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Efficiency in the Nordic Futures Power Market

An empirical study of the Nordic Futures Power Market

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Abstract

In this thesis, we investigate if the Nordic futures power market is efficient. To answer this question, we will perform cointegration tests, test the unbiasedness hypothesis and check the causal relationships between the spot price and futures prices with 1- to 6-months to maturity. We use daily observations from the period between 01.10.2015 and 15.09.2020. We have used price data of the spot price from Nord Pool, price data for the futures contracts from Bloomberg and volume data from Nasdaq OMX in our thesis.

We use cointegration techniques because the data is non-stationary. Cointegration is tested to see if there is a long-run equilibrium relationship between the spot and the futures prices. Our results suggest that the spot and the futures prices have a cointegration relationship for five out of six contract lengths. To further investigate these relationships, we perform a causality test to see which of the time series leads the other. The futures contracts lead the spot price for most of the contract lengths, which indicates that the futures market is having a price discovery function on the spot price. Having at least one cointegration relationship is a requirement for testing the unbiasedness hypothesis. The unbiasedness hypothesis test if the futures prices are the best predictor of the forthcoming spot price, i.e., if the market is efficient. The hypotheses only hold for the 1-month futures contract length, supporting efficiency. For the longer to maturity futures contracts, the futures market is inefficient, and the potential of observing a risk premium in the market increases.

Our findings are consistent with other fundamental research on the electricity futures market. Differences from other studies could be due to a different data set. Our research is done on futures and not DS futures, which may give some different results than previous studies. Nasdaq OMX issued the futures we apply in late 2015, and to our knowledge, there has not been any similar research on these futures contracts before.

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1. Introduction

Nord Pool is the leading power market in Europe (Nord Pool, 2020a). The Nordic power market's equilibrium price is settled here and is referred to as the spot price or the system price. Nord Pool has grown a lot in the last 25 years, from trading power in Norway to trading across 16 European countries. Nord Pool has been appointed Nominated Electricity Market Operator (NEMO) for multiple European power markets over the last five years (Nord Pool, 2020d). Hydro producers stand for the largest electricity production in Norway, and these producers are indeed selling their electricity at Nord Pool.

Nordic power futures products are trading at Nasdaq OMX (Nasdaq, 2020a). These futures are based on the spot price traded at Nord Pool. Stakeholders can use the futures market to make the future more predictable. This is because participants can hedge positions in the futures market to secure future price levels. In recent years there have been structural changes in the offered futures products. The Nordic power derivatives market had an exception provision until 2016, where the non-financial members of the market could use bank guarantees. In 2016 this exception provision expired, and non-financial members had to use cash or other securities as collateral. As a result, Nasdaq issued a new set of *less risky* futures contracts (Nasdaq, 2020a).

Physical and financial power products are trading in two different markets. Independent of which market, spot, and futures power prices are volatile. In other words, prices change rapidly. Recent observation of the changes in the electricity price works as evidence. Hafsaas (2020) writes about the significant electricity price reduction in 2019, where the prices decreased from 0,4 NOK /KWh to 0,05 NOK /KWh. The low-price level makes the production companies consider the opportunity of letting water pass by as production costs exceed revenue from sales.

There exist former studies on electricity spot and futures prices relationship. However, recent changes in the futures market dynamics and increased price volatility make it interesting to present new research on the relationship between the spot and futures prices. Also, discovering potential opportunities for market participants in the power market. This is creating our research question:

Is the Nordic futures power market efficient?

Fama (1970) presents empirical and theoretical literature on the efficient market model. The efficient market hypothesis (EMH) states that security prices should fully reflect all available information at any point in time. If market prices are fully reflecting all available information, market prices are fairly priced, making it impossible to buy products at a price under its fair value (Fama, 1970). Rejection of the EMH would then imply opportunities to outperform the market prices and earn a premium, as prices would not be reflecting all available information (Hodrick & Srivastava, 1984). Keynes (1930) first introduced how the spot and futures prices deviated from each other and the opportunity of a risk premium in the futures market. Since then, researchers have analyzed how prices can be derived from their correct fundamental value. Prices to be *fully reflecting* all available information are an extreme hypothesis, and the fundamental of full reflection could not be real (Fama, 1970). Therefore, a valid hypothesis is to test weak-form market efficiency. The weak form tests if market prices reflect all historical information (Fama, 1970). This is the efficient market hypothesis we will investigate and test in our thesis.

We found our time series to be non-stationary. This has some implications for our testing methods because conventional statistical procedures could give spurious results and wrongly answer our research question. Therefore, we must use methods that take these challenges into account. Lai and Lai (1991) used cointegration techniques to handle these challenges and investigate the weak-form efficient market hypothesis. If the time series are observed to be cointegrated, the time series have a long-run equilibrium relationship. Long-run equilibrium is a necessary foundation and a requirement for further claiming efficiency in the futures market (Beck, 1994).

Further, if there is a cointegration relationship between these prices, Lai and Lai (1991) show that the unbiasedness hypothesis could be used to test if the weak form market efficiency holds. The unbiasedness hypothesis tests if the futures prices are the best estimator of the forthcoming spot price (Hodrick & Srivastava, 1984). The statement is referred to as the unbiasedness hypothesis. The hypothesis is presented in different financial literature and is based on early empirical evidence by Frenkel (1977). This implies why we will be testing the cointegration relationship and the unbiasedness hypothesis to answer the EMH correctly. These elements are closely related to each other. The purpose is to test for efficiency and the absence of a risk premium (Brenner & Kroner, 1995). Unbiasedness is essential for a risk management purpose and implies no need to make speculative bets in the spot and futures market. Because there are no excess returns to be made, all information about the future spot prices is incorporated in current futures prices (Hodrick & Srivastava, 1984). However, a rejection of the market efficiency hypothesis and unbiasedness hypothesis can reflect the existence of a risk premium (Gjolberg & Brattested, 2011).

In relation to the cointegration relationships, we will investigate the price discovery function in the spot and futures market, i.e., if the futures prices lead the spot price (Schreiber & Schwartz, 1986). However, the relationship could also be the opposite, and the spot price could lead the futures prices, which is why we perform a causality test. The causality test reveals which of the prices leads the other (Silvapulle & Moosa, 1999). The causality tests are used to support the cointegration tests, and there must be at least one-directional causal relationship to confirm the existence of cointegration (Granger, 1988).

We have used daily observations on spot and futures prices retrieved from Bloomberg to perform our analysis. The period used is from 01.10.2015 to 15.9.2020. Our dataset consists of monthly futures contracts with 1- to 6-months to maturity. Our research suggests spot and futures prices having a cointegrated relationship, but not for the futures contract with the longest time to maturity. Further, we perform a causality test that supports our cointegration findings, where we find that the futures prices are leading the spot price. To formally check efficiency in the futures market, we test the unbiasedness hypothesis. The unbiasedness hypothesis holds for the closest contract length, 1-month to maturity. However, the rest of the monthly futures lengths are biased estimators of the subsequent spot price.

2. Nordic Electricity Market

This section will go more deeply into the Nordic electricity markets and describe the two different markets for electricity transactions: Nord Pool and Nasdaq OMQ. We will present the market structures, recent changes, and related consequences of these changes in the Nordic electricity markets.

2.1 Nord Pool – the Physical market

The Nordic power exchange is Nord Pool. Nord Pool is the leading transaction market for electricity contracts in Europe and is the marketplace for 16 European countries (Nord Pool, 2020a). Nord Pool consists of two different markets, the *Day-ahead* and *Intraday market*. Besides power trading, Nord Pool provides firms with all sorts of electricity data information. In the introduction, we mentioned that electricity is used simultaneously as it is produced, and therefore a well-functioning marketplace is required for production companies and consumers. The day-ahead market is the primary trading market, and the intraday market works as a supplement and helps the participants balance their positions (Nord Pool, 2020c). This is possible because the intraday market closes just one hour before the physical delivery of the electricity. The intraday market helps secure a fair and smooth balance between supply and demand (Nord Pool, 2020c).

2.1.1 The day-ahead and intraday market

The day-ahead market is where the different power market participants submit their estimated electricity trade. These estimates are predicted bids for purchase or sale for a given amount of electricity for the next 12-36 hours (Nord Pool, 2020b). The prices in the day-ahead market are settled at noon the day before the trade occurs. The settled price at the day-ahead market is known as the spot price and is made by the equilibrium between the bid and ask prices from the participants. The spot price submitted at Nord Pool is used as a reference price for the Nordic power futures traded at Nasdaq OMX, i.e., the futures products are constructed based on this spot price. This is how the spot price plays a vital role in our master thesis, as the system price is fundamental for the futures contracts we are investigating.

The time between the settlement of the spot price and electricity delivery can be up to 36 hours. Therefore, the intraday market plays the role of rebalancing the predetermined quantities by the participants and works to better fit the day-ahead market's supply and demand requests, i.e., rebalance the participants' needs (Nord Pool, 2020b). The intermittent renewable resources entrance in the latest years, such as wind and sun power, has increased the intraday market's total transaction volume (Nord Pool, 2020c). Because the amount of power produced from these types of resources is less stable than hydro production and gas, it has become more difficult for the participants to balance their trades in the day-ahead market. In this relation, the intraday market provides the participants with the opportunity to change and rebalance their offers based on the latest market information. This is necessary because unexpected changes are affecting the market price. These changes in the market could, for instance, be variations in the weather and closed power grids. The market is continuous, meaning it is open for transactions all around the clock but is closing one hour before delivery of the electricity. The prices are set on the *best price serves first principle* (Nord Pool, 2020c).

2.2 Nasdaq OMX – The Financial market

Nasdaq Commodities OMX (Nasdaq OMX) is where the financial products for Nordic electricity are traded. The financial derivatives are depending on the underlying product, the system price trading at Nord Pool. The Nordic power derivatives market is one of the most liquid derivatives markets globally (Nasdaq, 2020a). Nasdaq OMX has developed a lot over the last years to reduce risks, increase transparency, and protect their investors (Nasdaq, 2020a). Nasdaq only issues financial products, and there is no physical exchange of power, which is the main difference between Nasdaq and Nord Pool, as physical transactions are happening at Nord Pool. Another advantage for the participants is taking multiple financial positions before the financial products' expiration date. This opportunity increases the market transaction volume and can reduce the associated risks (Falbo et al., 2014). There are different financial products available for hedgers and speculators of the Nordic power market. Nasdaq's Nordic power products are futures, delayed settlement (DS) futures, electricity price area differentials (EPAD), and options.

DS futures have for a long time been the leading product. DS futures are futures contracts with no daily settlement, only a settlement at the expiration date, and work as a forward contract (Nasdaq, 2020b). Futures have daily settlements, where the profit or loss is calculated for each contract attached to the participants, and the settlements are due every open market day. DS futures and futures contracts have the spot price at Nord Pool as the underlying product. EPADs, on the other hand, is a futures contract used to hedge against risk between the different bidding areas. e.g., if the transmission grid between two areas is on full capacity, which causes a lower price in one area because of too much supply. The EPADs can then be used to hedge against this risk, which is calculated as the difference between the given area price and the system price at Nord Pool. The power options allow selling and buying the underlying contract at a predefined date to a predefined price (Nasdaq, 2020a). Our focus in this thesis will be on the futures contracts with a daily settlement and will be further explained below.

2.2.1 Reduced transaction volume in the futures market

After the financial crisis in 2008, the European Union (EU) established a collective European regulations system named the European Market Infrastructure Regulation (EMIR). The regulations were put in place to mitigate credit- and operational risk (Finanstilsynet, 2019). The Nordic power derivatives market had an exception provision until 2016 from some parts of the EMIR. When this exception provision ended, EMIR required non-financial members on Nasdaq OMX to use fully backed guarantees, such as cash or other securities. Previously, these members could use bank guarantees. This affected the Nordic power futures market because 60% of the exchange was non-financial members that used bank guarantees (Lindstad, 2019).

Financial members are investment firms, credit institutions, insurance companies, service pension, management companies of mutual funds, and alternative investment funds. Non-financial members are neither central counterparties nor financial counterparties of the trading process, e.g., a hydro producer (Finanstilsynet, 2019). The cost of using cash and other securities as collateral could be a significant amount of a company’s total financial capital. This is one reason for the decreased trend in total transaction volume trading in the Nordic derivatives market in recent years, displayed in Figure 2.1 (Lindstad, 2019).

The second reason for the falling trend in transaction volume is the increased amount of the *Power Purchase Agreements* (PPA). PPAs differ from futures contracts traded on Nasdaq in different ways (Næss-Schmidt et al., 2020). The PPAs can be custom-made in contrast with futures contracts that are standardized products. Secondly, for PPAs, guarantees and collateral are not restricted in the same way as in the futures market. If there is a default from one of the participants, the settlement could be canceled. Therefore, the risk of not having a counterparty could be a potential hidden cost for the PPAs. In comparison, the regulations in the financial futures market reduce counterparty risks significantly. At the same time, are the futures contracts associated with higher transaction costs. Thereby, there is a higher cost when trading futures contracts compared to the PPAs, but the risk is more significant for the PPAs. Næss-Schmidt et al. (2020) suggest that participants in the future market prefer the lower transaction costs associated with the PPAs, harming the transaction volume for futures contracts trading at Nasdaq OMX.

In addition to the observations related to decreased transaction volume in the futures market, we see from Figure 2.1 that monthly, quarterly, and annual futures contracts took over most of the market shares in 2017. The futures have outperformed the DS futures, which was the leading product with a higher transaction volume until 2016. Previously studies on the electricity market, which will be presented in the next subsection, have investigated the efficiency between DS futures and spot price in the electricity market. However, recent years' changes in transaction volume and product types, presented in this section, might affect the Nordic power market's price dynamics. This is relevant because, to our knowledge, there have not been any studies on Nasdaq's new futures from 2015.

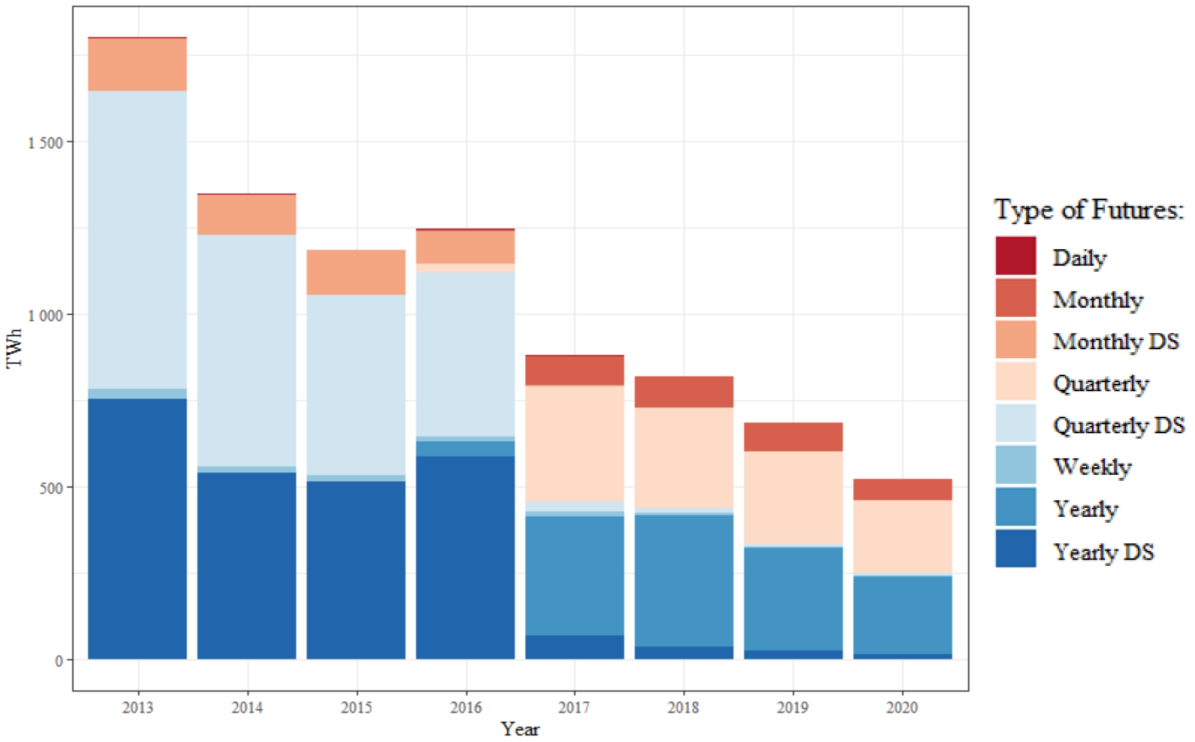

Figure 2.1: Volume development of futures contracts from Nasdaq OMX.

Note: Important notice is the pillar for 2020 only contains data until 15.09.2020. For this reason, the 2020 pillar is providing an unrealistic impression of the total volume in 2020.

2.2.2 Monthly futures contracts

In the previous subsection, we present structural changes from DS futures to futures contracts and the consequences of the changes. In this relation, it becomes relevant which of the futures contract we will investigate. As described in the subsection above, DS futures is outdated, and therefore, there are five options left to investigate from Figure 2.1. Our focus in this thesis will be on the monthly power futures contracts. This is the red colored futures contract from Figure 2.1. There are a few reasons why this is the preferred contract length to investigate. Smith-Meyer and Gjolberg (2016) and Gjolberg and Brattested (2011) investigated efficiency in the Nordic power market. They were studying nearby futures prices, i.e., futures prices with less than six months until the maturity date. Gjolberg and Brattested (2011) argue this to be the most relevant period to study efficiency in the electricity market. They also refer to a general acceptance among other researchers to study closer to maturity contract lengths when the research question is related to efficiency in the futures market.

It could be advantageous to study weekly futures, but we find monthly futures contracts more attractive because they have a higher trading volume, as shown in Figure 2.1. On the other hand, it could be questioned why we did not consider quarterly and yearly futures, especially when looking at the transaction volume in Figure 2.1. However, when investigated quarterly and yearly futures, two things should be considered. Firstly, these futures are cascaded into new futures rather than price settlement. The cascading process leads to a degradation of the yearly and quarterly futures. Wilkens and Wimschulte (2007) state the implications of this degradation of quarterly and yearly futures. The possibility to effectively study quarterly and yearly futures products disappear, and the only meaningful product to investigate becomes the end-product of the degradation process, which is monthly futures.

Secondly, we identified price gaps in the quarterly futures series when sorting the contracts on a rolling basis, further explained in section 4. The price gaps will affect our analysis with jumps in the prices that are up to ten percent, caused by the time series setup. In appendix A.1, a plot of quarterly futures is displayed, showing these price gaps. This is viable in the 5- and 6-quarters to the maturity date. For instance, at the start of 2017 and 2018, in the 5-quarters to maturity contract length. Further investigations on these contracts do not add any value to answering our research question and works as a response to why our focus will be on the monthly futures contracts.

2.3 The futures market effect on the spot market

Kalantzis and Milonas (2013) analyze the impact of electricity futures transactions on the overall electricity market. They find the introduction of a well-functioning futures electricity market increasing the liquidity and the overall electricity transactions volume, at the same time, reducing spot price volatility. One of the reasons is lower transaction costs for futures transactions compared to the spot market. A higher number of participants gets the opportunity to be involved in the electricity market, increasing market interest. Kalantzis and Milonas (2013) suggest higher information flow to be improving the market effectiveness for electricity transactions and prices to be more fairly set in the market. As the transaction volume increased related to electricity futures, activity is immigrating from the spot to the futures market.

Participants in the electricity market face several types of risks, and especially is there uncertainty related to the development of the spot price trading at Nord Pool. Producers are further interested in the overall production costs, and consumers are interested in the cost of electricity as input in their production. Therefore, participants are interested in the futures and spot electricity markets, as these markets provide an opportunity to hedge risks (McDonald, 2013). The mutual interest in risk reduction creates a shared interest in obtaining a well-functioning futures market for all participants (McDonald, 2013). Kroner and Sultan (1993) suggest hedging methods to reduce risks when the futures prices have a proven relationship to the development of the spot price. This is not supporting trading opportunities in the futures electricity market but instead displaying how the Nordic futures power market can help participants to reduce risk. However, electricity spot price, which is the underlying product, might be moving differently than the futures contracts. This is creating imperfections, and there might be opportunities for further speculations (Bessembinder & Lemmon, 2002).

In section 2, we have described the functions of Nord Pool and Nasdaq OMX, how the transactions are taking place, diverse types of products, and other new requirements relevant to the participants. The section introduced aspects related to risk reduction opportunities in the futures market or the potential of a risk premium. The next section will present relevant theories and aspects assessing the efficient market hypothesis and display the differences between market efficiency and inefficiency.

3. Historic elements and established theories

In this section, we will investigate central theories relevant to our research question. Theoretical frameworks are relevant to the upcoming tests in the next sections. Our study on electricity spot and futures prices is based on the following theoretical frameworks: The efficient market hypothesis, the unbiasedness hypothesis, and a risk premium model. Several influential theorists have reviewed these concepts, but the most relevant frameworks are Fama (1970), Fama and French (1987), Lai and Lai (1991), and Botterud et al. (2010).

3.1 Efficiency and Unbiasedness

The efficient market hypothesis (EMH) is presented by Fama (1970). The hypothesis defines a market as efficient if prices reflect all available information at any given point in time. If prices reflect all information, futures prices are the best estimator of the subsequent spot price, referred to as the unbiasedness hypothesis, and are presented by Hodrick and Srivastava (1984). If the EMH stands, and futures prices are unbiased predictors, research suggests an absence of risk premium, presented by Brenner and Kroner (1995). The following subsection will present central aspects related to these theories.

3.1.1 Efficiency market hypothesis

EMH proposes three diverse types of efficiency: *weak*, *semi-strong*, and *strong* (Fama, 1970). Prices in the weak-form efficient market reflect all historical information. In the semi-strong market, all public information is integrated, while in strong market efficiency, all internal information is available for the market participants. However, if tests and prognoses on weak form efficiency are satisfied, Fama (1970) suggests that to be enough for researchers to claim efficiency in a specified market, making weak-form market efficiency the most relevant establishment. Past price movements, earnings, and volume data are useless in predicting future spot prices; such information should already be incorporated into the current price (Malkiel, 1989). For instance, if the participants are sure of a price increase in the following week, and the price does not increase immediately, an arbitrage opportunity would be present in the market (Malkiel, 1989).

Market efficiency implies that futures prices should be equal to the expected future spot price and no risk premium (Beck, 1994). Alternatively, under the assumption that there is a risk-neutral relation between the spot price and futures prices, then a futures contract maturing in time (*t)*, with an expiration date (T), and the expected spot price at the time (*t*) should be equal to each other. Assuming the weak form market efficiency hypothesis and risk-neutral probabilities, should futures prices be the best predictor of the expected future spot price. These relations are interpreted in equation (1):

$$E_t(S_t|I_t) = F_{t,T} \tag{1}$$

The left-hand side of the equation is the expected spot price at the time (t), conditioned on all available information at the time (*t*). F_t is the futures price in time (*t*) with the expiration date (T). According to the market efficiency hypothesis, if the relationship in equation (1) breaks, this will support market inefficiency and be consistent with an arbitrage opportunity in the market, making it possible to earn a risk premium. The premium will be present until the equilibrium is re-established (Bessembinder & Lemmon, 2002).

3.1.2 Unbiasedness hypothesis

The above subsection presents the efficient market hypothesis and the capability of the prices being reflected by historical information. Closely related to the EMH is the unbiasedness hypothesis. The hypothesis suggests that current futures prices are unbiased predictors of the underlying subsequent spot price. This specific relation regarding unbiasedness is presented by Hodrick and Srivastava (1984). However, they founded their analysis based on empirical evidence from Frenkel (1977). If the market is efficient and the futures prices are an unbiased predictor of the subsequent spot price, the expected return from speculating in futures markets on available historical information is zero, i.e., there is no risk premium (Brenner & Kroner, 1995). This is how the unbiasedness hypothesis is consistent with the weak form efficiency hypothesis introduced by Fama (1970), which is true if all information about the future spot price is incorporated in the current futures prices. The unbiased hypothesis states, under risk neutrality and rational expectation that futures prices and spot price can be tested by regressing equation (2):

$$S_t = a + bF_{t,T} + u_t \tag{2}$$

u_t is the error term with a mean of zero and finite variance, the unbiasedness hypothesis that futures price is the best predictor of the forthcoming spot price is tested by setting $a = 0$ and $b = 1$. The restrictions on a and b in equation (2) represent jointly testing for market efficiency and no-risk premium (Lai & Lai, 1991).

If there is evidence of market efficiency and futures prices are unbiased estimators of the forthcoming spot price, opportunities arise in the futures market. Fleten et al. (2015) suggest that an efficient market creates possible hedging products for the participants. In this sense, taking a hedge position can reduce price risk and is relevant for both production companies and large consumers. Bansal and Lundblad (2002) suggest that efficiency increases with higher transaction volume. Because of increased transaction volume closer to maturity, these futures contracts change from being hedging products towards becoming speculative products, with the increased difficulty of earning risk premium (Fleten et al., 2015). Increased difficulty of earning risk premium is here related to the theoretical absence of risk premium given the EMH and unbiasedness hypothesis (Fama, 1970; Frenkel, 1977). Yang et al. (2001) suggest that participants should reduce the associated price risk seen with increased volatility by setting a hedge position in the futures market. This applies to EMH as producers, consumers, and other participants can take advantage of the futures market to hedge electricity prices and reduce risks.

3.2 Electricity market: Theory of Storage and risk premium

Rejection of the market efficiency hypothesis could imply market inefficiency or a time-varying risk premium (Beck, 1994). Fama and French (1987) present two different views on discovering premium in the futures market. These are *the theory of storage* and *expectation theory*. The theory of storage can be implied if there is possible to store the commodity. Expectation theory is more commonly used when considering non-storable commodities. These theories were first presented by Kaldor (1939) and Cootner (1960), respectively.

Fama and French (1987) elaborate on the expectation theory, first presented by Cootner (1960). They describe risk premium in the commodity market, which is primarily relevant for non-storable commodities, and deals with the relationship between spot and futures prices. When the commodity is difficult or even impossible to store, the premium associated with the futures contract derives from the risk related to the spot price's future development. If a trader sells a futures contract in a non-storable commodity market, the futures contract's value will be equal to the expected future spot price and a risk premium. However, if a trader sells a futures contract in a market where it is possible to store the commodity, the trader can hold the product until maturity and thereby eliminate the trade risk. This is the difference between storable and non-storable commodities, indicating that the trade risk and the uncertainty level will be higher for non-storable commodities. Electricity is known to be non-storable, and this is how the expectation theory becomes relevant for our thesis.

Kaldor (1939) presents the *cost of carry theory*, also known as the *theory of storage*, an alternative view of a commodity risk premium's exitance. The relevance of risk premium related to water storage cannot be underestimated; this is deeply assessed in Botterud et al., (2010). Water, as a storable resource, creates a foundation for further price speculations (Botterud et al., 2010). The storage theory can be exemplified by selling a futures contract and simultaneously buying the futures market's underlying product. Holding the product until delivery and thereby eliminating risk concerning price fluctuations. The difference between the sold futures contract and the commodity bought at spot price will be reflected by interest rate, storage cost, and the convenience yield. The intuition is based on futures prices' capability to reflect the exact storage cost and interest rate. Convenience yield is the *additional premium* received from holding the commodity (Botterud et al., 2010). The relationship between the spot and futures prices, studying storage theory, is presented in the following equation:

$$F_t = S_t * e^{(r_f+u-y)*(T-t)} \tag{3}$$

Futures price at time t is equal to the spot price, where the spot price takes a risk-free rate (r_f), storage cost (u), and a convenience yield (y) into account at the time (t). Storage cost is central in equation (3). Without the opportunity to store commodities, the arbitrary theory does not work efficiently (Kaldor, 1939; Fama and French, 1987). The arbitrary opportunity could further be seen through the convenience yield (y) referred to as a *liquidity premium* (Botterud et al., 2010). The premium is the associated value sitting on the specific commodity, i.e., storing water, reducing the volatility risks, and reflecting the market's expectations related to its future availability.

If the EMH holds, the person in position of the commodity will be compensated for a risk-free rate and the associated storage costs. This indicates a perfect relationship between the spot price and the futures price, where the futures price is equal to the expected future spot price, and the risk premium will be zero, i.e., the risk-adjusted discount rate for the commodity is equal to the risk-free rate (Botterud et al. 2010). However, if there is a premium in the futures prices, long-run prices would be deviating from the spot price, and the distance would provide an opportunity for a risk premium (Kaldor, 1939; Bessembinder & Lemmon, 2002). The futures prices as an estimator fail or miss because the subsequent spot price development is different from the ordinary predictions from the futures prices (Bessembinder & Lemmon, 2002). In this scenario, the unbiasedness hypothesis is rejected, suggesting that the commodity market futures prices are inefficient, i.e., expressing futures prices to be biased estimates of subsequent spot prices.

3.2.1 Contango and Normal Backwardation

The premiums associated with the cost of carry theory, introduced above, can be further exemplified through the Keynesian hypothesis, presented by Keynes (1930). The models are reflecting on the presence of a risk premium and the associated hedge position. The theory is referring to two different price situations; these are *contango* and *normal backwardation.* In a contango situation, the futures curve is above the spot price. When the spot price is below the futures price, the market is in normal backwardation (Keynes, 1930). Contango and normal backwardation can be explained by equation (3). If the sum of risk free-rate and storage cost is above the convenience yield value, the futures price will be above the spot price, and the market will be in contango. On the other hand, if the sum of the risk-free rate and storage cost is less than the convenience yield, F_t will become less than the spot price, and the market will be in normal backwardation.

Botterud et al. (2010) and Gjolberg and Brattested (2011) finds forwards and futures prices of electricity to, generally, be trading 3 to 5 percentage higher than the subsequent spot price for monthly futures contracts. This reflects a contango scenario, as they find a relatively high demand for long hedge positions in their studies as the consumers' fears increased spot market prices. If this is the market scenario, and the forward curve is above the spot price, the theory suggests investors could be gaining from holding a net short position, i.e., selling electricity on the futures market, and after that buy electricity at a lower spot price. This could be profitable if a contango situation where the futures curve is above the spot price (Keynes, 1930; Miffre, 2000).

The above subsections exemplify different aspects of the potential risk premium and market situations in the electricity markets. However, even if there is a risk premium, research suggests that the premium is decreasing as futures contracts are getting closer towards the maturity date, and the futures prices will at some time be equal to the spot price (Fleten et al., 2015). This argument suggests that there are some differences between longer and closer to maturity contract lengths. Bunn and Gianfreda (2010) further suggest that the price convergence between the spot price and closer to maturity contract lengths to be caused by increased transaction volume.

3.3 Evidence from futures markets

When testing efficiency in futures markets, the spot and futures time series are often non-stationary processes. If this is true, conventional statistical procedures are no longer valid and appropriate to test market efficiency (Lai & Lai, 1991). The regression result could indicate significant relationships between two variables when the variables' accurate modeling should have stated no significant relationships between the variables; this is referred to as spurious effects (Kočenda & Černý, 2015). The following subsection will describe how previous studies, such as Lai and Lai (1991) and others, used Engle and Granger (1987) and Johansen's (1988; 1991) cointegration methodology to investigate the market efficiency, as these methods effectively account for non-stationary time series (Lai & Lai, 1991). We will display relevant findings from previous studies that have used these cointegration tests. The tests' methodology will be presented in section 5.

Hall et al. (1992) used the Engle and Granger methodology to determine if the yield of different bonds with different maturity dates expelled the cointegration relationship with the spot price. Their results are interesting as they rejected the null hypothesis of no cointegration for futures contracts with 1-, 2-, 3-, and 11-months to the maturity date when testing futures contracts with 1 to 12 months to maturity. The results showed that the futures contracts with a shorter time to maturity have a cointegration relationship with the spot price. This supports Fleten et al.'s (2015) research that futures prices will converge towards the spot price as the time to maturity decreases, caused by increased transaction volume.

Johansen (1988) introduced another cointegration test that is repeatedly used to test market efficiency and the unbiasedness hypothesis. Kugler and Lenz (1993) suggest that the Engle and Grange methodology suffers from several fundamental issues, arguing that the methodology creates less precise results due to the model's simplicity compared to other cointegration methods. Simplicity is in this sense relating to only being able to discover one cointegration relationship. Shrestha and Bhatta (2018) refer to the same weaknesses. They present the Johansen procedure as an improved cointegration model as the model addresses these weaknesses. Lai and Lai (1991) select the Johnsen methodology when testing for market efficiency and do this for the same reasons as mentioned above. The methodology allows for testing multiple interactions between variables and can incorporate different short and long-term dynamics of a system with different economic variables. Lai and Lai (1991) tested cointegration in futures prices among five different currencies and studied the spot price against monthly futures using the Johansen cointegration test. The test is rejecting the null hypothesis of no cointegration, suggesting spot and futures to be cointegrated. However, the futures prices appear to be biased as predictors of the forthcoming spot price, and the unbiasedness hypothesis is rejected. Their observations and results do not support market efficiency.

Phengpis (2006) also used the Johansen test to study market efficiency between spot and futures for European and Asian currencies. The Johansen testing results suggest cointegration between spot and futures prices in both the European and Asian markets. However, after adding multiple tests into their studies, they express skepticism and become critical to their first observations using the Johansen test's method. Phengpis (2006) suggest the Johansen test to be a better research instrument supplemented with other tests. Nasseh and Strauss (2000) test the long-run cointegration relationship between stock prices in six European economies and disagree with Phengpis's (2006) findings related to the Johansen test. They used the Johansen cointegration procedure and defended their choice of a model by referring to the model's size properties and power. Amount of power is used to express the model's capability to incorporate dynamic co-movements and simultaneously interactions in the prices to enhance the produced estimates and predictions (Nasseh & Strauss, 2000). Size properties measure the summed influence of the model's performance. Based on the overall argumentation and related to previous research, it seems reasonable to present both the Engle and Granger (1987) and the Johansen test (1991) to test cointegration and unbiasedness when the data consists of non-stationary time series.

4. Data

This section presents an overview of the data used to test cointegration relationships, the unbiasedness hypothesis, and price discovery in the Nordic futures power market. We have collected data from multiple sources such as Nord Pool, Nasdaq, and Bloomberg. Thereby, created a data set consisting of the spot price and 1- to 6-months to maturity futures contracts. The data set consists of 1297 observations from 01.10.2015 to 15.09.2020. This section will present data set up, descriptive statistics, unit root testing, and lag specifications for our data.

4.1 Data set up

In this subsection, we will describe how we have ordered our data. We collected the data from three separate sources: Nord Pool, Nasdaq, and Bloomberg. From Nord Pool, we collected daily observations of the electricity spot price.[1] Nord Pool's spot price is set on all days throughout the year, while futures prices are only settled when Nasdaq OMX is open. Therefore, we removed closed days on Nasdaq from the spot price data to get time series with the same length.

The Nasdaq data was raw and unstructured, consisting of 1.75 million derivatives transactions and volume data from 01.01.2013 until 17.09.2020.[2] Monthly futures were filtered from the raw data and sorted on a rolling basis from 1- to 6-months to maturity. The data material then consisted of price series and volume data. However, one key issue followed the data from Nasdaq. There were days without any transactions, creating multiple missing values inside the data set. For this reason, we collected Bloomberg data. They interpolated the bid and asked prices when there were no transactions settled during a specific day, making the data set fulfilled. Therefore, the Nasdaq data was used to present the transaction volume data displayed in Figure 2.1, while we used the Bloomberg data for the forthcoming analysis.

[1] Spot price data can be accessed from: https://www.nordpoolgroup.com/historical-market-data/

[2] Nasdaq data can be requested and applied for through this source: https://www.nasdaqtrader.com/content/administrationsupport/AgreementsData/Academic_Waiver_Form.pdf

The data from Bloomberg consisted of daily observations on monthly futures contract prices from 01.10.2015 to 15.09.2020.[3] The futures are sorted on a rolling basis from 1- to 6-months to maturity, and a total of six different time series variables. Monthly futures contracts are average rate futures, and the expiration date is the last business day of the delivery period. The final settlement is the average spot price for the delivery period. For instance, (ENOAFUTBLMOCT-20), the monthly average future has an exercise period in October 2020, and the expiration date will therefore be the last business day of the month 30.10.2020.

Wu et al. (2018) found that data with higher frequency consists of more mean-reversion information. They issued a specific problem related to lower frequency data as lower frequencies potentially can affect the unit root tests. For instance, if using monthly observations, information can be lost due to excluded observations compared to daily observations. Therefore, we chose to use daily observations of the spot and futures prices.

4.2 Descriptive statistics

Table 4.1 shows descriptive statistics of our price data for the spot and futures prices. We describe our descriptive statistics because it provides a solid overview of the data, which we will further use in the tests presented in section 5 and 6.

We observe significant differences between the highest and lowest prices, especially for the spot price in Table 4.1. The spot price is trading at its lowest at 1.02 EURO/ KWh to 80.99 EURO/KWh at the highest. The average spot price is 31.46 EURO /KWh. We observe that the average futures prices are lower than the spot price and tend to decline as the time to maturity increases. Lower futures prices than the spot price indicate that we have a normal backwardation situation. Normal backwardation is going against earlier observations presented by Botterud et al. (2010) and Gjolberg and Brattested (2011), related to the development of futures prices in the Nordic power market. They suggested a contango market scenario where consumers use futures contracts to secure and stabilize upcoming income. Therefore, they accept buying electricity at a higher futures contract price.

[3] Futures prices are retrieved from the Bloomberg terminal at NHH.

A decline in average futures prices as the time to maturity increases could indicate an inverted futures curve. The futures market is inverted if the spot price is higher than the monthly futures prices. We observe this to be true for all contract lengths in the table as the average spot price is higher than the average futures prices. There are two exceptions from the inverted futures curve, where the 2- and 3-month futures contract lengths are higher than the 1-month contract. Nevertheless, they are still below the spot price, indicating normal backwardation. Oliveira and Ruiz (2020) comment on the futures electricity market and point at possible interpretations of observing an inverted market. The observed trend in the table could be caused by market expectations of lower electricity prices in the future. An inverted market could also provide investors with intensives to take long positions in the futures market. This is discussed in section 3.2.1 related to normal backwardation and is based on the theory first presented by Keynes (1930).

Another observation from Table 4.1 is that most of the futures prices are positively skewed. This is true as the mean price is greater than the median. The futures price series are fairly symmetrical, indicated by a low absolute value of the skewness, where the absolute value is below 0.5. The spot price breaks the rule of thumb. It has negative skewness, and the mean price is bigger than the median. Von Hippel (2005) finds the same results when there are multiple peaks present when investigating the data distribution. Observing spot price with negative skewness seems reasonable based on the overall movements in the spot price in our dataset. The electricity spot price has been turning downwards, especially in the latest period, affecting the data distribution (Scheben et al., 2020).

The excess kurtosis for the futures prices is negative and indicates that they are platykurtic distributed. The mean's peak is lower in the distribution, and there are fewer outliers than normally distributed data, i.e., it has a flatter distribution than normally distributed data. We observe that the excess kurtosis decreases for the futures contracts with a longer time to maturity and indicates fewer outliers in the data. The standard deviation support this where it decreases when the time to maturity increases for the futures contracts (Brooks, 2019). To further investigate the normality of the data, we perform the Bera-Jarque test. We identify that only the 2-month futures contract length is normally distributed. The normality is rejected at a 1% level for the other futures contract, while the spot price is rejected at a 10% significance level.

The standard deviation is highest for the spot price, with a standard deviation of 13.03 EURO/KWh, which is not very strange because the gap between the minimum and maximum price is most significant for the spot price. As standard deviation is a statistical measure of market volatility, this further indicates that the electricity spot price is most volatile based on the period's data observations. Among other things, this could be due to instant changes in the spot price due to shocks. Most often, these shocks are expressed in the spot price (Miffre and Rallis, 2007). This could further explain the decline in standard deviation as the time to maturity increases, as instant changes in price levels reduce as the time to maturity increases due to lower transaction volume. This is in line with the Samuelson hypothesis. The Samuelson hypothesis argues that futures price volatility increases as the time to maturity decreases as the contract is approaching its expiration date (Samuelson, 1965).

Table 4.1: Descriptive statistics of spot and futures prices.

	Min	Max	Median	Mean	St.dev.	Skewness	Excess Kurtosis	Normality
Spot Price	1.02	80.99	30.80	31.46	13.03	-0.16	0.03	[0.06]*
1-Month	2.33	60.05	31.00	30.61	12.38	-0.24	-0.14	[0.00]***
2-Month	3.90	60.75	30.40	30.77	12.39	0.02	-0.16	[0.52]
3-Month	4.25	58.85	30.20	30.69	12.17	0.10	-0.37	[0.01]***
4-Month	4.45	59.15	28.20	30.57	11.82	0.14	-0.56	[0.00]***
5-Month	4.98	59.00	28.35	30.50	11.34	0.18	-0.68	[0.00]***
6-Month	7.25	61.00	28.70	30.31	10.77	0.23	-0.66	[0.00]***

Note: The p-values from the Bera-Jarque test are displayed in the Normality column. *** and * marks 1% and 10% significance level, respectively.

The development of the 1- to 6-months to maturity futures contracts is displayed in Figure 4.1. We observe how the prices are evolving related to the spot price. General assumptions can be drawn based on descriptive statistics and from the observations in the figure. We see how the spot price, in general, is moving above the futures prices and how the spot price is fluctuating more, i.e., having a higher volatility than the futures price series; these observations are exemplifying the higher mean and standard deviation values from Table 4.1. We observe, as the time to maturity increases, the deviations between the spot and futures prices increases. The spot and futures prices are more effectively following each other on the closest contract lengths. These relationships between price deviation and time to maturity will be further analyzed and tested in section 6.

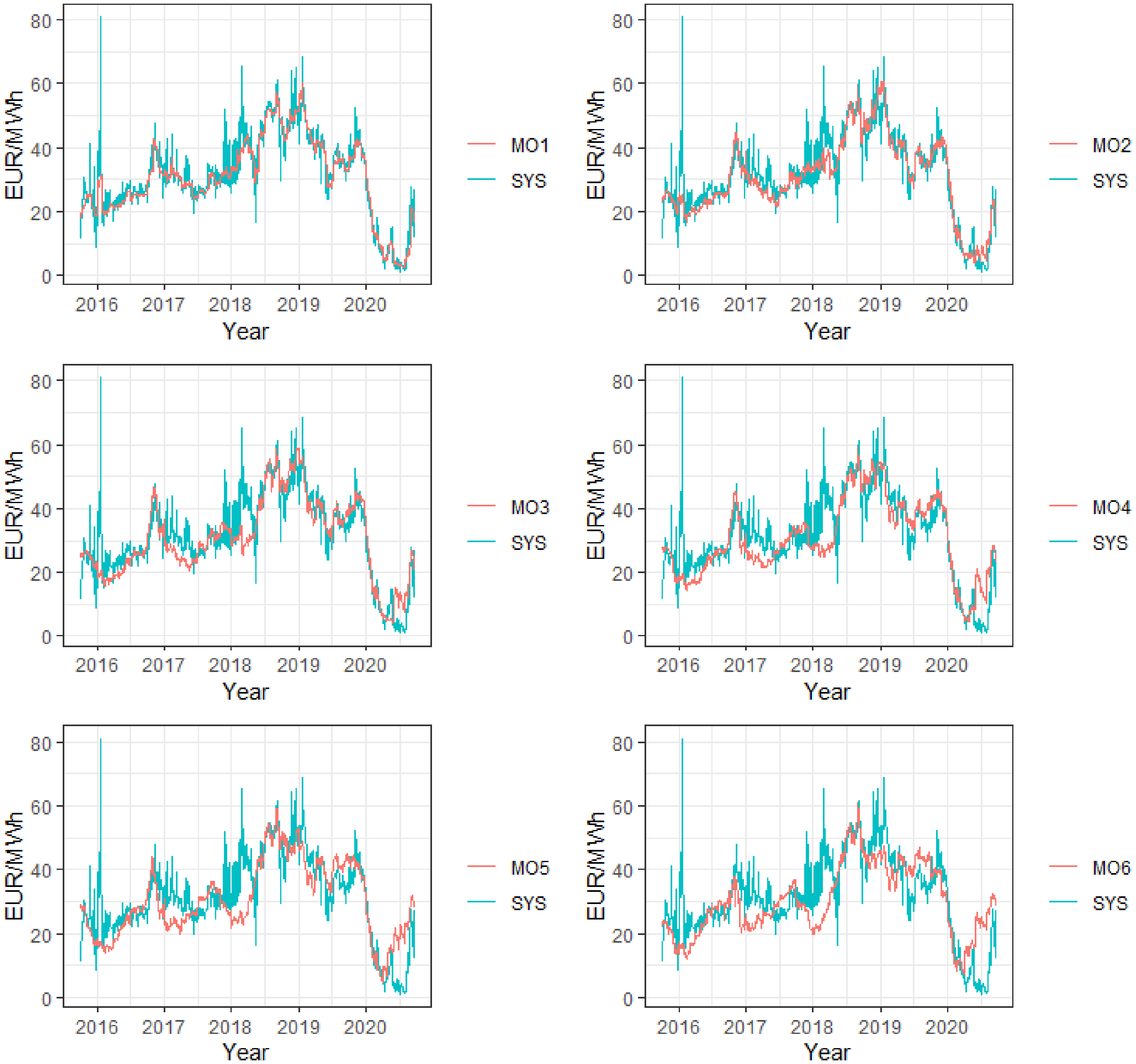

Figure 4.1: Spot price plotted against 1-6 months to maturity futures contracts.

4.3 Seasonality

Usually, the electricity spot price is affected by seasonality, where the prices are lower in the summer months and higher in the winter months. We must investigate our data to identify if this is the case for our sample period. In Figure 4.2, all the monthly average spot prices are displayed. We can see that the spot price has fluctuated a lot in recent years, making it difficult to identify seasonal patterns in the figure. We observe some of the highest spot price levels during July and August 2018. However, on the bottom line in Figure 4.2, we also observe some of the lowest spot price levels during summer 2020. As shown in the figure, the summer months exhibit both some of the highest and the lowest spot prices. Thereby, if we adjust for seasonal patterns, this will affect the later sections' analysis and complicate these analyses. Therefore, we decide not to make any seasonal adjustments to our data.

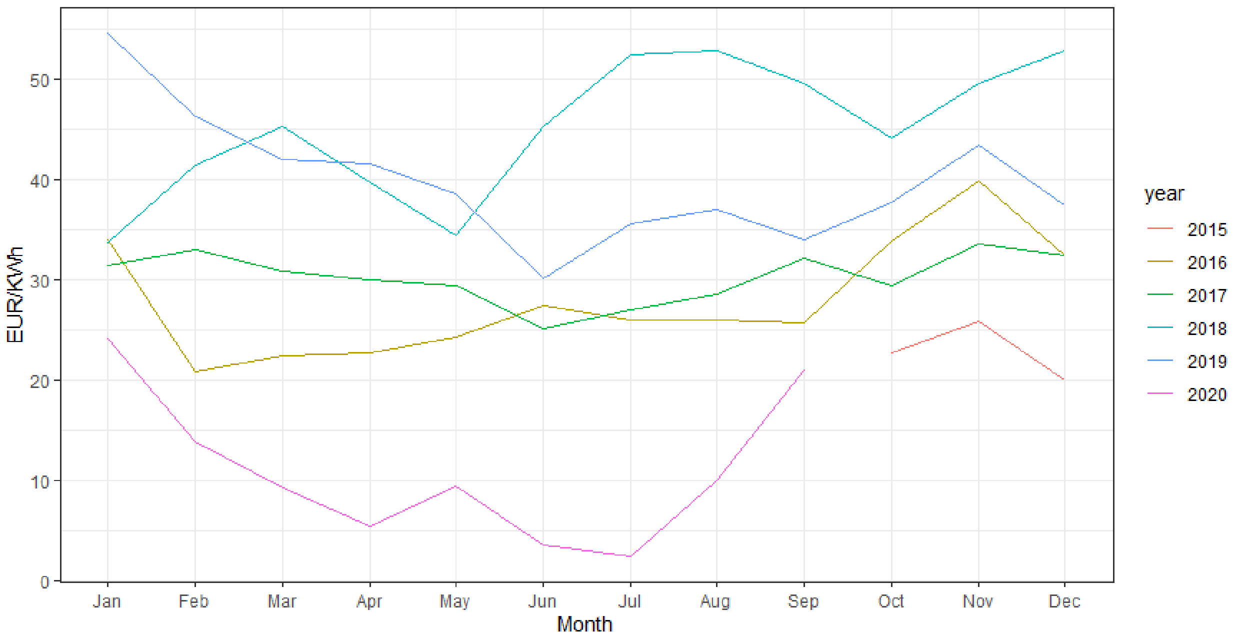

Figure 4.2: Average monthly spot price.

4.4 Stationarity and Unit Root Tests

The following subsection will present unit root testing to assess whether the data is stationary or non-stationary and other implications regarding model selections. Financial time series are often observed to be non-stationary because of economic growth (Kočenda & Černý, 2015).

Time series is found to be non-stationary if a unit root is causing the statistical properties to be changing over time. For instance, if variance, covariance, or mean is changing over time. As a consequence, carefulness is required when drawing interpretations and conclusions based on a non-stationary time series. The results could become spurious and incorrectly display causal relationships leading to wrongly rejections of the null hypothesis. This is called type-I-error (Kočenda & Černý, 2015). In other words, implications may occur when working with non-stationary data, and that is one of the reasons why we test the time series.

Another reason to test the data's property and the data order is to decide which models to continue with when answering the research question. We will present two different unit root tests to identify the data properties: ADF and KPSS tests. The ADF test has been criticized for being poorly functional when it comes to near-unit root time series cases. Therefore, we chose to include the KPSS test. The advantage of using these two tests is that the null hypothesis is being tested in the opposite directions, increasing the possibility of getting the correct results from the observed values (Nelson & Plosser, 1982).

4.4.1 ADF test

The first method we present to assess the data material is the ADF test. The ADF test's null hypothesis states that our data is non-stationary and the presence of a unit root in the time series. The null hypothesis is compared to the critical values presented by Dickey and Fuller (1981). If the calculated t-value is smaller than the critical values, we reject the null hypothesis and find the data to be stationary. The ADF test is presented in equation (4):

$$\Delta y_t = \alpha + \beta t + \delta y_{t-1} + \sum_{i=1}^{p} \theta_i \Delta y_{t-i} + \varepsilon_t \tag{4}$$

In equation 4, α is an intercept, and β is a trend component. There are three different models of the ADF test, where the intercept and trend component can be included, one by one, both, and none. The test states that a unit root is present if $\delta = 0$, which is the null hypothesis. θ_i are the parameters for the lagged values of Δy. ε_t is the residuals for the model.

Before we continue with the ADF test result's interpretation, we present how the optimal lag length (p) is set for the dependent variable in equation (4). Choosing the right lag length for a model is not a straightforward process. If the lag length is too small, the model could be biased due to autocorrelation in the residuals. To test for autocorrelation, we use the Durbin Watson test (Durbin & Watson, 1950).[4] However, by increasing the lag length (p) in the estimated equation, we correct for possible autocorrelation. On the other hand, as the number of lags included to correct autocorrelation increases, the test's power decreases, and the model loses its statistical power.

Consequently, selecting the number of lags creates a trade-off between the model's goodness of fit and its complexity; therefore, a central aspect is to estimate the model's most appropriate lag length using information criteria, and the purpose is to find the lag length that is minimizing the estimated information loss (Akaike, 1974). We are using Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) to find the appropriate lag length. BIC penalizes the number of lags included in the model compared to AIC, and it is necessary to investigate the autocorrelation in the residuals together with using the information criteria (Schwarz, 1978).[5]

Table 4.2 identifies our futures price data to be non-stationary in log levels, using the ADF test. This is because the t-value obtained from the ADF test is higher than the critical values, and we cannot reject any of the null hypotheses. On the other hand, we see that the spot price is significant at a 5% level when an intercept is included, but as we mentioned above, the ADF test could be struggling in near-unit root situations. Log transformation is used to make the variance more constant (Brooks, 2019). We performed the test with three different combinations of equation (4), one without intercept and trend, one with a trend, and one with both intercept and trend.

[4] Durbin-Watson test in presented in appendix section A.2.

[5] Functions for the information criteria are given in appendix section A.3.

From the ADF test, we observe our data to be non-stationary in levels. Therefore, we examine if the time series is integrated in the first order, i.e., I(1), and check for stationarity. We do this by differentiating the time series. First differencing time series is performed by subtracting the time series' consecutive observation, displayed as $\Delta y_t = y_t - y_{t-1}$. By differencing time series, we help stabilize the mean by removing the changes in levels and reducing the trend. From the right-hand side of Table 4.2, we observe that the data is stationary in the first order. This is due to the t-statistics from the ADF-test being smaller than the critical values. We reject the null hypotheses and any presence of a unit root for the spot and futures prices.

Table 4.2: ADF test on log levels and first differenced time series.

	Log levels			First difference		
	$\alpha = 0, \beta = 0$	$\alpha \neq 0, \beta = 0$	$\alpha \neq 0, \beta \neq 0$	$\alpha = 0, \beta = 0$	$\alpha \neq 0, \beta = 0$	$\alpha \neq 0, \beta \neq 0$
Spot Price	-0.526(3)	-2.877(2)**	-3.153(2)	-24.2(2)***	-24.20(2)***	-24.21(2)***
Monthly futures:						
1 Month	-0.336(1)	-1.636(1)	-1.895(1)	-25.32(1)***	-25.30(1)***	-25.31(1)***
2 Month	-0.470(1)	-1.774(1)	-1.918(1)	-25.86(1)***	-25.85(1)***	-25.85(1)***
3 Month	-0.354(1)	-1.706(1)	-1.749(1)	-23.96(1)***	-23.95(1)***	-23.94(1)***
4 Month	-0.331(1)	-1.782(1)	-1.781(1)	-23.26(1)***	-23.25(1)***	-23.24(1)***
5 Month	-0.238(1)	-1.921(1)	-1.928(1)	-23.70(1)***	-23.69(1)***	-23.68(1)***
6 Month	-0.050(1)	-1.838(1)	-1.819(1)	-25.11(1)***	-25.10(1)***	-25.09(1)***

Note: ADF test for the spot and futures prices with their respective t-values. To reject the null hypothesis, i.e., no unit root in the time series, the t-value must be below the critical values. t-values marked with *** and ** are significant at a 1% and 5% level, respectively. The number of lags is calculated using information criteria and is presented in the parenthesis. The three different tests $\alpha = 0, \beta = 0$; $\alpha \neq 0, \beta = 0$; and $\alpha \neq 0, \beta \neq 0$ are the ADF test without trend and intercept, with intercept and with intercept and trend, respectively.

4.4.2 KPSS test

The spot price with intercept was stationary at a 5% significance level. Nelson and Plosser (1982) observed that the ADF test performed poorly in near-unit root time series situations. Therefore, we present the KPSS test to support and check the results from the ADF test. We use both tests to decrease the probability of getting incorrect results. KPSS test is based on linear regression and uses ordinary least square (OLS) to estimate the model. The test uses a different method to select the number of lags. The equation used to select the number is $4(T/100)^{1/4}$, where T is the number of observations in the time series (Kwiatkowski et al., 1992). This can be visualized in Table 4.3. To test the null hypothesis in the KPSS test, they use the LM test to identify if the model's variance is significantly different from zero.

Kwiatkowski et al. (1992) computed critical values to compare with the LM statistics. The main difference between the KPSS test and the ADF test is the null hypothesis. In the ADF test, the null hypothesis states that the data is non-stationary. In contrast, the KPSS null hypothesis states that the data is stationary. This can be observed in Table 4.3, showing the KPSS testing results. In our case, we reject the null hypothesis when the test is performed on data in log levels, i.e., the data is non-stationary in log levels. Simultaneously, when we perform the test on the first differenced time series, we cannot reject the null hypothesis, i.e., the data is stationary in the first order and supports the results from the ADF test. Therefore, we can conclude that the spot and futures prices are stationary in the first order, I(1), but not in log levels.

Table 4.3: KPSS test on levels and first differenced time series.

	Log levels		First difference	
	μ	τ	μ	τ
Spot Price	2.852(7)***	2.211(7)***	0.071(7)	0.017(7)
Monthly futures:				
1 Month	2.899(7)***	2.357(7)***	0.120(7)	0.051(7)
2 Month	2.486(7)***	2.314(7)***	0.119(7)	0.050(7)
3 Month	2.071(7)***	2.079(7)***	0.088(7)	0.060(7)
4 Month	1.931(7)***	1.929(7)***	0.078(7)	0.065(7)
5 Month	2.076(7)***	1.814(7)***	0.071(7)	0.069(7)
6 Month	2.642(7)***	1.781(7)***	0.074(7)	0.055(7)

Note: LM statistics for testing the null hypothesis for the KPSS test are reported. The null hypothesis is rejected if LM statistics are above critical values. LM statistics marked with *** are significant at a 1% level, and the null hypothesis is rejected. The number of lags is presented in parenthesis. μ test for level stationarity with an intercept, τ test for trend stationery with both intercept and trend.

5. Methodology

This section will present the methodology that fits our data's properties, making us able to identify if the Nordic futures power market is efficient. There are multiple tests and approaches available to answer our research question. In the following section, we will describe our preferred empirical approaches. The applied methods are further supported by earlier studies regarding market efficiency in different spots and futures markets presented in section 3.4. We will investigate the following concepts: Two different cointegration tests, a vector error correction model (VECM), a causality test, and further set restrictions on the VECM to test the unbiasedness hypothesis.

5.1 Cointegration

Two time series are observed to be cointegrated if the time series have a long-run equilibrium relationship. The time series can deviate from the linear cointegration relationship in the short run but should eventually adjust towards the long-run equilibrium. This equilibrium exists due to economic power or economic force, causing the prices to be moving related to each other (Kočenda & Černý, 2015). Observing variables to be out of equilibrium and out of the balance-point is natural and normal in this sense. Nevertheless, they should never drift too far away from the equilibrium, and if they do, they would effectively be forced back into the system if there exists a cointegrated relationship between them. Long-run equilibrium is a necessary foundation and a requirement for further claiming efficiency among spot and futures prices (Beck, 1994).

The concept of finding cointegration relationships between non-stationary time series was first introduced by Granger (1981), but the most classical reference is the Engle-Granger methodology accessible in Engle and Granger (1987). The method is widely used when researchers are examining cointegration relationships between non-stationary financial time series. The second cointegration approach is presented in Johansen (1988). The Johansen approach builds on the Engle-Granger method, but there are some superior elements in the Johansen methodology. Both methods can be applied when time series variables are non-stationary in levels and stationary in the first order, I(1), which we identified in section 4.

5.1.1 Engle-Granger test

Engle-Granger test is known to be simple and straight forward. The first step is to estimate cointegration relationships using ordinary least square (OLS) regression. Since the spot price is our dependent variable and the underlying product, we only test one direction. If this had not been the case, the test should have been presented in two directions. From the OLS regression, we retrieve the residuals and test if they are stationary. The Engle-Granger test identifies the two time series variables as cointegrated if the residuals are stationary. The hypotheses for the Engle-Granger cointegration test can be displayed with the following:

$$H_0 : u_t \sim I(1)$$

$$H_1 : u_t \sim I(0)$$

u_t is a vector of the residuals obtained from the OLS regression. We reject the null hypothesis if the residuals are stationary. The stationarity test used on the residuals is the ADF-test presented in section 4.3.1, without intercept and trend. Nevertheless, there is one difference from the test in section 4.3.1, which is the critical values. The residuals obtained here are from an estimated model rather than from raw data. Obtaining the residuals from the estimated model could be an issue as there is an increased chance of having spurious residuals. However, Engle and Yoo (1987) made a new set of critical values which consider the estimated residuals, and these critical values are stricter than the standard critical values.

5.1.2 Johansen test

The second approach presented for testing the cointegration relationship between spot and futures prices is the Johansen cointegration test (Johansen 1988; 1991). The test has some advantages; the Johansen test treats all variables as endogenous variables, compared to the Engle-Granger test, where the endogenous variable must be chosen before the estimation. The Johansen test can yield useful estimators for further investigations when various assumptions are set, meaning we can test with the use of restrictions. This will be presented in a later subsection when we consider the unbiasedness hypothesis. Another advantage is the opportunity to test for multiple cointegration relationships at the same time.

On the other hand, the model is by far more complicated than the Engle-Granger test. Johansen modifies a vector autoregressive (VAR) framework to identify cointegration relationships.[6] The approach is using maximum likelihood estimators to make the cointegration vectors. This approach creates better estimates compared with the regressed estimates obtained from the OLS in the Engle-Granger approach. The Johansen test takes the underlying process's error structure into account, thereby delivers better estimates (Johansen, 1988). We need to test the rank of the matrix (Π) in a VECM to perform the Johansen test; this is presented in equation (5):

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \varepsilon_t \tag{5}$$

In equation (5), Y_t is an $n \times 1$ vector in time t, $\Delta Y_t = Y_t - Y_{t-1}$, Γ, and Π are coefficient matrices. Π can be decomposed into a matrix consisting of a vector or a matrix of the speed of adjustment coefficients, α, and the vector or matrix of cointegration vectors β, and can be displayed as $\Pi = \alpha\beta'$. The size of α and β is affected by the rank of Π and the number of variables included in the model. In the end, ε_t are the error terms of the model of a vector that is $n \times 1$, assumed to be independent and identical distributed (i.i.d).

To formally use the Johansen cointegration test, we need to test the matrix (Π) rank in equation (5). The rank of (Π) is recognized by the number of linearly independent rows and columns present in the matrix, e.g., two columns are linearly independent if it is not possible to express one of the columns as a multiple of the other one. We will denote the rank of the matrix (Π) as *(r)*. If *(r)* is equal to zero, there exist no cointegration relationships between the variables. On the other hand, if *(r)* is equal to the number of variables included in VECM, all variables are stationary in levels. To observe one or more cointegrating relationships in the model, *(r)* must be lower than the number of variables and greater than zero. We will consider a bivariate VECM in our study, meaning that we individually test futures contract length up against the spot price.

[6] The modifications from a VAR to a VECM is displayed in appendix section A.4.

The Johansen approach calculates two different test statistics. These are the maximum eigenvalue (λ_{max}) and trace (λ_{trace}) statistics. Both are used and compared against the critical values to identify (r).[7] The two statistics' critical values are depending on a few factors: It depends on how big (r) is, the number of variables present in the model, and if there is a constant included or not. Furthermore, the critical values used in our thesis is provided by Osterwald-Lenum (1992). When using a bivariate VECM, the Johansen tests hypotheses can be presented in two stages:

Table 5.1: The hypotheses for the Johansen test.

	λ_{trace}	λ_{max}
Stage one	$H_0 : r = 0$ $H_1 : r > 0$	$H_0 : r = 0$ $H_1 : r = 1$
Stage two	$H_0 : r \leq 1$ $H_1 : r = 2$	$H_0 : r \leq 1$ $H_1 : r = 2$

Table 5.1 consists of two stages. In the first stage, we test if there exists one cointegration relationship. If the null hypothesis is rejected, we can conclude that there exists at least one cointegration relationship. Thereby, we go to the next stage and test if there exists more than one cointegration relationship. If the null hypothesis is rejected in stage two, both time series variables are stationary in levels because (r) is equal to the model's number of variables. On the other hand, if the null hypothesis is not rejected at stage two, we can conclude that the two variables have a long-run equilibrium.

[7] The functions for λ_{trace} and λ_{max} are presented in A.5 in the appendix.

We will use a bivariate VECM since we individually test the spot price against the futures prices. The VECM in equation (5) is presented in general matrix form and can further be displayed as a bivariate VECM. This is exemplified in the two equations below:

$$\Delta S_t = \underbrace{\alpha_1(S_{t-1} - a - bF_{t-1,T})}_{\text{Long-run}} + \underbrace{\sum_{i=0}^{k} \delta_{11,i}\Delta F_{t-i,T} + \sum_{i=1}^{k} \delta_{12.i}\Delta S_{t-i}}_{\text{Short-run}} + \varepsilon_{1t} \tag{6}$$

$$\Delta F_{t,T} = \underbrace{\alpha_2(S_{t-1} - a - bF_{t-1,T})}_{\text{Long-run}} + \underbrace{\sum_{i=1}^{k} \delta_{21,i}\Delta F_{t-i,T} + \sum_{i=0}^{k} \delta_{22,i}\Delta S_{t-i}}_{\text{Short-run}} + \varepsilon_{2t} \tag{7}$$

α_1 and α_2 are the speed adjustment coefficients in the two equations. If the rank in a bivariate VECM is equal to one, the cointegration vector (β) can be displayed as $\beta = (1, -b, -a)$. The coefficient vectors for the lagged time series variables are $\delta_{11,i}$, $\delta_{12,i}$, $\delta_{21,i,}$ and $\delta_{22,i}$. The last part of the equations is the error terms. The transformed form into equations (6 & 7) will further be used in the next subsections.

5.2 Price discovery

This subsection will present deeper analyzes of the cointegration relationships found in the previous subsection. With prices in equilibrium, unexpected fluctuations due to added information and increased transaction volume create adjustment away from the equilibrium, which is happening until a new equilibrium is recognized (Clark, 1973). The upcoming tests are used to identify where the changes between spot and futures prices occur, i.e., we will investigate the lead-lag relationship between the spot and futures prices in the Nordic power market, which is called *the price discovery function*. A market is said to have price discovery when new information is distributed quickly (Hiemstra & Jones, 1994). Price discovery is a vital function to be performed by the financial market as it indicates which of the spot or futures prices leads the other. The adjustment coefficients (α) from VECM will be analyzed to investigate the long-run relationship between spot and futures prices, and a causality test will be presented to investigate the short-run causal relationship.

5.2.1 Adjustment coefficients

The adjustment coefficients measure the long-run causal relationship between time series variables. From the bivariate VECM presented in equations (6 & 7), we identified α_i as the adjustment or loading coefficients. We retrieve two adjustment coefficients from each of the estimated VECM when the rank of matrix $\Pi = 1$ and the two time series variables are cointegrated. Two elements of the adjustment coefficients should be investigated, and these elements are the significance level and the numerical value of the coefficients. The coefficients state the amount of time it takes for the time series variable to get back to the equilibrium. In a normal situation, the adjustment coefficients should be $\alpha_1 < 0 < \alpha_2$. This has a logical interpretation: If the spot price in equation (6) is too high, then α_1 will make the price go back to equilibrium since α_1 is a negative number and the spot price inside the long-run relationship is positive. On the other hand, if the futures price in equation (7) is too high, α_2 will force the estimated price back towards equilibrium.

5.2.2 Causality test

The causality test we use to test the short-run causal relationship between time series variables was presented by Granger (1969). The Granger causality test is performed through a VAR model, and if the data is stationary, the standard χ^2- or F-tests (Wald test) can be used.[8] If the variables are non-stationary, the distributions of χ^2 may not have the linear restrictions that it usually holds. However, Lütkepohl and Reimers (1992) found that this problem does not affect a bivariate VAR process when testing the Granger causality. Therefore, we use the VAR framework displayed in appendix A.4. The test is performed on the coefficients to the lagged independent variables, which are denoted δ in the equations (6 & 7), separately. The difference between the VAR we use here and the VECM presented in equations (6 & 7) is that the VAR model is in levels format, and it does not have the cointegration term presented as the long-run term in equation (6 & 7). Thereby, the δ terms will be identical in the VAR and are used to display the hypotheses below:

[8] Wald F and χ^2 is expressed in appendix section A.7.

Table 5.2: Hypotheses for Granger causality.

	No rejection: H_0: $\delta_{11,1} = \delta_{11,2} = \ldots = \delta_{11,i} = 0$	Rejection: H_0: $\delta_{11,1} = \delta_{11,2} = \ldots = \delta_{11,i} = 0$
No rejection: H_0: $\delta_{22,1} = \delta_{22,2} = \ldots = \delta_{22,i} = 0$	S_t do not affect F_{t-T} $F_{t,T}$ do not affect S_t (No granger causality)	S_t do not affect F_{t-T} $F_{t,T}$ affect S_t ($F_{t,T}$ Granger causing S_t)
Rejection: H_0: $\delta_{22,1} = \delta_{22,2} = \ldots = \delta_{22,i} = 0$	S_t affect F_{t-T} $F_{t,T}$ do not affect S_t (S_t Granger causing $F_{t,T}$)	S_t affect F_{t-T} $F_{t,T}$ affect S_t (bidirectional Granger causality)

Table 5.2 shows the four outcomes for the Granger causality test. We start testing the lagged futures price coefficients ($\delta_{11,i}$) from equation (6) to see if they are significantly different and affect the spot price in the short run. Furthermore, the test is turned, and we test in the opposite direction if the lagged spot price coefficients ($\delta_{22,i}$) from equation (7) affect the futures price in the short run. If only one of the time series variables affects the other one, we can say that the variable is Granger causing the other one. On the other hand, if the time series variables affect each other, there is evidence of bidirectional Granger causality.

5.3 Unbiasedness hypothesis

We test the unbiasedness hypothesis by putting restrictions on the VECM. The test's purpose is to find out if the futures prices are an unbiased estimator of the forthcoming spot price (Hodrick & Srivastava, 1984). If this is true, Brenner and Kroner (1995) argue there to be no risk premium present in the market. Lai and Lai (1991) used the Johansen (1988; 1991) framework to examine the unbiasedness hypothesis. We will use the same approach as Lai and Lai (1991), putting restrictions on the VECM. We will now further display the restrictions on the VECM to test the unbiasedness hypothesis.

5.3.1 Restricts on the VECM

Market efficiency in weak form can be examined based on equation (2) (Lai & Lai, 1991). To formally state the market as efficient or inefficient depends on the results from the unbiasedness hypotheses. The unbiasedness hypothesis is tested by setting the terms: $a = 0$ and $b = 1$ in equation (2). Equation (2) has a common term with equations (6 & 7), the long-run term in equations (6 & 7). This is the same term as equation (2) and is known as the cointegration term. The likelihood ratio test is used to test the null hypothesis where the restricted VECM is tested against the unrestricted VECM: If the null hypothesis is rejected, we reject that the futures prices are the best estimator of the forthcoming spot price (Hodrick & Srivastava, 1984).[9]

[9] Likelihood ratio test is displayed in appendix section A.6.

6. Results and comments

This section presents our results to answer our research question: Is the Nordic futures power market efficient. Firstly, we are examining the cointegration between the spot and futures prices. This is assessed through the Engle-Granger and Johansen cointegration tests. Secondly, we investigate the cointegration relationships further by retrieving the adjustment coefficients from the VECM, and we perform granger causality to test the causal relationship between the spot and futures prices. Thirdly, the results from testing the unbiasedness hypothesis are presented. The testing approach is related to the cointegration tests as we only test the contracts where we found a cointegrating relationship with the spot price. We investigate if they are unbiased estimators of the forthcoming spot price by restricting the VECM. Finally, we summarize our results.

We use the same interpretation of how to choose the optimal lag length for the models in this section as we did with the ADF test in section 4.3.1, using the information criteria and the Durbin Watson test to identify the lag length, unless otherwise is stated. Logarithm transformation is used to stabilize the variance of the data. Hendry and Juselius (2000) found that if there is observed a cointegrated relationship in log levels, it would be the same for the time series in levels.

6.1 Cointegration

The results from our cointegration tests are presented in Table 6.1. Results from the Engle-Granger test are presented on the left-hand side. The t-value denotes the test statistics from the Engle-Granger cointegration test. We reject the null hypothesis of no cointegration for all the observations at a 10% significance level. Besides, are the first five monthly futures contracts also significant at a 1% level. The Engle and Granger cointegration test results suggest that all the monthly futures contract lengths have a cointegration relationship with the spot price, and the spot and futures prices are tied together in long-run equilibrium.

The right-hand side of Table 6.1 shows the results from the Johansen cointegration test. Both of Johansen's test statistics are presented, the trace (λ_{trace}) and maximum eigenvalue (λ_{max}). The number of lags is chosen based on a VAR framework explained in appendix A.4, and the information criterions explained in appendix A.1, but we subtract the number of lags from the VAR with one because the Johansen test is performed in first difference while VAR is in levels. When the number of lags is settled, both hypotheses presented in Table 5.1 are tested. The null hypotheses from stage one are rejected if the test statistics are above the critical values, i.e., rejecting the null hypothesis of no cointegration. For the monthly futures contract lengths, we identify the test statistics to be decreasing when the time to maturity increases. 1- and 2-months to maturity are significant at a 1% level, and 3-,4- and 5-months to maturity are significant at a 5% level. The 6-months to maturity contract is not significant at all for the maximum eigenvalue test. Test statistics from stage two of the Johansen cointegration test suggest none of the null hypotheses being rejected. This supports that the time series are cointegrated because the rank of the matrix (Π) is bigger than zero and less than the number of variables.

To summarize, we identify a long-run equilibrium relationship between the spot price and the monthly futures contracts with 1- to 5-months until maturity.

Table 6.1: Cointegration test results.

	Engle-Granger		Johansen				
			Stage one			Stage two	
				r = 0		$r \leq 1$	
Variables	Lags	t-value	Lags	λ_{trace}	λ_{max}	λ_{trace}	λ_{max}
S, M_1	7	-12.14***	25	67.53***	65.86***	1.66	1.66
S, M_2	2	-8.04***	26	33.31***	28.55***	4.76	4.76
S, M_3	2	-5.68***	27	23.39**	28.60***	3.79	3.79
S, M_4	3	-4.67***	22	23.70**	18.41**	5.28	5.28
S, M_5	2	-4.20***	27	21.67**	15.29**	6.37	6.37
S, M_6	5	-3.35*	22	16.40*	11.40	5.00	5.00

Note: The statistics for the Engle-Granger and Johansen test is presented in the table. S and M_T represent the spot price and the futures contract with *T* months to maturity. The number of lags is selected based on the goodness of fitness of the model. For trace and eigenvalue tests, the results from the hypothesis tests of the rank r = 0 and r ≤ 1 are presented. Critical values for the Engle-Granger test are: -4,0 (***), -3,37 (**) and -3,02 (*), where ***, ** and * represent significance levels of 1%, 5% and 10%. Critical values for the Johansen test are found in Osterwald-Lenum (1992).

6.2 Price discovery

The results from long- and short-run causality tests are presented in Table 6.2 and Table 6.3. The adjustment coefficient is measuring the long-run relationship, and the Granger-causality test displays the short-run relationship. If we recognize the futures prices to lead the spot price, we can argue that the futures market has price discovery for the spot market (Silvapulle and Moosa, 1999).

6.2.1 Adjustment coefficients

The value of the adjustment coefficients is presented in Table 6.2. A long-run causal relationship is identified if the adjustment coefficients are significant. The α_1 coefficients are all significant at a 1% significance level. This supports the assumption related to the causal relationship. We find the futures prices to lead the spot price, and there is a long-run causal relationship. The significant coefficients' value explains how the long-run equilibrium deviation from the last period is corrected in the current period. In other words, the speed of the long-run causality. When α_1 is negative, it tells us that there is a long-run relationship, and the prices will eventually converge back towards the equilibrium. For 1-month to maturity contract length, the value is -0.572. This indicates that 57,2% of the deviation from long-run equilibrium will be adjusted in one day because we work with daily data. We observe from Table 6.2 that the adjustment coefficient's speed decreases as the time to maturity increases for the futures contract lengths. On the other hand, the α_2's from the VECM is not significant for any of the futures contract's lengths, indicating a univariate relationship between the spot and futures prices.

Table 6.2: Adjustment coefficients from the VECM.

Contract length (T)	Dependent variable	Lags	α_i	Adjustment coefficients
Monthly futures:				
1	ΔS_t	25	α_1	-0.572***
	ΔM_{t-T}	25	α_2	0.007
2	ΔS_t	26	α_1	-0.103***
	ΔM_{t-T}	26	α_2	0.013
3	ΔS_t	27	α_1	- 0.062***
	ΔM_{t-T}	27	α_2	0.004
4	ΔS_t	22	α_1	-0.034***
	ΔM_{t-T}	22	α_2	0.003
5	ΔS_t	27	α_1	-0.022***
	ΔM_{t-T}	27	α_2	0.003

Note: ΔSt and ΔM_{t-T} indicate which of the variables are the dependent variable. α is measuring the adjustment speed. ***, ** and * is referring to significance levels at 1%, 5% and 10%, respectively.

6.2.2 Granger causality

Table 6.3 presents the Granger causality test results, which identify the short-run causal relationship between the spot and the futures prices in the Nordic power market. The test is based on the VAR framework displayed in Appendix A.4. The VARs are in levels, so the results are presented with one more lag than the VECM. 1-month to maturity futures contract has a bidirectional relationship, which means that both the spot and futures prices affect each other. The other futures contract lengths have a univariate relationship where the futures prices are Granger-causing the spot price at a 1% significance level. Granger-causing is, in this sense, measuring the lead-lag relationship between the spot and the futures prices. The Granger causality test results support the cointegration relationships we found in section 6.1 because the observed results suggest that there is at least one-directional causal relationship between time series. Granger (1988) required at least a one-directional relationship to support the cointegration test.

There are minimal differences between the two tests displayed below. The F-test states that the spot price is Granger-causing the futures price for the 2-months contract length at a 10% significance level, while the Wald test rejects it. The Wald test says that the 5-months contract length is Granger-causing the spot price with a 5% significance level when the F-test indicates it at a 1% significance level. These differences are minimal and do not have further implications on the results.

Table 6.3: Granger causality test performed with F-test and Wald test.

Contract length (T)	Dependent variable	Lags	F-test	Wald test
Monthly futures:				
1	S_t	26	[0.000]***	[0.000]***
	M_{t-T}	26	[0.000]***	[0.000]***
2	S_t	27	[0.000]***	[0.000]***
	M_{t-T}	27	[0.063]*	[0.170]
3	S_t	28	[0.000]***	[0.000]***
	M_{t-T}	28	[0.500]	[0.520]
4	S_t	23	[0.000]***	[0.000]***
	M_{t-T}	23	[0.567]	[0.730]
5	S_t	28	[0.000]***	[0.036]**
	M_{t-T}	28	[0.935]	[0.820]

Note: The p-values for the F-test and Wald test are presented. ***, ** and * is referring to significance levels at 1%, 5% and 10%.

6.3 Unbiasedness

We have previously, and until this point, identified that the time series are integrated in the first order, I(1), and results in the previous subsection suggest the cointegration relationship for five out of six of the monthly futures contract lengths. The cointegration relationship needs to be present before testing the unbiasedness hypothesis, and the causality tests are used to support the cointegration relationships. We will now present the results from the unbiasedness hypothesis, which answer our research question if the Nordic futures power market is efficient.

Table 6.4 displays LR statistics and p-value from the unbiasedness hypothesis. If the statistics are significant, we reject the null hypothesis that the futures price is an unbiased predictor of the forthcoming spot price. The 1-month to maturity contract length is the only contract that is not rejected. All the other monthly futures contract lengths are significant and therefore considered as biased predictors of the forthcoming spot price. The 1-month contract length supports the efficient market hypothesis, saying that the futures price is an unbiased predictor of the forthcoming spot price. On the other hand, the rest of the futures contract lengths do not support market efficiency. Therefore, the market is seen as inefficient when the time to maturity increases. This is further discussed in section 7.

Table 6.4: LR statistic from testing the unbiasedness hypothesis.

	VECM	
	Lags	LR
ΔS, ΔM_1	25	1.92[0.17]
ΔS, ΔM_2	26	5.83[0.02]**
ΔS, ΔM_3	27	6.29[0.01]***
ΔS, ΔM_4	22	4.84[0.03]**
ΔS, ΔM_5	27	4.49 [0.03]**

Note: LR statistic results for the unbiasedness hypothesis are presented in the table, with the p-value denoted inside the brackets. ΔS and ΔM_t represent the spot price and the futures contract with *T* months to maturity. The numbers of lags are selected based on the well-specified model principal. Restrictions for the model are $a = 0$ and $b = 1$. ** and *** denotes for 5% and 1 % significance levels, respectively.

6.4 Summary of the results

We found cointegration relationships between the spot price and 1- to 5-months futures contract lengths from the cointegration tests. The spot and futures prices might be deviating in the short run, but the prices eventually converge towards equilibrium because of the long-run equilibrium relationship. The 6-months futures contract length is not significant, suggesting no cointegration relationship with the spot price.

In relation to the cointegration tests, we investigate the price discovery function and the lead-lag relationship between the spot and the futures prices. Our findings supported the cointegration relationships where we found at least one-directional causal relationship between the two-time series. We found a univariate relationship for 2- to 5-months to maturity futures contracts, where the futures prices lead the spot price supporting the price discovery function. However, we found a bidirectional relationship for the 1-month futures contract, where the spot and futures prices are Granger-causing on each other. The futures prices tend to have a price discovery function on the spot price development based on the results.

The unbiasedness hypothesis is tested for all futures contract lengths with a cointegration relationship with the spot price. We found that the unbiasedness test to hold for 1-month contract length, and therefore the market efficiency hypothesis holds for this futures contract length. This futures contract length is an unbiased estimator of the subsequent spot price. The unbiasedness hypothesis is rejected for all the other significant futures contracts having a cointegration relationship with the spot price. Our results suggest that these futures contract lengths are biased estimators of the forthcoming spot price. Based on the observations from the tables above, we get that the results from the unbiasedness hypothesis are deviating, where we find the futures market to be both efficient and inefficient. In relation to these observations, we see that the time to maturity affects the results. This will be further discussed in the next section.

7. Discussion

This section will address our results and compare them with earlier studies from the Nordic power market. The overall discoveries from our research will be presented, and we will investigate exciting findings related to the development of the Nordic power market. After that, future studies of our research will be presented. There are also some limitations to our data that could affect our results, and these will be presented at the end of this section.

7.1 Discussion of the results

The results from our tests are displayed in section 6. The upcoming subsection will address these results and give the reader a better understanding of what the results express related to the Nordic power market. We start by discussing how time to maturity could affect our results before we move on to discussing efficiency in the Nordic futures power market. These elements are leading to our study's conclusion that will be given in the next section.

7.1.1 Implications of time to maturity

We observe a clear trend from both the Engle-Granger and the Johansen cointegration tests, presented in Table 6.1. Longer to maturity corresponds to decreased test statistics, making us less likely to reject the null hypothesis correctly. The chance of observing a cointegration relationship reduces as the time to maturity increases; this is additionally supported in Figure 4.1. The figure shows increased deviations between the spot price and the futures prices series as the time to maturity increases. Two explanations are likely to contribute to these results, when the time to maturity decreases, the transaction volume in the futures market increases. Moreover, the uncertainty increases when the time to maturity increases because the future is harder to anticipate. This is supported by previous studies that we present below.

The Samuelson hypothesis argues that futures price volatility increases as the time to maturity decreases, and the contract lengths are approaching the expiration date (Samuelson, 1965). Jaeck and Lautier (2016) explain the hypothesis, reflecting on the futures market. They argue that contract lengths with a shorter time to maturity react more strongly to information shocks. These contract lengths are closing in towards the expiration date and will ultimately converge towards the spot price. Therefore, closer to maturity contract lengths are considered more sensitive to new information. In relation, Jones and Lipson (1995) suggest increased volatility to correlate with increased transaction volume. Our results support these studies and are available in Table 4.1 and Figure 4.1, where we observe that the standard deviation and volatility are higher for the closer to maturity futures contracts. In this relation, Gjolberg and Brattested (2011) express that shorter time to maturity futures contracts are more applicable for participants and states this to be a key factor for the increased volumes among futures with shorter maturity dates. This could also be used as an argument, explaining why longer to maturity futures contracts are associated with more uncertainty, making sense as less information is available for the investors.

We are referring to Granger (1988) in section 6. This is because causality in at least one direction is a prerequisite for obtaining a cointegration relationship between two variables. The interpretation of the adjustment coefficient could also be reflected by the time to maturity. The adjustment coefficient (α) from equation (6 & 7) measures the percentage adjustment towards equilibrium for the significant values and reflects the long-term equilibrium relationship. The coefficient specifies how long it takes for deviating prices to get back to the equilibrium; these coefficients are presented in Table 6.2. We see that closer to maturity futures exhibit bigger numerical changes and are quicker to adjust back towards equilibrium when a cointegration relationship is present. This explains how the long-run causality is relevant and supports the observations from the cointegration tests.

Our observations from the short-run causality test support the long-run causality, where we identify at least one-directional relationship between the spot and futures prices. We see from Table 6.3 that the only futures contract length with a bidirectional relationship is the 1-month to maturity contract. Which makes sense as this is the contract length with the closest time to maturity. Fleten et al. (2015) describe how spot and futures prices ultimately will converge towards each other. Because the 1-month futures contract is the closest to maturity and expiration date, will the price, at the time, be closely connected to the spot price, and therefore will the prices be causal-affecting on each other. This is supported by Miffre (2000) and the development of the futures curve. As the maturity date comes closer, the futures price will move towards the spot price. Simultaneously, we observe that the longer time to maturity contracts is Granger-causing on the spot price and that futures prices lead the spot price.

Based on the causality test results, we identify that the futures prices lead the spot price in the electricity market, supporting a cointegration relationship (Granger, 1988). In this relation, Deng and Oren (2006) suggest that leading futures prices could be used to manage risk and reduce uncertainty, increasing the participants' utility. This is based on our test results, indicating more deviation from the equilibrium price for longer to maturity contract lengths, providing participants with hedging opportunity. Oliveira and Ruiz (2020) support this view, pointing at increased uncertainty levels among electricity futures contracts as the time to maturity increases. Fleten et al. (2015) is also referring to futures with longer to maturity as hedging products. However, the same argumentation related to the abnormality could also be addressed related to the risk premium. This is presented by (Bessembinder & Lemmon, 2002). They explain a potential risk premium for futures contracts with longer to maturity, arguing that the premium disappears closer to maturity when the equilibrium is restored. In this sense, risk premium and risk reduction need to be carefully addressed. The associated risk for the hedging and the speculative participants will be depending on the market and has to be seen in relation to market efficiency or inefficiency. Therefore, the unbiasedness hypothesis becomes relevant to investigate if the risk premium is present or not in the futures market.

7.1.2 Interpretations of the unbiasedness hypothesis

We test the unbiasedness hypothesis on all the contract lengths which have a cointegration relationship with the spot price. This is related to the results from Table 6.1, which suggest five out of six contract lengths to have a cointegration relationship with the spot price. Table 6.4 shows that the only unbiased contract length is the 1-month futures contract, and the rest of the contract lengths are biased estimators of the subsequent spot price. Our observations and results are in line with Gjolberg and Brattested (2011) for the longer time to maturity futures contracts. They suggest that the futures prices are biased forecasts of the forthcoming spot price and states inefficiency in the Nordic futures power market.

Further, they suggest a potential risk premium in the electricity futures market related to the biased observations. This is in line with Botterud et al. (2010). They indicate a risk premium in electricity prices that are influenced by deviations from equilibrium prices. The unbiasedness hypothesis is rejected for longer to maturity futures contracts. With such a result, Lai and Lai (1991) suggest that the market analysis does not support the efficient market hypothesis and is neither supporting the absence of a risk premium. In other words, the futures prices as a biased estimator of the subsequent spot price are opening up for possibly speculative gains in the futures market. This is in line with both Botterud et al. (2010) and Gjolberg and Brattested (2011), which are essential literature assessing efficiency in the electricity market.

The potential risk premium in the electricity futures market is exciting and needs to be assessed. Gjolberg and Brattested (2011) suggest risk premium opportunities based on the significant demand for long hedges. These demands are based on the consumer's constant fear of increased electricity prices. Their need to secure themselves for the correct quantity is the argument for a contango market situation, where the futures prices are above the spot price (Keynes, 1930). Gjolberg and Brattested (2011) presented results on futures prices between 1998 and 2010. We, on the other hand, present data from 2015. In between, it looks like the futures prices have changes dynamics. Our results suggest that the futures prices are traded below the spot price and a market in normal backwardation. This is based on observation from Table 4.1. Oliveira and Ruiz (2020) suggest that this is caused by changes in the hedging demand, where cost and demand uncertainty have increased. In this relation, risk-averse generators prefer to sell electricity to a lower futures price, in contrast to the observations presented by Gjolberg and Brattested (2011).

Smith-Meyer and Gjolberg (2016) presented research on electricity prices, responding to Gjolberg and Brattested (2011). Before 2008, they observe the market as inefficient, supporting Gjolberg and Brattested (2011). However, they suggest efficiency in the Nordic power market after 2008, and the risk premium disappears. Smith-Meyer and Gjolberg (2016) argue increased integration in the European electricity market with the opening of new power grids and risk exposure changes to explain the market changes and why it is efficient after 2008. Our observations on power prices after 2015 suggests that most of the futures contract lengths are biased estimator of the subsequent spot price.

Recent changes in the electricity price and new studies can explain some of our research and previous studies' differences. First, they used DS futures prices in their research, while we have used the new futures that entered the market in 2015, which we have deeply described in section 2. Secondly, Figure 4.1 displays high volatility in recent years' electricity prices, with a massive fall in both spot and futures prices in 2019. This could affect our results, where we find inefficiency for most of our futures contract lengths.

7.1.3 Recent year electricity price change

Above, we introduce recent price changes and increased volatility in electricity prices, but it is interesting to go deeper into recent price changes. These price changes could explain why the futures power market has changed from efficient to inefficient.

Hafsaas (2020) presents natural reasons for the decreased electricity price level in 2020, stating this price drop to be caused by a general higher temperature, more snow-melting, and higher water levels in the reservoirs. However, there could also be other underlying explanations for the recent price observations in the Nordic power market. Nord Pool (2020b) presents how increased focus on renewables has made it harder for the market participants to balance their portfolios in the day-ahead market. Renewable energy resources, such as wind and solar power, are difficult to predict. The total production amount is uncertain for these renewable resources related to intermittency in the production capacity, where the wind speed and the solar capacity come from outside events that are impossible to control.

Ruggiero and Lehkonen (2017) suggest that the increased supply of renewable energy negatively affects the electricity spot price level and increases the uncertainty related to long-term price levels. However, we cannot exclusively point at the renewable focus as a factor that will only increase the supply side. The electricity demand will also be affected by the increased focus on green energy and increased electricity consumption. Kapustin and Grushevenko (2020) refers to increased electrical focus in the car industry and suggest the demand to be growing a lot in the future, indicating a higher future electricity price level. This is also related to a general focus on green economic growth in the industry sector. Uncertainty of both supply and demand for electricity increases the tension related to long-term price expectations in the futures market and could explain why the futures market has become inefficient.

7.2 Future studies

Our research shows that the futures electricity prices have changed from being in a contango market situation towards normal backwardation, where the futures prices are below the spot price. Further investigations of these price changes between the spot price and futures prices could be exciting to study and investigate further. We suggest that the observed price relationships could be caused by the shift in hedging demand and the risk-aversion to both producers and consumers.

Further, there is an increased focus on renewable energy, where intermittency is creating price fluctuations, and producers prefer to secure market prices in the futures market. Goodarzi et al. (2019) suggest that increased renewable energy production creates complexities. Renewable energy is creating lots of opportunities for electricity production. On the other hand, there is an enormous focus on the consumption side, shifting the economic value creation towards green production, increasing electricity demand (Kapustin & Grushevenko, 2020). Research on how these factors will affecting electricity prices is interesting. It might be affecting futures electricity prices and the hedging demand for both producers and consumers.

Another exciting element is the European power collaboration and increased power transportation between countries. The European Union aims to establish energy collaboration between countries to support an overall strategy where the target is increased sustainability and economic competitiveness (Child et al., 2019). One example of this collaboration is the new power-grid between Norway and Germany, called *Nordlink*. Increased production in Germany in times with much wind could increase their export to Norway, affecting and potentially reducing the hydropower production. How is this affecting the future development of both spot and futures electricity prices? The argumentation is showing how European power collaboration could stabilize electricity prices. Related to our findings, we find that the longer to maturity futures contracts are biased estimators of the subsequent spot price. If the power collaborating between European countries could stabilize electricity prices, this could affect the futures market's efficiency.

Another aspect to investigate is the potential relationship between the adjustment coefficients from VECM and market efficiency. We found a high value measuring the adjustment for the 1-month to maturity contract length, with an adjustment coefficient of 0.572, indicating that the spot price adjusts relatively quickly back towards equilibrium. The adjustment coefficients were lower for the other futures contract lengths, and for these contract lengths, the unbiasedness hypothesis was rejected. Therefore, it could be interesting to investigate if there exists a relationship between the adjustment coefficient and market efficiency.

7.3 Limitations of our data

Figure 2.1 shows a decreasing trend in the total transaction volume of futures contracts at Nasdaq OMX. Reasons for the decreasing trend could be that non-financial members at Nasdaq OMX have lost the opportunity to use bank guarantees and the increased use of PPAs. The reduced volume does not have any significant implications for our study. However, if the trend continues, and the futures transaction volume keeps falling, this might have implications for forthcoming studies on electricity futures prices.

Electricity prices are often affected by seasonality, where the spot price is higher in the winter and cheaper in the summer. From Figure 4.2, we concluded that it would be difficult to adjust for seasonality because the average monthly spot price could be highest in one year, while in later years could be the opposite. We have observations for five years because the futures we investigate were first issued in late 2015. If the sampling period had been longer, it could have been easier to investigate a seasonal pattern, which could be a limitation for this part of our study. However, we did not find a reasonable way to adjust for seasonality, as we argue to be difficult based on the observations in Figure 4.2.

Cheung and Lai (1993) found that not normally distributed data could affect the Johansen test results. They found the trace test from the Johansen test presented in section 5 more robust than the maximum eigenvalue test when considering non-normality time series. We identify from Table 4.1 that multiple of the time series were non-normal distributed using the Bera Jarque test, but considering our variables’ excess kurtosis and skewness; the data is close to being normally distributed. We also identified that the spot price could have multiple peaks in the distribution, affecting the time series’ normality.

8. Conclusion

The research question assessed in this thesis: Is the futures electricity market efficient? We have conducted daily electricity spot price data from Nord Pool and daily observations of futures contracts with 1- to 6-months to maturity from Bloomberg. Our data consist of observations from the period 01.10.2015 to 15.09.2020. The data material has been treated carefully in statistical programs, excel and R. This is done to create suitable analyses for us to assess efficiency in the Nordic futures power market.

When the time series are non-stationary, conventional statistical procedures will give spurious results and wrongly answer our research question. Therefore, we had to use approaches that could handle the challenge of non-stationary time series. Cointegration techniques developed by Engle and Granger (1987) and Johansen (1988) consider this problem. The cointegration technique identifies if there is a long-run equilibrium between the spot and futures prices. The Engle-Granger test and the Johansen test found a cointegration relationship between the spot price and 1- to 5-months futures contract lengths. However, we observe the test statistics from the cointegration tests to decrease as the time to maturity increases, suggesting the cointegration relationship to be stronger for the contract lengths closest to the expiration date.

To support the cointegration tests results, the Granger causality test is implemented, and we investigated the adjustment coefficients obtained from the VECM. We identified that 2- to 5-months futures contracts lead the spot price. The 1-month to maturity contract length has a bidirectional relationship with the spot price, meaning that both the spot and the futures price affect each other. These testing methods supported each other and suggests at least one directional relationship between the spot and the futures prices, which is a prerequisite for the cointegration tests.

We test the unbiasedness hypothesis for all the futures contract lengths with a cointegration relationship with the spot price. The results suggest that the unbiasedness hypothesis holds for the 1-month to maturity contract, indicating that the weak-form efficient market hypothesis holds for the closest contract length. The rest of the contract lengths is biased estimators of the forthcoming spot price, and the unbiasedness hypothesis was rejected for these contract lengths. These observations are in line with Botterud et al. (2010) and Gjolberg and Brattested (2011), which indicates that the market seems inefficient and opens up potential risk premium in the futures market.

We have seen significant changes in the Nordic futures power market, which has affected the relationship between the spot and futures prices, and we find inefficiency for most of the contract lengths. Based on our results, we suggest a potential risk premium in the Nordic futures power market, and likewise, the risk reduction opportunities in the futures market are uncertain.

Other observations from our thesis support these findings: we have seen that the electricity spot price trading at Nord Pool is volatile as a commodity product. In recent years, we have observed tremendous changes in the spot price, where the market has experienced a spot price level close to zero, and in some areas, prices have been below zero. We have seen structural changes in the futures market, introducing a new type of futures contract, regulatory changes for non-financial members, and introduced renewable energy as resources that will affect the electricity futures market. However, some of these changes are relatively new, and the market effects of these changes are not entirely settled. This makes it hard to predict the development of the forthcoming electricity futures prices and makes it even harder to state the market as efficient.

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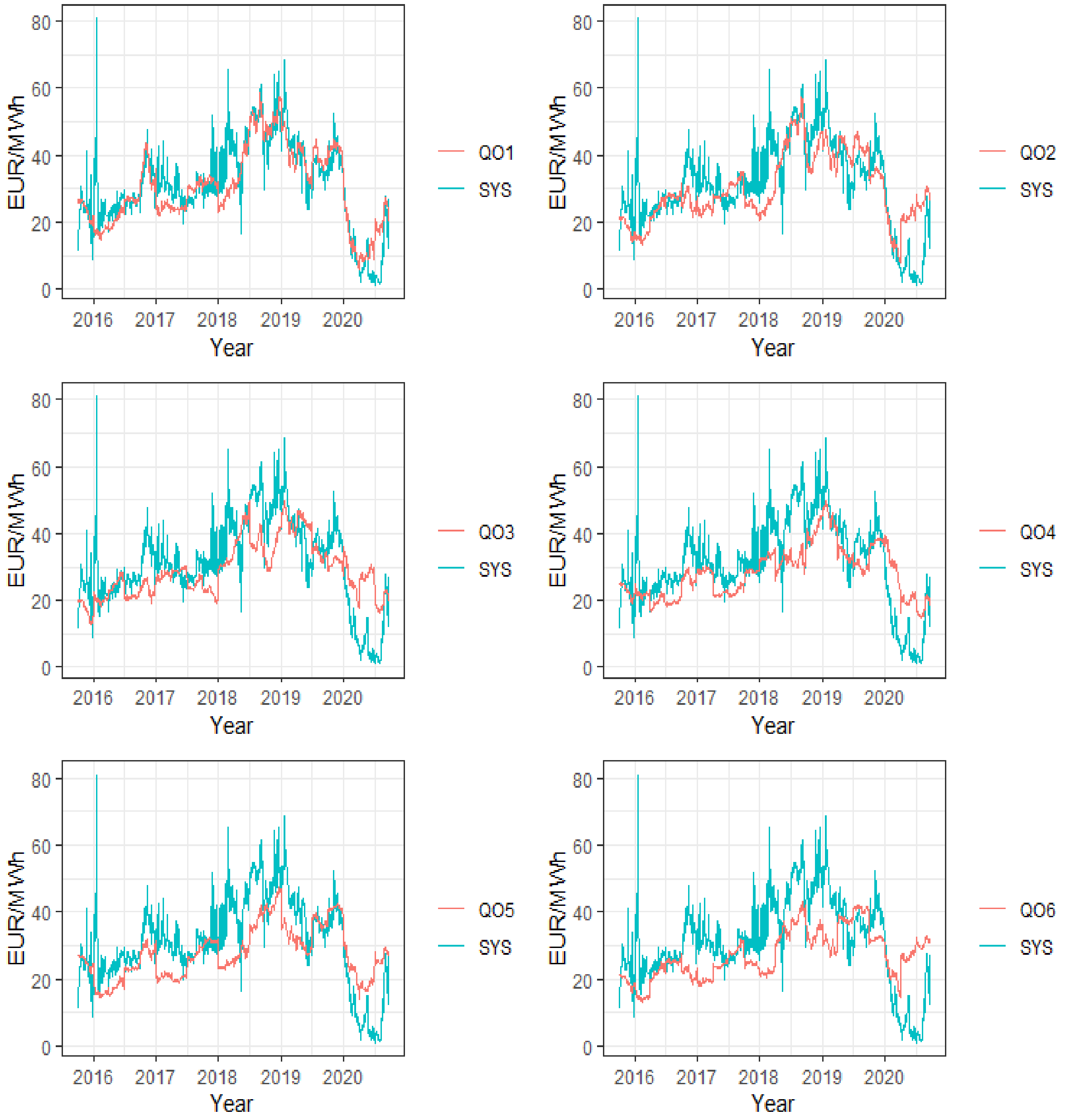
Appendix

A1 Quarterly price plots



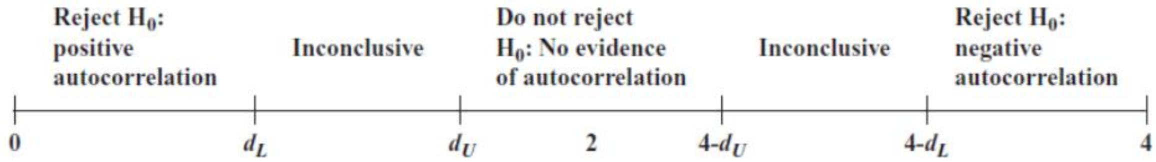
A. 1: Price gaps in quarterly futures contracts.

A2 Autocorrelation

Durbin-Watson (DW) test investigating the first-order autocorrelation:

$$DW = \frac{\sum_{t=2}^{T}(\hat{u}_t - \hat{u}_{t-1})^2}{\sum_{i=2}^{T}\hat{u}_t^2}$$

T is the number of observations and $\hat{u}$ is the estimated error term. The DW test does not follow any standard statistical distribution but has two critical values: *upper* and *lower* critical values. The DW statistic can lie in the range from 0 to 4, and if the test statistic is equal to 2, there is no autocorrelation. If the test statistics is in the middle section in the figure below, the null hypothesis cannot be rejected (Brooks, 2019). Furthermore, there is an inconclusive section between the upper and lower critical values where the test is insecure about the outcome. The inconclusive area between the critical values becomes smaller when the sample size becomes bigger and will also be affected by the increase in explanatory variables.



A3 Information criteria functions

The functions of the information criteria's used in this thesis are presented below:

$$AIC = \ln(\hat{\sigma}^2) + \frac{2k}{T}$$

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

$\hat{\sigma}^2$ is the variance from the residuals, k is the number of parameters, and T is the number of observations.

A4 Vector Autoregressive model

An autoregressive model (AR) of a variable is a model that is a regression of itself. In other words, it uses past values of the variable to estimate a model. Logically, a VAR is an extension of the AR where there is more than one variable estimating the model. A bivariate VAR, consisting of two variables and with lag length p = 1, can be displayed as:

$$y_t = \beta_{y0} + \beta_{y1}y_{t-1} + \alpha_{y1}x_{t-1} + u_t^y$$

$$x_t = \beta_{x0} + \alpha_{x1}y_{t-1} + \beta_{x1}x_{t-1} + u_t^x$$

In matrix form:

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} \beta_{y0} \\ \beta_{x0} \end{pmatrix} + \begin{pmatrix} \beta_{y1} & \alpha_{y1} \\ \alpha_{x1} & \beta_{x1} \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} u_t^y \\ u_t^x \end{pmatrix}$$

y_t and x_t are two variables, β_{y0} and β_{x0} are the constants, α_{i1} and β_{i1} are parameters that depend on the lagged values y_{t-1} and x_{t-1}, and the last terms u^y and u^x are the white noise terms with an expected value equal to zero. When modifying a VAR into a VECM, the model is made into error correction form. This is because all variables need to be in I(0) to be OLS regressed. Taking ($_{t-1}$) from both sides:

$$\begin{pmatrix} y_t - y_{t-1} \\ x_t - x_{t-1} \end{pmatrix} = \begin{pmatrix} \beta_{y0} \\ \beta_{x0} \end{pmatrix} + \begin{pmatrix} \beta_{y1} - 1 & \alpha_{y1} \\ \alpha_{x1} & \beta_{x1} - 1 \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} u_t^y \\ u_t^x \end{pmatrix}$$

$$\begin{pmatrix} \Delta y_t \\ \Delta x_t \end{pmatrix} = \begin{pmatrix} \beta_{y0} \\ \beta_{x0} \end{pmatrix} + \begin{pmatrix} \pi_{y1} & \pi_{y1} \\ \pi_{x1} & \pi_{x1} \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} u_t^y \\ u_t^x \end{pmatrix}$$

$\pi_{y1} = \beta_{y1} - 1, \pi_{y1} = \alpha_{y1},\ \pi_{x1} = \alpha_{x1}, \pi_{x1} = \beta_{x1} - 1.$

The bivariate VECM with lag length p = 1 can be displayed in a general form as:

$$\Delta Y_t = \beta_0 + \Pi Y_{t-1} + u_t$$

The equation above is the general form of a bivariate VECM, and if more lags are included in the model, it will be equal to equation (5).

A5 Trace and maximum likelihood functions for the Johansen test

$$\lambda_{trace}(r_0, n) = -T \sum_{i=r_0+1}^{m} \ln{(1 - \hat{\lambda}_i)}$$

$$\lambda_{max}(r_0, r_0 + 1) = -T ln(1 - \hat{\lambda}_{r_0+1})$$

T is the number of observations, k is the number of linear independent relationships and $\hat{\lambda}$ is the eigenvalues calculated from the VECM. Trace test identifies if the matrix Π is equal to r_0 up against the alternative hypothesis, that the rank of Π is bigger than r_0 and less than the number of variables (n). The maximum eigenvalue test identifies if the largest eigenvalue r_0 is zero against the alternative hypothesis of r_0+1. r_0 is the null hypothesis testing if the rank of Π is equal to zero.

The two functions above create the test statistics used to compare against the critical values presented by Osterwald-Lenum (1992).

A6 Likelihood ratio test

The likelihood ratio test presented in this thesis can be expressed with the following model:

$$LR = T\sum_{i=1}^{r} \ln\left(\frac{1-\lambda_i^*}{1-\lambda_i}\right)$$

λ^* is the eigenvalues retrieved from the restricted model, and λ is the eigenvalues under the unrestricted model. *T* is the number of observations.

A7 Wald- and F-test

Wald- and F-test is used to see if independent variables add valuable information to a model by investigating if the variables are significant. These tests can be performed on both univariate and multivariate models.

$$Wald\ test = \left(\hat{\theta} - \theta_0\right)' [Var\left(\hat{\theta}\right)]^{-1} \left(\hat{\theta} - \theta_0\right)$$

$\hat{\theta}$ is the maximum likelihood of the parameter(s), θ_0 is the value of the parameter(s) for the null hypothesis, and $Var\left(\hat{\theta}\right)$ is the variance of the maximum likelihood of the parameters(s).

$$F - test = \frac{(SSR_R - SSR_{UR})/p}{SSR_{UR}/(N - p - 1)}$$

SSR is the sum of squared residuals, *R* and *UR* are the restricted and unrestricted regression models, *N* is the number of observations, and *p* the number of parameters.