.0268*	0.0428	0.0142	-0.0344	0.0151	0.0231***	-0.0001	0.0799*	0.081	0.043
	LRP2	-0.0521**	-0.0149	0.0786**	0.0208	-0.0264	0.0231	0.0259*	-0.0001	0.0933	0.075	0.036
	LRP3	-0.0712**	-0.0183	0.0863*	0.0286	-0.0042	0.0293	0.0159	0.0002	0.0137	0.069	0.030
M0	LRP4	-0.0902*	0.0050	0.1214**	0.0343	-0.0053	0.0599*	0.0033	0.0007	-0.0972	0.119	0.082
	LRP1	-0.0297**	0.0287*	0.0438	0.0122	-0.0275**	0.0176	0.0211***		0.0477	0.079	0.046
	LRP2	-0.0530**	-0.0136	0.0793*	0.0194	-0.0218	0.0249	0.0245*		0.0709*	0.074	0.041
b	LRP3	-0.0685*	-0.0226	0.0842*	0.0331	-0.0188	0.0238	0.0204		0.0858**	0.066	0.032
	LRP4	-0.0827*	-0.0064	0.1157*	0.0466	-0.0443	0.0452	0.0154		0.0970*	0.100	0.068

Multicollinearity

Table 14: The table shows correlation measures between the explanatory variables in Equation (6.1) from 2004-2020. Due to concerns regarding multicollinearity and the unknown distribution of the variables, it is not straightforward to interpret these measures.

	CONSD	INFD	WIND	RESM	RESD	TEMP	VAR	S
CONSD	1							
INFD	-0.178	1						
WIND	0.396	0.143	1					
RESM	0.031	0.127	0.046	1				
RESD	0.080	0.327	0.164	0.442	1			
TEMP	-0.146	0.088	-0.374	0.366	0.105	1		
VAR	0.247	0.027	0.003	-0.012	-0.018	-0.211	1	
S	0.132	-0.381	-0.077	-0.188	-0.594	-0.244	0.244	1

Unit root tests

Table 15: Unit root test for Jan 2004- Dec 2022. Due to concerns regarding seasonality, temporary shocks or market inefficiencies, it is not straightforward to interpret these measures.

	ADF p-value	ADF rejection	KPSS p-value	KPSS rejection
Spot	0.9527	NO	0.0318	YES
First closing M1	0.9990	NO	0.0431	YES
First closing M2	0.9989	NO	0.0494	YES
First closing M3	0.9929	NO	0.0625	NO
First closing M4	0.9975	NO	0.0725	NO
Average M1	0.9913	NO	0.0374	YES
Average M2	0.9825	NO	0.0449	YES
Average M3	1	NO	0.0576	NO
Average M4	0.9906	NO	0.0670	NO
Last closing M1	0.8321	NO	0.0341	YES
Last closing M2	0.6247	NO	0.0508	NO
Last closing M3	0.7430	NO	0.0543	NO
Last closing M4	0.9702	NO	0.0643	NO
Log spot	0.0378	YES	0.1	NO
Log first closing M1	0.3900	NO	0.1	NO
Log first closing M2	0.6934	NO	0.1	NO
Log first closing M3	0.6543	NO	0.1	NO
Log first closing M4	0.7223	NO	0.1	NO
Log average M1	0.2839	NO	0.1	NO
Log average M2	0.8099	NO	0.1	NO
Log average M3	0.1808	NO	0.1	NO
Log average M4	0.2226	NO	0.1	NO
Log last closing M1	0.0503	NO	0.1	NO
Log last closing M2	0.2081	NO	0.1	NO
Log last closing M3	0.6897	NO	0.1	NO
Log last closing M4	0.1224	NO	0.1	NO

Table 16: Unit root test for Jan 2004- Dec 2020. Due to concerns regarding seasonality, temporary shocks or market inefficiencies, it is not straightforward to interpret these measures (see under).

	ADF p-value	ADF rejection	KPSS p-value	KPSS rejection
Spot	0.0015	YES	0.1	NO
First closing M1	0	YES	0.1	NO
First closing M2	0.0207	YES	0.1	NO
First closing M3	0.0479	YES	0.1	NO
First closing M4	0.0740	NO	0.1	NO
Average M1	0.0003	YES	0.1	NO
Average M2	0	YES	0.1	NO
Average M3	0	YES	0.1	NO
Average M4	0	YES	0.1	NO
Last closing M1	0.0002	YES	0.1	NO
Last closing M2	0.0267	YES	0.1	NO
Last closing M3	0.0001	YES	0.1	NO
Last closing M4	0	YES	0.1	NO
CONSD	0.0010	YES	0.01	YES
INFD	0	YES	0.1	NO
WIND	0.9164	NO	0.01	YES
RESM	0.0011	YES	0.1	NO
RESD	0.0038	YES	0.1	NO
VAR	0	YES	0.1	NO
TEMP	0.0382	YES	0.1	NO
Log spot	0.2563	YES	0.1	NO
Log first closing M1	0	YES	0.1	NO
Log first closing M2	0.0227	YES	0.1	NO
Log first closing M3	0.0753	NO	0.1	NO
Log first closing M4	0.1231	NO	0.1	NO
Log average M1	0.0003	YES	0.1	NO
Log average M2	0.0242	YES	0.1	NO
Log average M3	0.0279	YES	0.1	NO
Log average M4	0.0227	YES	0.1	NO
Log last closing M1	0	YES	0.1	NO
Log last closing M2	0.0222	YES	0.1	NO
Log last closing M3	0.0253	YES	0.1	NO
Log last closing M4	0.0382	YES	0.1	NO

The Limitations of ADF and KPSS Tests in Analyzing Energy Prices

The analysis of energy prices poses challenges when employing traditional unit root tests such as the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. These tests assume stationarity or non-stationarity of the time series, making their application to energy prices problematic. Energy prices exhibit unique characteristics such as seasonality, temporary shocks, and market inefficiencies, which can lead to non-stationarity in the short term. Therefore, relying solely on ADF and KPSS tests may not provide reliable results in capturing the underlying dynamics of energy prices (Enders, 2014; Malkiel, 2003; Schwert, 2002; Shiller, 2003).

Cointegration test

Table 17: Cointegration test (Engle-Granger two-step method)

Dependent variable	Independent variable	T-stat	P-value
log S_T	log_first_closing_M1	-5.99	0.000
log S_T	log_first_closing_M2	-5.44	0.000
log S_T	log_first_closing_M3	-3.86	0.011
log S_T	log_first_closing_M4	-5.19	0.000
log S_T	log_average_M1	-5.13	0.000
log S_T	log_average_M2	-5.16	0.000
log S_T	log_average_M3	-3.89	0.010
log S_T	log_average_M4	-4.18	0.003
log S_T	log_last_closing_M1	-5.16	0.000
log S_T	log_last_closing_M2	-4.92	0.000
log S_T	log_last_closing_M3	-7.07	0.000
log S_T	log_last_closing_M4	-6.06	0.000

Residual plots:

Plot for LRP1

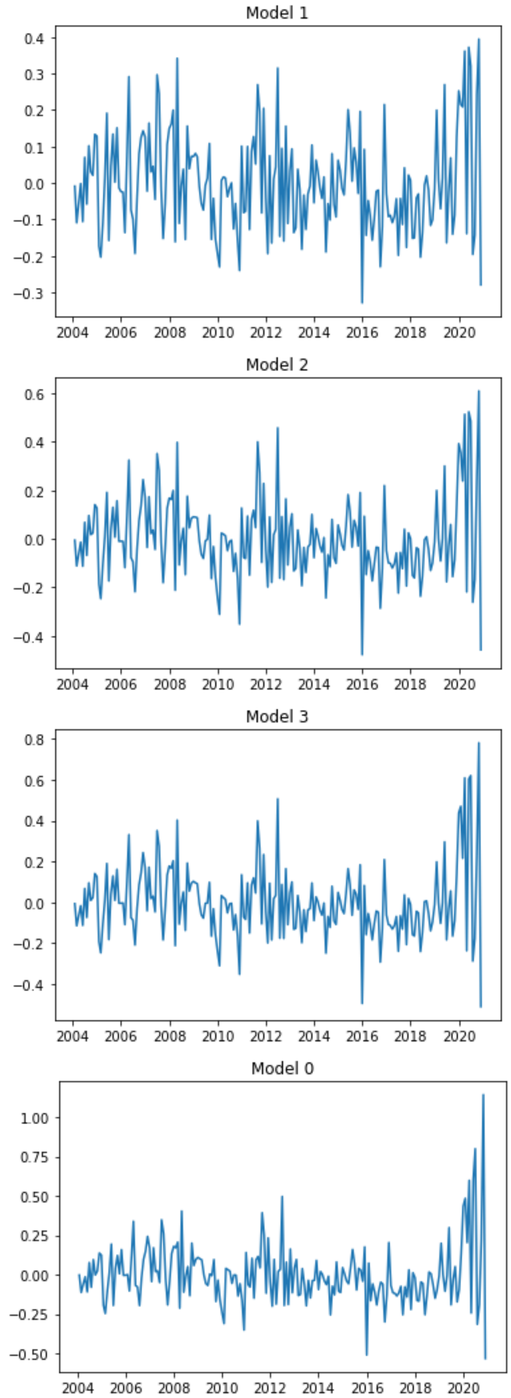


Figure 13: Equation (6.1): *The figures plot the residuals from regression on LRP1 using, Model 1, Model 2, Model 3 and Model 0, respectively.*

Plot for LRP4

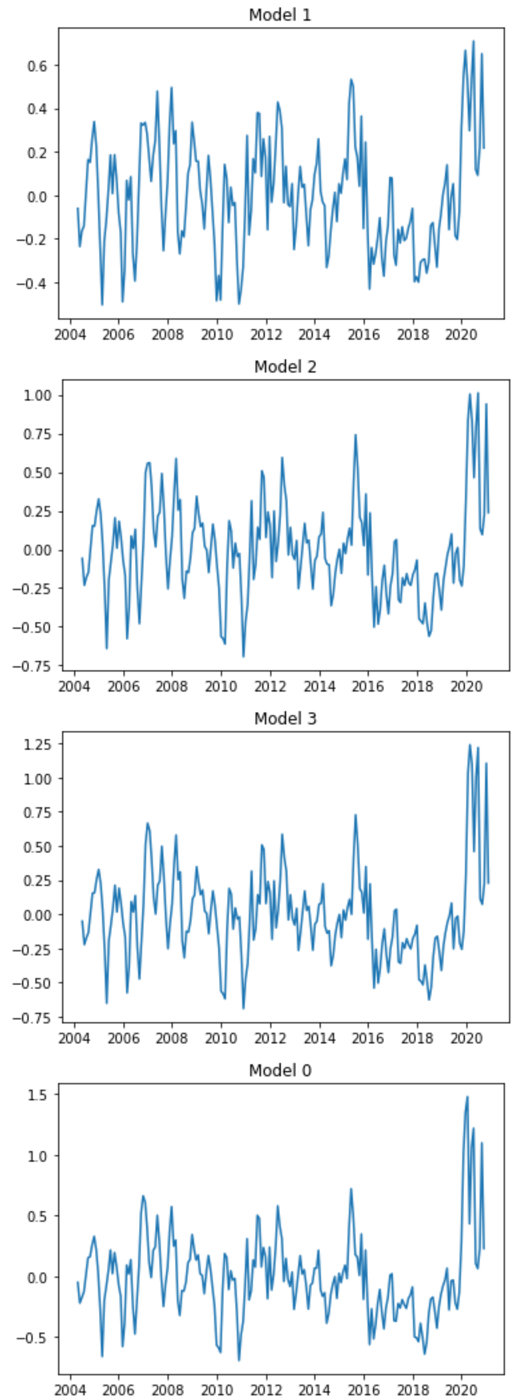


Figure 14*:* Equation (6.1): *The figures plot the residuals from regression on LRP4 using Model 1, Model 2, Model 3 and Model 0, respectively.*