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Master Thesis

Thesis Master of Science

HEDGING WITH ELECTRICITY FUTURES

Hedge Performance and Market Development in the Nordic Electricity Market

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Start: 15.01.2020 09.00

Finish: 01.09.2020 12.00

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MSc in Business with Major Finance

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Oslo, June 30, 2020

ABSTRACT

This Master Thesis estimates and applies three various futures hedging strategies for the spot exposures at the Nordic electricity market. We compare the variance and hedging effectiveness of the traditional naïve hedge, the static Ordinary Least Squares (OLS) hedge, and the dynamic Constant Conditional Correlation GARCH (CCC-GARCH) hedge. The various hedging strategies are implemented on monthly- and quarterly futures contracts with different hedging durations. The key finding of our study is that futures contracts can reduce some price uncertainty compared to an unhedged position, even with the lack of straight forward arbitrage possibilities in the electricity market. The results indicate that dynamic hedge ratios can in some cases be more efficient than a static approach, when ARCH-effects are present. Furthermore, we find that an electricity producer will not benefit from hedging over a longer duration. The main reason for this is that that the correlation between spot- and futures returns are generally higher for the contracts with a shorter duration. This might indicate that noise in the Nordic electricity market is not cancelled over time. We find that both spot- and futures returns have developed to become even more volatile over the years, which may be explained by the market developing towards more renewable- and intermittent energy.

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1.0 Introduction

The electricity market was deregulated in the 1990s to increase the competition and get a more efficient allocation of economic resources (Nord Pool, 2020c). Consequently, prices are now determined by the integration between supply and demand. This shift in price determination led to higher price volatility. In the new market situation, electricity producers sell their electricity in potentially volatile spot markets and can therefore be at risk if spot prices are insufficient to cover production costs. This price uncertainty introduces market risk for all participants, creating an incentive for risk management. The market liberalization has resulted in an increased interest in electricity derivatives as a risk management tool.

Electricity can be considered as a flow commodity that is strongly characterized by its limited storability and transportability, and the prices are substantially more volatile than other commodity prices. The Nordic electricity market is split between a physical and a financial market, where trading takes place on separate exchanges (Norwegian Ministry of Petroleum and Energy, 2020b). The physical electricity trading takes place on Nord Pool AS, while Nasdaq Commodities accounts for the financial trading. The special characteristics of the electricity market as well as its continuous development, makes a further investigation of the market and the effectiveness of various hedging strategies an important and interesting research topic. A lot of the research on hedging effectiveness in the electricity market is from the early 2000s. The key contribution of this thesis is that we examine the development of the market and if our results on electricity price hedging using futures are consistent with earlier research.

The scope of this thesis is to test if hedging with electricity futures contracts available at NASDAQ Commodities result in reducing the volatility an electricity producer face when selling at the spot market. The thesis investigates naïve one-to-one, static OLS, and CCC-GARCH hedging approaches. In addition, we analyse the effect of different contracts with various holding periods. The optimal hedge ratios are estimated with the minimum variance method and the various hedging approaches are compared using Ederington (1979) hedge effectiveness metric. The results are also compared in- and out-of-sample. In addition, we observe how the effectiveness of hedging with futures has changed over time and study how the electricity market has developed.

Our results show that hedging with electricity futures contracts reduce volatility in the Nordic electricity market, however, the hedge effectiveness depends on the strategy, the contract, and the hedging duration. When ARCH-effect are present, dynamic hedge ratios can in some cases be more efficient than a static approach. Hedging with futures that have longer hedging durations does not obtain superior performance compared to hedging with shorter durations. The spot- and futures returns in the market have developed to become even more volatile over the years, which might give a strong incentive for electricity producers to manage the risk.

The next section of this paper presents background information regarding the Nordic electricity market and electricity price characteristics. Section 3 provides a brief review of the related literature. Section 4 explains the empirical methods and models, which includes statistical tests, the minimum variance method, the various hedging strategies, the hedge effectiveness metric, and backtesting. Section 5 gives an overview of how the data is collected and transformed, as well as a preliminary data analysis. Based on the preliminary analysis, the expected results are discussed. Section 6 provides a discussion of the results. Lastly, section 7 of the thesis concludes upon the performance of the various hedging strategies, the impact of contracts with different maturity and holding periods, and the market development.

2.0 Background

2.1 The History

In the 1990s, the Nordic countries deregulated their electricity markets and brought their individual markets together into a common Nordic market, Nord Pool (Nord Pool, 2020c). Norway deregulated their electricity market in 1991, Sweden followed in 1996, and Finland and Denmark joined the exchange by 2000 (Nord Pool, 2020b). A deregulation of the electricity market means that free competition is introduced, and that the electricity price is determined by the balance between supply and demand. This change was undertaken to create a more efficient market, including exchange of electricity between countries and increasing the security of supply. Consequently, integrating the markets enhance productivity and the electricity capacity can be used more efficiently.

Nord Pool has later grown to become the market for selling and buying electricity in most of northern Europe, and one of its roles is to provide accurate information to the market and ensuring transparency (Nord Pool, 2020b). The market is split into a physical- and financial market (Norwegian Ministry of Petroleum and Energy, 2020b). The physical market consists of three organized markets: the day-ahead market, the intraday market, and the balancing market. The day-ahead and intraday trading take place on the Nord Pool exchange, while the balancing market is run by the Nordic transmission system operators (TSOs). Nasdaq Commodities accounts for the trading at the financial market. Today, the electricity market covers large parts of Europe, since the transmission capacity and coupling are in place between the Nordic countries, the European continent, and the Baltics (Nord Pool, 2020c). This means that electricity comes from many different sources such as hydro, thermal, nuclear, wind and solar, ensuring a liquid market.

2.2 Risk Factors in the Electricity Market

Participants in the electricity market are exposed to both quantity and price risk on an hourly basis, due to the characteristics of electricity (Souhir, Heni, & Lotfi, 2019). Electricity prices are characterized by seasonal variations, where the prices are normally higher during the winter compared to the summer (Ek & Thorbjørnsen, 2014). Furthermore, the limited storability of electricity results in price spikes due to for example extreme weather conditions causing price variations. The limited storability of electricity is an important characteristic of the electricity market and is the major reason for the high volatility in electricity prices (Geman, 2008). Consequently, electricity prices are considerably more volatile compared to other commodity prices (Souhir et al., 2019). Another factor causing price fluctuations is the physical restrictions of transferring electricity in the transmission grid, causing disturbances in the electricity supply (Saakvitne & Bjønnes, 2015). The liberalization of electricity markets has increased price volatility and has led to the creation of an organised market where electricity is traded like other commodities. In several other commodity market producers can hedge against the price volatility by storing the commodity until the price is favourable. Since electricity has limited storability, electricity producers rely more on the use of electricity derivatives in securing future prices.

The electricity production in the Nordic market consists of a relatively large amount of renewable energy sources, such as hydropower and wind (Veie et al., 2019). Over half of the electricity production is generated from hydropower (Nordic Energy Regulators, 2019). This means that the market is also exposed to a significant amount of quantity risk, because of for example variation in water inflow to storage reservoirs and wind force near the turbines. The electricity supply is higher when the inflow is high, and prices are pushed down. In contrast, lower electricity inflow result in rising prices. Furthermore, electricity production capacity is generally split into flexible- and intermittent sources (Norwegian Ministry of Petroleum and Energy, 2020a). Electricity plants can adjust production according to market developments in a flexible production. Intermittent production means that the electricity can only be generated when the energy is available. Hydropower producers have some ability to store electricity since many plants have storage reservoirs, enabling the producers to govern outflow. The plants therefore have the advantage of scaling down during periods of low prices and scaling up when prices are higher.

The high price volatility in the market is not likely to diminish soon. There is a considerable amount of uncertainty associated with the development of the electricity market, mainly due to the global climate challenge (Bøhnsdalen et al., 2016). To be able to follow climate policies and reach climate goals, a larger share of the total electricity production needs to consist of renewable energy sources. The Nordic electricity market is expected to still be dominated by hydropower in the years to come, however, the amount of highly variable and intermittent sources such as solar- and wind power will increase (Veie et al., 2019). As a result, the production in periods with a lot of sunshine and wind can exceed consumption, where the high production is balanced with lower prices due to non-storability. Hence, an increased portion of solar- and wind power is expected to increase price volatility. This may result in price risk management being even more important in the future.

2.3 Hedging Electricity Price Risk

Electricity market participants are confronted with high price volatility, and in order to deal with this risk, they can apply risk management tools to control risk while maximizing their profits (Souhir et al., 2019). Therefore, more effective risk management has become a central issue in the electricity market. Souhir et al. (2019) define risk management as the process of accomplishing a desired profit or return, considering the risks, by implementing a strategy. In the financial field, one can mitigate risk either by adopting hedging strategies or apply diversification to decrease exposure to risks. Hedging of the mentioned price risk has become an important part of the risk management process for electricity producers. This strategy can be used to limit or offset the probability of loss from price fluctuations, helping to protect from uncertainty (Edwards, 2014).

In order to obtain successful hedging, it is of importance to understand how the price of futures behave relative to the price of the commodity being hedged. Hedging the highly volatile electricity prices in the electricity market is more difficult than in other commodity markets, making the implementation of a perfect hedge difficult (Lucia & Schwartz, 2002). The looser relationship between spot and futures prices might be because of the lacking cash-and-carry arbitrage (Torró, 2009). In addition, the special characteristics of electricity prices contribute to a lower correlation. Madaleno and Pinho (2010) state that the basis risk is lower when the correlation is higher. The noise in the market does not tend to be cancelled over time, and the relationship is especially looser when futures maturity increases (Dewally & Marriott, 2008). Furthermore, it can also be difficult to reduce the quantity risk through hedging due to the limited storability of electricity (Souhir et al., 2019).

2.4 The Nordic Electricity Market

The Nordic electricity market is divided into 15 bidding areas at Nord Pool (Nord Pool, 2020a). Norway is divided into five areas, Sweden into four, and Denmark into two. In addition, Finland, Estonia, Latvia, and Lithuania all have their own area price. The area prices are different since the available transmission capacity can vary and congest the flow of electricity between bidding areas. The prices are higher if there is a supply deficit, and lower where there is a supply surplus. Participants in each respective area pay or receive the area price when they trade electricity on the physical market at Nord Pool. The area prices for the following day is calculated based on all the purchase and sell orders on the day-ahead market at Nord Pool as well as the transmission capacity available (Norwegian Ministry of Petroleum and Energy, 2020b). The day-ahead market ensures balance between supply and demand, and the intraday market is used to balance the difference between the actual consumption and production of the market participants and their position in the day-ahead market. Furthermore, there are events that disturb the balance between production and consumption within a specific hour of operation. The Nordic TSOs use the balancing markets to regulate production or consumption up or down to correct for these events.

If congestions in the Nordic transmission grid is disregarded, the theoretical price that would occur is the system price (Nord Pool, 2020a). This is the equilibrium price when aggregating all supply and demand curves for every area in the system. The system price is used as a reference price for most of the financial contracts on Nordic electricity market. Hence, technical conditions such as grid congestion and access to capacity are not taken into consideration when entering contracts on the financial electricity market. However, buyers and sellers can still manage the risks associated to the physical market prices with the help of this market (Nord Pool, 2020c).

An electricity producer can reduce the price uncertainty by using financial electricity market contracts (Nord Pool, 2020c). Financial electricity trading includes trading with financial instruments used for risk management purposes as well as speculation, where the contracts are settled financially without any physical electricity deliveries. The contracts are priced in Euros per MWh and have a time horizon up to ten years, covering daily, weekly, monthly, quarterly, and annual contracts. Most of the Nordic financial electricity trading takes place at Nasdaq Commodities, through the Nasdaq Oslo ASA Exchange and Nasdaq Clearing AB (Nasdaq, 2020). The contracts are cleared and standardized, facilitating the creation of a more liquid derivatives market. The financial products offered are both contingent claims and forward commitments, including futures, forwards (deferred settlement futures), options, and electricity price area differential (EPAD) contracts. Contingent claims provide the right, but not the obligation, to purchase or sell the underlying at a predefined price (McDonald, 2014). Forward commitments provide the ability to lock in a price that the underlying can be bought or sold for in the future. All contracts, except EPADs, use the system price as a reference price. The reference price for EPADs is the difference between the area price and the system price (Nasdaq, 2020). Hence, it hedges against the price area risk caused by constraints in the transmission grid.

3.0 Literature Review

After the deregulation of the Nordic electricity market in the 1990s there has been a vast amount of research on spot prices and derivatives. This section of the paper will review the most important and relevant research for our research question. Researchers have some agreement on how the market function and the effectiveness of various hedging methods.

Modigliani and Miller (1958) claim that hedging cannot add value since markets are efficient and investors can hedge themselves. However, the hedging literature provides theoretical arguments and to some level empirical evidence that hedging can add value for a firm. McDonald (2014) defines a hedge as an investment in a derivative, where the value is determined by an underlying asset such as the electricity price. Hedging theories today has its foundation in old corporate finance hedging theories like Keynes' theory, which states that the derivative market function as an insurance system (Keynes, 1930). The naïve one-to-one hedge approach was early challenged by Markowitz's minimum variance framework (Working, 1953). Further, Johnson (1960) and Stein (1961) proposed a minimum variance hedge ratio approach due to the imperfect correlation between spot and future prices. Ederington (1979) formally developed this approach, where the optimal hedge ratio is estimated by regressing spot prices on future prices using Ordinary Least Squares (OLS). Further, he proposed a measure for hedging effectiveness, which measures the variance reduction of the hedged portfolio compared to the unhedged spot position.

The mean variance portfolio theory by Ederington (1979) is extensively employed in the literature on hedging, such as in Hill and Schneeweis (1981) and Myers and Thompson (1989). In Byström's (2003) study of the Nordic electricity market, he states that the OLS hedging strategy reduces the hedge portfolio variance. Furthermore, Mandaleno and Pinho (2008) find that the OLS hedge outperforms the naïve hedge strategy. Zanotti, Gabbi, and Geranio (2010) find that OLS static hedge performs better than OLS dynamic hedge for all the electricity markets tested. Torró (2009) concludes that hedging at the Nordic electricity market can reduce risk between 60-80% depending on the duration of the hedge. In contrast, Torró (2008) finds that hedging strategies can generate ineffective performances in the Nordic electricity market due to the characteristics of electricity prices.

Even though the OLS approach has an acceptable level of performance, it has its limitations. The OLS hedge ratio assumes that the variance-covariance matrix of returns is constant over time, which can be difficult to accept for a highly volatile electricity market. Therefore, research has turned its attention more towards time-varying hedge ratios. The conditional Heteroskedastic Autoregressive Specification (ARCH) was presented by Engle (1982), and was a few years later extended by Bollerslev (1986) to the Generalized Conditional Heteroskedastic specification (GARCH). Baillie and Myers (1991) and Kroner and Sultan (1993) conclude that bivariate GARCH models result in improved hedge performance compared to the OLS approach, using a bivariate Constant Conditional Correlation GARCH (CCC-GARCH) model proposed by Bollerslev (1990). Research has further looked at how correlations change over time by introducing the multivariate Dynamic Conditional Correlations GARCH (DCC-GARCH) model (Engle, 2002).

Kroner and Ng (1998) state that the choice of the GARCH model affects the hedge ratio and is important for the hedge effectiveness. In contrast, Malo and Kanto (2006) find few differences in hedging performance when implementing various GARCH specifications. According to Byström (2003), the GARCH approaches reduce the volatility in returns, however, it cannot outperform the conventional OLS approach in reducing portfolio variance. Zanotti et al. (2010) find that CCC-GARCH is the best performing model for the Nordic electricity market, and the model seems to be able to capture the time-varying nature of spot and futures returns. Lien, Tse, and Tsui (2002) state that it is important to choose a model that is computationally convenient. The CCC-GARCH model is computationally simple and is relatively easy to ensure the positive semi-definiteness of the conditional variance-covariance matrix during the optimization.

In addition to comparing static and dynamic hedging approaches, several researchers investigate the effect of different hedging durations. Ederington (1979), Geppert (1995), and Lien and Tse (2002) find that the in-sample hedging effectiveness increases as the investment duration increases. Lien and Shrestha (2007) estimate optimal hedge ratios for 23 diverse futures contracts with different durations and conclude that the performance improves with the increase in the length of the hedging duration. Hanly, Morales, and Cassells (2018) find that electricity market participants may struggle to reduce their exposure using futures hedging over short durations.

A lot of the research on hedging effectiveness in the electricity market is from the early 2000s and does not investigate the continuous development of the electricity market. This study complements existing studies by examining the development of the market and if our hedging results are consistent with earlier research. As in past research, this paper compares the hedge effectiveness of both static and dynamic hedge ratios. We implement this in the form of the naïve one-to-one, static OLS, and CCC-GARCH hedge ratios. It can be argued that the preferred strategy should have the lowest return reduction and the highest hedging effectiveness, however, the focus of this thesis is on hedging effectiveness. This is because it is a more valid result due to the overall return depending on the underlying trends in the returns of spot and futures (Zanotti et al., 2010). In addition, the analysis will include contracts with different maturities and holding periods in order to observe the impact of this on hedge effectiveness.

4.0 Theory and Methodology

In this section we introduce the theory and methods of calculating the optimal hedge ratios for the three hedging strategies; naïve one-to-one, static OLS, and CCC-GARCH, as well as introduce methods for comparing how effective the strategies are.

4.1 Required Data

In order to test the strategies mentioned above, we need spot and futures prices on electricity.

4.2 Statistical Tests

The following statistical tests are performed in order to get an impression of how the data behaves.

4.2.1 Jarque-Bera

The Jarque-Bera test is a test for normality (Brooks, 2019). The null hypothesis states that skewness and excess kurtosis are jointly zero. The normality assumption is violated if the null hypothesis is rejected, indicating a non-normal distribution of the residuals.

4.2.2 Augmented Dickey-Fuller (ADF) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS)

ADF is a unit root test completed to check for stationarity in the time series (Brooks, 2019). Unit root tests are poor at rejection when the process is stationary, but with a root close to the non-stationary boundary. KPSS is a stationarity test performed in this paper to confirm the results of the ADF test (Brooks, 2019). The conclusion regarding stationarity is robust when the tests give opposite results. Stationary and non-stationary time series should be treated differently, since non-stationary time series can produce unreliable and spurious results.

4.2.3 Ljung Box

The Ljung Box test is useful as a general test of linear dependence in time series (Brooks, 2019). It tests the joint hypothesis that all m (m = max length lags) of autocorrelation are simultaneously equal to zero. Autocorrelation, also known as serial correlation, is repeating patterns or similarities between data observations. If the null hypothesis is rejected, the residuals are autocorrelated and the model shows a lack of fit. Ljung Box is implemented instead of Box Pierce since it is known to give better properties for small sample sizes (Brooks, 2019).

4.2.4 Autoregressive Conditional Heteroskedasticity (ARCH)

Even though a time series is not autocorrelated, the residuals can still be serial dependent due to a dynamic conditional variance process. This is called heteroscedasticity, and if present in the data it is said to have ARCH-effects (Brooks, 2019). We use Engle's ARCH-test and the Ljung Box test with squared residuals to test for ARCH-effects. If we have significant evidence of heteroscedasticity, the standard errors could be wrong, and it might be appropriate to use a model that does not assume constant variance.

4.3 Minimum Variance Hedge

The minimum variance approach is implemented in this paper in order to find the optimal hedge ratio. This approach estimates the hedge ratio that gives the minimum variance for the value of the hedged position for the electricity producer (Brooks, 2019). The producer is long the asset and hedges its position by shorting futures contracts. The portfolio return of a long position in the spot market and a short position in the futures market, at time *t+1*, can be expressed as:

$$R_{t+1} = \Delta S_{t+1} - \beta_t \, \Delta F_{t+1}$$

R_{t+1} is the return between *t* and *t+1*, ΔS_{t+1} and ΔF_{t+1} are the log spot and futures returns between *t* and *t+1*, and $\boldsymbol{\beta_t}$ is the optimal hedge ratio. The conditional variance of this portfolio is:

$$Var(R_{t+1}) = Var\,(\Delta S_{t+1}) + \beta_t^2 \, Var\,(\Delta F_{t+1}) - 2\,\beta_t \, Cov\,(\Delta S_{t+1}, \Delta F_{t+1})$$

The conditional minimum variance hedge ratio is obtained by minimizing the variance of the hedge portfolio with respect to β_t:

$$\beta_{t,min,var} = \frac{Cov(\Delta S_{t+1}, \Delta F_{t+1})}{Var\ (\Delta F_{t+1})}$$

The hedge ratio specifies how many futures contract should be either bought or sold to hedge the underlying position in order to minimize the portfolio variance.

4.4 Hedging Strategies

This paper compares three various hedging strategies: the naïve one-to-one, static OLS, and dynamic CCC-GARCH. The aim of the hedging strategies is to find the optimal hedging ratios and reduce the amount of variance for the producer.

4.4.1 The Naïve Hedge

The naïve one-to-one hedge implies that each spot position is offset completely by one futures contract (Brooks, 2019). The strategy assumes that the covariance between futures and spot returns equals the variance of futures returns.

4.4.2 The Ordinary Least Squares (OLS) Hedge

The OLS minimum variance hedge ratio is estimated running a linear regression (Brooks, 2019):

$$\Delta S_{t+1} = \alpha + \beta \Delta F_{t+1} + u_t$$

β gives an estimate for the unconditional minimum variance hedge ratio:

$$\beta_{min,var} = \frac{Cov(\Delta S_{t+1}, \Delta F_{t+1})}{Var\ (\Delta F_{t+1})}$$

4.4.3 The Constant Conditional Correlation GARCH (CCC-GARCH)

The GARCH-model allows the conditional variances to be dependent upon previous own lags (Brooks, 2019). We use a univariate GARCH (1,1) to calculate conditional variances. These are one-period ahead estimates that are based on past information.

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2$$

As mentioned, this paper implements the CCC-GARCH to hedge electricity prices. The CCC-GARCH model requires correlation to be fixed through time. The conditional covariances are not fixed, however, they are tied to the conditional variances in the CCC-GARCH model. The conditional variances are identical to the ones from the univariate GARCH-model (see equation above). The conditional covariances are calculated as follows:

$$h_{ij,t} = \rho_{ij}\, h_{ii,t}^{1/2}\, h_{jj,t}^{1/2}$$

Where $h_{ii,t}$ and $h_{jj,t}$ are conditional variances for spot and futures, respectively. ρ_{ij} represents the fixed correlation between spot and futures.

The optimal hedge ratios are calculated using the conditional covariances and conditional variances. The hedge ratios vary with time and is conditioned on previous information.

4.5 Hedge Effectiveness

In order to compare the performance of the hedge, the hedge effectiveness (HE) metric introduced by Ederington (1979) is implemented. This metric measures the percentage of variance reduction of the hedged position compared to the unhedged spot position:

$$HE = 1 - \frac{Variance_{hedged}}{Variance_{unhedged}}$$

A positive HE indicates that the hedge is effective, and the hedging strategy that gives the highest percentage variance reduction is considered the best. In contrast, the hedging is inefficient and could even increase the variance when the obtained HE is zero or negative.

4.6 Backtesting

Backtesting is performed to see how well the various hedging strategies perform ex-post. This step can be important in optimizing the strategy and validating results. In-sample testing is implemented for statistical tests and hedging strategies, and the out-of-sample testing is implemented to test how well the models perform using a different time period (Brooks, 2019). The out-of-sample testing allow for a more realistic hedging effectiveness.

5.0 Data

5.1 Data Description

When setting up the framework for the electricity hedges, this thesis takes the point of view of an electricity producer. In order to evaluate the performance of various hedging strategies on the Nordic electricity market, we observe weekly and monthly spot- and futures prices for monthly futures contracts, and monthly and quarterly spot- and futures prices for quarterly contracts denoted EUR/MWh. The spot prices are collected directly from the Nord Pool website, and the futures prices traded at Nasdaq Commodities are collected from Bloomberg. The spot price refers to the Nordic system price. This means that the hedge is not against the area price risk and a perfect hedge is only possible when there are no transmission grid congestions in the market area. Hence, hedging with Nordic electricity futures imply an additional basis risk equal to the difference between the area price at the producer's physical location and the system price.

The study includes an in-sample period and an out-of-sample period, where the in-sample period is 2015Q4-2018 and the out-of-sample period is 2019. Both sample periods are used on monthly and quarterly contracts with the different holding periods explained above. We roll over the hedges after the respective holding periods. When we roll over the hedges before the maturity date, we introduce basis risk as the futures prices are not tied directly to the spot prices prior to the expiration date (Byström, 2003). Different holding periods are tested to see if it influences the hedge effectiveness.

We need a sufficient amount of data in order to get valid results and models. This paper has close to a 3 year in-sample and a 1 year out-of-sample, which might be too small to get generalized and valid results. A larger number of observations would be preferable to obtain insightful results, especially for the quarterly contracts trading quarterly (Appendix 1). We would also get a larger amount of observations by focusing on weekly futures contracts, but this data was not available at Bloomberg. In addition, we use overlapping contracts that possibly could introduce autocorrelation in the time series (Torró, 2008).

5.2 Data Transformation

The spot and futures prices are transformed into log-returns before implementing them. It is preferable not to work directly with raw price series for several statistical reasons, and price series are therefore usually converted into series of returns (Brooks, 2019). Returns also have the added benefit of being unit-free, avoiding the problem of non-stationary time series. Log-returns have been implemented since they can be interpreted as continuously compounded returns and are time-additive. In addition, taking a logarithm can result in a more constant variance, a positively skewed distribution getting closer to a normal distribution, and making a non-linear, multiplicative relationship between variables into a linear, additive one. Continuously compounded returns are achieved as follows:

$$r_t = 100\% * ln\,(\frac{p_t}{p_{t-1}}) = 100\% * (ln\,p_t - ln\,p_{t-1})$$

Where r_t denotes the continuously compounded return at time *t*, p_t denotes the asset price at time *t* and *ln* denotes the natural logarithm.

5.3 Descriptive Statistics

This section shows and discusses the results of the statistical tests mentioned earlier in the paper.

Table 1: Descriptive statistics for spot and futures log returns

	MONTHLY CONTRACTS				QUARTERLY CONTRACTS			
	Traded weekly		Traded monthly		Traded monthly		Traded quarterly	
	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
Mean	0.008	0.006	0.018	0.022	0.018	0.020	0.096	0.079
Standard deviation	0.168	0.082	0.238	0.162	0.238	0.149	0.225	0.202
Skewness	-0.611	0.010	-0.181	-0.029	-0.181	-0.699	-0.239	-0.818
Kurtosis	9.177	14.071	3.344	4.355	3.344	3.616	1.966	3.557
Jarque Bera	279.174	863.145	0.395	2.914	0.395	3.697	0.648	1.492
ADF								
Price levels	0.268	0.832	0.267	0.720	0.267	0.753	1.317	1.309
First differences	-17.450	-13.293	-8.193	-8.913	-8.193	-6.710	-4.027	-3.364
KPSS								
Price levels	0.528	0.901	0.083	0.209	0.083	0.252	0.071	0.137
First differences	0.013	0.025	0.017	0.022	0.017	0.044	0.064	0.055
Q(6)	15.509	19.185	13.830	11.222	13.830	5.008	6.895	4.721
Q(12)	19.029	20.094	22.831	18.595	22.831	13.027	-	-
$Q^2(6)$	44.191	40.271	3.267	12.489	3.267	3.560	7.594	5.006
$Q^2(12)$	45.272	43.308	5.782	14.029	5.782	11.353	-	-
ARCH(6)	56.071	37.149	2.881	4.225	2.881	3.515	6.000	6.000
ARCH(12)	50.948	49.672	6.343	9.904	6.343	11.115	-	-
Correlation	31.01%		14.92%		34.87%		11.31%	

The 99% critical values of Jarque Bera are 12.053 for contracts traded weekly, 11.934 for contracts traded monthly, and 6.857 for contracts traded quarterly. The null hypothesis of the ADF test is that at least one unit root exists, and for the KPSS test the null hypothesis is that the time series are stationary. The ADF 99% critical values for price levels and first differences are –1.942 for contracts traded weekly, -1.948 for contracts traded monthly, and –1.958 for contracts traded quarterly. The KPSS 99% critical value for price levels and first differences is 0.146 for all contracts. Q(6) and Q(12) are the Ljung Box tests for autocorrelation in residuals. $Q^2(6)$ and $Q^2(12)$ are Ljung Box tests with squared residuals testing for ARCH-effects. ARCH(6) and ARCH(12) are Engle's ARCH-tests. These tests have 99% critical values of 12.592 for the 6th order tests and 21.026 for the 12th order tests.

The weekly spot and futures returns exhibit means close to zero, skewness, and high excess kurtosis. Both the monthly and quarterly spot and futures returns have means close to zero, the series are negatively skewed, and have low excess kurtosis. Another significant point is that the standard deviations of the spot and futures are different within the same market, with the spot volatility being higher than the futures volatility. The Jarque Bera test shows that the weekly spot and futures returns have a non-normal distribution of the residuals. All other times series follow a normal distribution with a 1% significance level. The issue of non-normality can be caused by outliers or heteroscedasticity in the time series (Brooks, 2019). The solution to outliers can be to remove them or introduce dummy variables, but one can argue that every data point contains useful information. Heteroscedasticity in the time series confirms that GARCH models can be appropriate.

The ADF test on price levels fails to reject the null hypothesis in all cases, indicating that all time series have at least one unit root. The KPSS test on price levels rejects the null hypothesis of stationary in weekly spot and futures returns and monthly futures returns. In the cases where the null hypothesis is not rejected, the ADF and KPSS test are inconclusive on stationarity. When taking first differences in the ADF test, the null hypothesis is rejected for all time series. This indicates that they have one-unit root. All time series are also stationary when taking first differences in the KPSS test. Even though the tests on price levels are inconclusive regarding stationarity in some of the cases, the results from first differences confirm that it would be beneficial to transform the time series into returns before implementing.

In the Ljung Box test with 6 lags, the time series have residual autocorrelation in weekly spot and futures returns and in monthly spot returns for both contracts. The Ljung Box test with 12 lags concludes that monthly spot returns for both contracts have autocorrelation in the residuals. The null hypothesis is not rejected in the other time series, indicating no pattern in the true residuals. Autocorrelation in the residuals can lead to inefficient OLS coefficients, and further could give wrong standard errors (Brooks, 2019). The Ljung Box tests with squared residuals show significant ARCH effects in the residuals in weekly spot and futures returns. Furthermore, Engle's ARCH-test also rejects the null hypothesis of no ARCH effects for weekly spot and futures returns. This reveals heteroscedasticity for weekly returns, however, the remaining time series show no ARCH effects. This confirms that implementing time varying variances in the hedging model can be beneficial. However, it does not make sense to use a time varying model if there is no evidence of volatility clustering, hence, we will only test GARCH on weekly returns. For the OLS hedge, we apply the Newey-West estimator to overcome the issues with autocorrelation and heteroscedasticity. This procedure gives heteroscedasticity- and autocorrelation consistent standard errors (Brooks, 2019).

The correlation between the spot and futures returns are quite low and varies, with a higher correlation for monthly contracts with a one week holding period, and quarterly contracts with a holding period of one month. The basis risk is higher when the correlation is lower and the low correlation between spot and futures conditions the effectiveness of electricity hedging.

5.4 Expected Results

It is expected that hedging the spot prices at the Nordic electricity market will reduce the uncertainty of the hedged portfolio. The naïve hedge assumes a perfect linear correlation between spot- and futures price returns and does not take basis risk into account (Rossi & Zucca, 2002). In contrast, the static OLS hedge recognizes the less than perfect correlation. Therefore, the OLS hedge is expected to perform better in-sample than the naïve hedge due to the low correlation seen in Table 1. The naïve hedge is expected to perform similar to the OLS hedge when the OLS hedge ratio is close to one, otherwise, a lower performance is expected. The OLS hedge imposes the restriction of a constant joint distribution of spot- and futures price returns, which is suboptimal in periods with high basis volatility (Rossi & Zucca, 2002). The CCC-GARCH model is expected to be an appropriate strategy to apply for time series with ARCH-effects. Based on the statistical tests, we expect that the CCC-GARCH model would obtain an increased hedge effectiveness on monthly contracts traded weekly due to the detected ARCH-effects. Since the other time series have no ARCH-effects, we will only perform naïve hedge and OLS hedge on these time series. Based on past research, the hedge effectiveness is expected to increase as the holding period increases.

6.0 Hedging Results

This section presents the obtained results of the in- and out-of-sample hedge performances, as well as an overall analysis, of the naïve, OLS, and CCC-GARCH hedging approaches. In addition, we present the development of spot- and futures price volatility and hedging effectiveness. The hedge performances are examined and compared by looking at the variances and the hedge effectiveness metric of each strategy. The obtained hedge effectiveness is calculated for the in-sample and out-of-sample periods for the monthly and quarterly contracts. The hedge effectiveness of the CCC-GARCH strategy is only calculated for the monthly contract traded weekly, since this is the only contract with evidence of ARCH-effects.

6.1 In-Sample Performance

Table 2 presents the in-sample hedge performance of the various contracts and hedging strategies.

Table 2: Variances and hedge effectiveness

		No hedge	Naïve	OLS	CCC
Monthly contracts	Weekly				
	Variance	0.0281	0.0263	0.0254	0.0252
	Hedge Effectiveness	-	6.36%	9.62%	10.03%
	Monthly				
	Variance	0.0568	0.0714	0.0555	-
	Hedge Effectiveness	-	-25.73%	2.23%	-
Quarterly contracts	Monthly				
	Variance	0.0568	0.0542	0.0499	-
	Hedge Effectiveness	-	4.53%	12.16%	-
	Quarterly				
	Variance	0.0507	0.0810	0.0500	-
	Hedge Effectiveness	-	-59.93%	1.28%	-

For the monthly contract traded weekly the hedge effectiveness is 9.62% and 10.03% for OLS and CCC-GARCH, respectively. Both contracts are efficient, but the CCC-GARCH approach performs slightly better. The naïve hedge resulted in reducing the variance by 6.36%, indicating that it performs less good compared to the abovementioned strategies. For the monthly contracts trading monthly, the naïve hedge strategy results in a higher variance compared to the unhedged position and a hedge effectiveness of -25.73%. The OLS hedge strategy has a positive hedge effectiveness of 2.23%, reducing the variance of the portfolio. Both the naïve- and OLS hedge strategy reduce the variance when implementing quarterly contracts trading monthly. The hedge effectiveness is 4.53% and 12.16%, respectively, indicating that the OLS approach performs better. The naïve hedge strategy has a hedge effectiveness of –59.93% for the quarterly contract trading quarterly, which means that the hedge is inefficient and increases the variance. The OLS hedge strategy is effective, with a positive hedge effectiveness of 1.28%.

The in-sample analysis shows that the dynamic CCC-GARCH hedge performs better than the static naïve- and OLS hedge when hedging with monthly contracts trading weekly. The dynamic model appears to be able to capture the property of the time varying variances of the spot and futures returns. As a result, the CCC-GARCH approach improves the hedge performance compared to the static hedges in the analysis.

The performance of the naïve hedge strategy is highly variable, with both efficient and inefficient results. The strategy results in a positive hedge effectiveness for the monthly contract trading weekly and the quarterly contract trading monthly. In contrast, the strategy performs poorly with the monthly contract trading monthly and the quarterly contract trading quarterly, where the hedge effectiveness is negative. The variable results may be explained by the highly volatile electricity prices and low correlations between spot and futures returns. The correlation coefficients are higher for the efficient contracts, and the naïve approach performs better as the correlations get higher. Furthermore, we observe that the closer the OLS hedge ratio is to one, the better the naïve hedge strategy performs (Appendix 2). When the OLS hedge ratio is low, the naïve hedge strategy is inefficient. Also, the OLS hedging strategy performs better when the correlation is higher due to lower basis risk. The volatility of the futures returns is lower compared to the spot returns for the two contracts with higher correlations, which contributes to a better hedge result. Furthermore, we observed non-normality in the weekly spot- and futures returns which might give inefficient estimates, hence this strategy could have done better if the time series were normal.

6.2 Out-of-Sample Performance

In order to test the out-of-sample performance of the naïve- and OLS hedge, we apply the static hedge ratios from in-sample to the out-of-sample data. For the dynamic CCC-GARCH model we need forecasted hedge ratios. Therefore, we forecast the conditional variances from the in-sample period. The obtained hedge ratios are reported in Appendix 3. Further, we use the obtained hedge ratios and conditional variances from the out-of-sample data to compute the hedged variance and hedge effectiveness. The results are presented in Table 3.

Table 3: Variances and hedge effectiveness

		No hedge	Naïve	OLS	CCC
Monthly contracts	Weekly				
	Variance	0.0350	0.0263	0.0286	0.0276
	Hedge Effectiveness	-	24.76%	18.41%	21.15%
	Monthly				
	Variance	0.0862	0.0323	0.0702	-
	Hedge Effectiveness	-	62.57%	18.58%	-
Quarterly contracts	Monthly				
	Variance	0.0862	0.0197	0.0423	-
	Hedge Effectiveness	-	77.18%	50.96%	-
	Quarterly				
	Variance	0.2167	0.0592	0.1902	-
	Hedge Effectiveness	-	72.66%	12.24%	-

The out-of-sample performance presented indicates that all hedging strategies reduce variance. The naïve hedge performs best for the monthly contracts trading weekly, with a variance reduction of 24.76%. The OLS- and CCC-GARCH hedging strategy reduce the variance by 18.41% and 21.15%, respectively. For monthly contracts trading monthly, the naïve hedge results in a hedge effectiveness of 62.57%. The hedge effectiveness is 18.58% for the OLS hedge strategy. For quarterly contracts, the naïve hedge reduced the variance by 77.18% and 72.66% for contracts trading monthly and quarterly, while OLS reduced the variance by 50.96% and 12.24% for the respective trading periods. These results show that the naïve hedge, somewhat surprisingly, performed better than the OLS hedge for all the strategies.

The spot standard deviations are significantly higher than the futures standard deviations in the out-of-sample period (Appendix 4), which indicates that the unhedged spot portfolio is more volatile than the hedged futures portfolio. The out-of-sample analysis results in a higher variance reduction in the hedged portfolio compared to the in-sample analysis, which is somewhat unexpected. The out-of-sample correlations are much higher than the in-sample, which also affects the hedge performances. We find that all strategies were able to reduce variance. However, a limitation of the out-of-sample test is that we have fewer observations than what might be preferable.

The naïve approach performs better than both OLS and CCC-GARCH for the monthly contracts traded weekly. This is due to the volatility of spot returns being higher and volatility of futures returns being lower for the out-of-sample period, compared to the in-sample period. In addition, the higher correlation contributes to an even better performance for the naïve approach. The dynamic model seems to be able to capture the time-varying variance also for the out-of-sample period. Furthermore, the naïve hedge performs significantly better than the OLS hedge for the three latter cases. This indicates that the naïve hedge is the overall best out-of-sample hedge in our analysis. This can also be explained by higher correlations (Appendix 4) as well as a significantly higher standard deviations on spot returns compared to futures returns. The correlations vary between 0.85 and 0.96 for the three strategies. Since the naïve hedge assumes perfect correlation and that the spot position is completely offset by the futures position, the out-of-sample test performs well. The same reasoning applies for the OLS hedge. The hedge is efficient due to positive hedge ratios, but the naïve hedge performs better since the OLS hedge ratios are lower than one. The OLS approach performs better for the quarterly contracts traded monthly due to a higher hedge ratio compared to the monthly contract trading monthly and the quarterly contract traded quarterly.

6.3 Overall Performance and Market Development

The overall result of both the in-sample and out-of-sample analysis is that hedging with futures contracts reduce volatility compared to the non-hedged spot position, even though the electricity market lack straight forward arbitrage possibilities. This indicates that hedging with futures contracts can be profitable for a variance-minimizing trader. Hence, the results of this study confirm previous empirical studies of the electricity market, stating that futures contracts have the capability of variance reduction (Byström, 2003; Torró, 2009; Madaleno & Pinho, 2010).

In the in-sample analysis we find that CCC-GARCH outperforms the naïve- and OLS approaches when ARCH-effects are present, while in the out-of-sample analysis the naïve approach performs best. Further, the CCC-GARCH performs better than OLS. Our out-of-sample results are similar to the research by Byström (2003). Byström (2003) finds that the static models, naïve and OLS, outperformed the dynamic GARCH hedges out-of-sample. This indicates that modelling with time-varying variance does not necessarily result in a better hedge than the static hedges. On the contrary, we observed lower cluster volatility out-of-sample compared to in-sample, which can be explained by a shorter period. If we implemented a longer period, we might have seen the same pattern of volatility clustering as in-sample, and hence the CCC-GARCH might have performed better out-of-sample. In contrast to Byström (2003), Zanotti et al. (2010) find that static hedging ratios are inefficient when markets are characterized by high time-varying volatility, and hedging errors are reduced when dynamic volatility- and correlation approaches are implemented. Madaleno and Pinho (2010) report similar results for the German electricity market, where the dynamic hedging strategies provide higher variance reductions.

The cost and time spent on the various hedging strategies are important aspects when deciding on the optimal hedge. The static naïve- and OLS hedging approaches have constant hedge ratios, whilst in the CCC-GARCH model the position taken in derivatives changes over time. The dynamic hedge ratios indicate that an electricity producer must frequently rebalance the portfolio to adjust for time varying hedge ratios. The economic gain of the dynamic hedging may be reduced compared to the static hedges due to the higher cost and time spent on updating the hedge (Byström, 2003). Dynamic hedging can especially be costly if there are significant transaction costs in the market.

Torró (2009) and several other researchers find that hedging performance improves as hedging duration increases. In our in-sample analysis, the hedge effectiveness is higher for the contracts with a shorter hedging duration. Hedging with monthly futures contracts trading weekly provides superior hedge performance compared to holding the same contract for a month. In addition, hedging with quarterly futures contracts trading monthly perform better than holding the contract for a quarter. The correlation coefficients between the spot- and futures returns are higher for the contracts with a shorter holding period. The out-of-sample results are variable in relation to the hedging duration. For the monthly contracts, the monthly hedging duration performs better than the weekly. In contrast, the monthly hedging duration results in a higher hedge effectiveness than the quarterly hedging duration for the quarterly contracts. Hence, the results do not show that the hedge effectiveness improves when hedging over longer durations.

Byström (2003) hedge with weekly futures with one-week hedge durations, using spot and futures prices from January 1996 to October 1999. He finds that the spot- and futures returns in the Nordic electricity market have standard deviations of 0.0655 and 0.0418, respectively. Zanotti et al. (2010) find standard deviations of 0.0531 for spot returns and 0.02397 for futures returns when implementing monthly futures from January 2004 to February 2006. Comparing this to our analysis, the volatility has increased for both the spot and futures returns in the years 2015Q4 to 2018. One reason for this can be an increased portion of renewable energy, indicating that price risk management can be even more important in the future. Higher volatilities require higher hedge ratios to achieve the same level of predictability. The spot returns are still much more volatile than the futures returns.

7.0 Conclusion

This Master Thesis studies the hedging performance of electricity futures traded on Nasdaq Commodities. The overall result of this study is that the futures contracts can reduce price uncertainty of the hedged portfolio compared to an unhedged position, despite of low correlations between spot- and futures prices and the lack of straightforward arbitrage opportunities. However, the performance varies with the hedge approach, the maturity of the contract, as well as the holding period.

When ARCH effects are present, this study shows that a dynamic model, such as the CCC-GARCH, has some ability to improve the hedge performance compared to a static approach. This shows gains from taking time-varying variances into account when calculating the hedge ratios. This is not the case for the out-of-sample results, but we might have seen the same pattern of volatility clustering as in-sample if we implemented a longer sample period. The transaction- and clearing costs associated with daily updating the dynamic hedges must be considered. Furthermore, the results of this study indicate that increasing the hedging duration does not improve the performance of the hedge, which might indicate that the noise in the market is not cancelled over time. The results show that spot- and futures returns in the market have developed to become more volatile over the years. This development might indicate that price risk management is even more important than earlier, where higher hedge ratios are needed to achieve the same level of predictability.

We suggest further research on the behaviour of the futures market and its relation to the spot price, which will assist in a better understanding of the hedge effectiveness in the market. Further research on hedging in different areas of the Nordic electricity market, by implementing EPADs, would be interesting even though these contracts are less liquid. It would also be interesting to investigate the performance of other hedging methods outside derivative trading such as Pumped Hydro Storage (PHS). PHS allows water storage in an upper reservoir, pumped from a reservoir at a lower elevation when demand and prices are low. Since over half of the electricity production at the Nordic electricity market is generated from hydropower, PHS can solve some of the issues related to electricity hedging by providing an improved energy-balance and more stability.

Bibliography

Baillie, R. T., & Myers, R. J. (1991). Bivariate GARCH estimation of the optimal commodity futures hedge. *Journal of Applied Econometrics*, *6*(2), 109-124.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307-327.

Bollerslev, T., 1990. Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. *Review of Economics and Statistics*, 72(1), 498-505.

Brooks, C. (2019). *Introductory econometrics for finance* (4th ed.). New York, USA: Cambridge University Press.

Byström, H. N. (2003). The hedging performance of electricity futures on the Nordic power exchange. *Applied Economics*, *35*(1), 1-11.

Bøhnsdalen, E. T., Västermark, K. L., Døskeland, I. H., Holmefjord, V., Aarstad, J., & Kringstad, A. (2016). Long-Term Market Analysis, the Nordic Region and Europe 2016–2040. Retrieved from https://www.statnett.no/globalassets/for-aktorer-i-kraftsystemet/planer-og-analyser/long-term-market-analysis-the-nordic-region-and-europe-2016-2040.pdf.

Dewally, M., & Marriott, L. (2008). Effective base metal hedging: The optimal hedge ratio and hedging horizon. *Journal of Risk and Financial Management*, *1*(1), 41-76.

Ederington, L. H. (1979). The hedging performance of the new futures markets. *The Journal of Finance*, *34*(1), 157-170.

Edwards, D. (2014). *Risk management in trading: techniques to drive profitability of hedge funds and trading desks*. John Wiley & Sons.

Ek, K. M. N., & Thorbjørnsen, I. S. (2014). *Optimizing Hedging Strategies for Hydropower Producers Using Forwards: Investigating the Effects of Seasonality in the Price-Load Relationship for the Norwegian Electricity Market* (Master's thesis, Institutt for industriell økonomi og teknologiledelse).

Engle, R. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, 50(4), 987-1007.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, *20*(3), 339-350.

Geman, H. (2008). *Risk management in commodity markets: From shipping to agricultural and energy*. West Sussex, England: Wiley Finance.

Geppert, J. M. (1995). A statistical model for the relationship between futures contract hedging effectiveness and investment horizon length. *The Journal of Futures Markets*, 15(5), 507-536.

Hanly, J., Morales, L., & Cassells, D. (2018). The efficacy of financial futures as a hedging tool in electricity markets. *International Journal of Finance & Economics*, *23*(1), 29-40.

Hill, J., & Schneeweis, T. (1981). A note on the hedging effectiveness of foreign currency futures. *The Journal of Futures Markets*, *1*(4), 659-664.

Johnson, L. L. (1960). The theory of hedging and speculation in commodity futures. *Review of Economic Studies*, 27(3), 139-151.

Keynes, J. M. (1930). *Treatise on money: Pure theory of money.* London: MacMillian.

Kroner, K. F., & Ng, V. K. (1998). Modeling asymmetric comovements of asset returns. *The Review of Financial Studies*, 11(4), 817-844.

Kroner, K. F., & Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of Financial and Quantitative Analysis*, 28(4), 535-551.

Lien, D. and Shrestha, K. (2007). An empirical analysis of the relationship between hedge ratio and hedging horizon using wavelet analysis. *Journal of Futures Markets*, 27(2), 127-150.

Lien, D. and Tse, Y. K. (2002). Some recent developments in futures hedging. *Journal of Economic Surveys,* 16(3), 357-396.

Lien, D., Tse, Y. K., & Tsui, A. K. (2002). Evaluating the hedging performance of the constant-correlation GARCH model. *Applied Financial Economics*, *12*(11), 791-798.

Lucia, J. J., & Schwartz, E. S. (2002). Electricity prices and power derivatives: Evidence from the nordic power exchange. *Review of Derivatives Research*, *5*(1), 5-50.

McDonald, R. L. (2014). *Derivatives markets* (3rd ed.). Harlow: Pearson Education.

Madaleno, M., & Pinho, C. (2008). The hedging effectiveness of electricity futures. Working paper.

Madaleno, M., & Pinho, C. (2010). Hedging performance and multiscale relationships in the German electricity spot and futures markets. *Journal of Risk and Financial Management*, 3(1), 26-62.

Malo, P., & Kanto, A. (2006). Evaluating multivariate GARCH models in the Nordic electricity markets. *Communications in Statistics—Simulation and Computation*, 35(1), 117-148.

Myers, R. J., & Thompson, S. R. (1989). Generalized optimal hedge ratio estimation. *American Journal of Agricultural Economics*, 71(4), 858-868.

Nasdaq (2020). Nordic power products. Retrieved from https://www.nasdaq.com/solutions/nordic-power-products-european-commodities.

Nordic Energy Regulators (2019). An overview of the nordic electricity market. Retrieved from https://www.nordicenergyregulators.org/about-nordreg/an-overview-of-the-nordic-electricity-market/.

Nord Pool (2020a). Bidding areas. Retrieved from https://www.nordpoolgroup.com/the-power-market/Bidding-areas/.

Nord Pool (2020b). History. Retrieved from https://www.nordpoolgroup.com/About-us/History/.

Nord Pool (2020c). The power market. Retrieved from https://www.nordpoolgroup.com/the-power-market/.

Norwegian Ministry of Petroleum and Energy (2020a). Electricity production. Retrieved from https://energifaktanorge.no/en/norsk-energiforsyning/kraftproduksjon/.

Norwegian Ministry of Petroleum and Energy (2020b). The power market. Retrieved from https://energifaktanorge.no/en/norsk-energiforsyning/kraftmarkedet.

Rossi, E., & Zucca, C. (2002). Hedging interest rate risk with multivariate GARCH. *Applied Financial Economics*, 12(4), 241-251.

Saakvitne, J. A., & Bjønnes, G. H. (2015). Hva skjer med det nordiske kraftderivatmarkedet om aktørene ikke får stille sikkerhet gjennom bankgarantier?. Magma, 8(1), 39-48.

Souhir, B. A., Heni, B., & Lotfi, B. (2019). Price risk and hedging strategies in Nord Pool electricity market evidence with sector indexes. *Energy Economics*, 80(1), 635-655.

Stein, J. L. (1961). The simultaneous determination of spot and futures prices. *The American Economic Review,* 51(5), 1012-1025.

Torró, H. (2008). *Hedging weekly electricity price risk with futures at Nord Pool: duration and maturity effects.* University of Valencia, Spain: Working Paper.

Torró, H. (2009). *Assessing the influence of spot price predictability on electricity futures hedging*. University of Valencia, Spain: Working Paper.

Veie, C. A., Sidelnikova, M., Skau, S., Koestler, V. J., Aksnes, N. Y., Hole, J., Arnesen, F., Birkeland, C. (2019). *Kraftproduksjon i Norden til 2040* (Report 43-2019). Oslo: Norges vassdrags- og energidirektorat.

Working, H. (1953). Futures trading and hedging. *The American Economic Review*, *43*(3), 314-343.

Zanotti, G., Gabbi, G., & Geranio, M. (2010). Hedging with futures: Efficacy of GARCH correlation models to European electricity markets. *Journal of International Financial Markets, Institutions and Money*, *20*(2), 135-148.

Appendices

Appendix 1

Appendix 1 gives an overview of the number of observations for the two different contracts with two different hedging durations. The in-sample period is 2015Q4-2019 and out-of-sample is 2019.

Number of observations		
	In-sample	Out-of-sample
Monthly contracts		
Traded weekly	169	51
Traded monthly	38	11
Quarterly contracts		
Traded monthly	38	11
Traded quarterly	13	3

Appendix 2

Appendix 2 contains the hedge ratios used in this paper for the in-sample period.

Table A2.1: Hedge ratios for OLS-hedge for the different contracts

	Monthly contracts		Quarterly contracts	
	Traded weekly	Traded monthly	Traded monthly	Traded quarterly
Beta	0.6322	0.2201	0.558	0.126

Table A2.2: Dynamic hedge ratios for monthly contracts traded weekly

11/10/2015	1.1004	06/11/2016	0.2955	03/12/2017	0.4639
18/10/2015	0.6785	13/11/2016	0.3307	10/12/2017	0.4728
25/10/2015	0.4402	20/11/2016	0.4513	17/12/2017	0.5315
01/11/2015	0.4522	27/11/2016	0.3978	24/12/2017	0.8868
08/11/2015	0.4620	04/12/2016	0.3586	31/12/2017	0.6025
15/11/2015	0.4145	11/12/2016	0.4842	07/01/2018	0.5164
22/11/2015	0.4775	18/12/2016	0.4120	14/01/2018	0.4880
29/11/2015	0.8145	25/12/2016	0.7920	21/01/2018	0.5773
06/12/2015	1.2790	01/01/2017	0.5009	28/01/2018	0.7413
13/12/2015	1.6590	08/01/2017	0.3314	04/02/2018	0.6383
20/12/2015	1.7154	15/01/2017	0.3005	11/02/2018	0.5107
27/12/2015	0.6964	22/01/2017	0.3375	18/02/2018	0.6748
03/01/2016	0.7507	29/01/2017	0.3371	25/02/2018	0.4536
10/01/2016	0.4641	05/02/2017	0.3614	04/03/2018	0.4319
17/01/2016	0.3588	12/02/2017	0.3224	11/03/2018	0.5289
24/01/2016	0.3463	19/02/2017	0.3936	18/03/2018	0.4387
31/01/2016	0.6824	26/02/2017	0.3679	25/03/2018	0.4855
07/02/2016	0.2569	05/03/2017	0.3839	01/04/2018	0.4524
14/02/2016	0.3145	12/03/2017	0.4092	08/04/2018	0.4230
21/02/2016	0.2718	19/03/2017	0.4104	15/04/2018	0.4328
28/02/2016	0.3895	26/03/2017	0.4446	22/04/2018	0.5862
06/03/2016	0.3049	02/04/2017	0.4408	29/04/2018	0.4705
13/03/2016	0.3487	09/04/2017	0.4424	06/05/2018	0.9538
20/03/2016	0.3517	16/04/2017	0.5149	13/05/2018	0.8657
27/03/2016	0.5894	23/04/2017	0.4617	20/05/2018	0.9459
03/04/2016	0.5759	30/04/2017	0.4626	27/05/2018	1.2351
10/04/2016	0.4229	07/05/2017	0.4479	03/06/2018	0.4719
17/04/2016	0.4613	14/05/2017	0.4547	10/06/2018	0.3918
24/04/2016	0.5666	21/05/2017	1.4351	17/06/2018	0.3853
01/05/2016	0.4517	28/05/2017	0.7234	24/06/2018	0.3743
08/05/2016	1.0262	04/06/2017	0.6624	01/07/2018	0.4361
15/05/2016	0.8693	11/06/2017	0.6381	08/07/2018	0.4395

22/05/2016	0.6012	18/06/2017	0.5772	15/07/2018	0.4221
29/05/2016	0.5155	25/06/2017	0.7184	22/07/2018	0.4205
05/06/2016	0.5207	02/07/2017	0.6687	29/07/2018	0.4523
12/06/2016	0.6221	09/07/2017	0.7123	05/08/2018	0.4448
19/06/2016	0.5217	16/07/2017	0.5335	12/08/2018	0.5249
26/06/2016	0.4709	23/07/2017	0.4738	19/08/2018	0.4646
03/07/2016	0.5305	30/07/2017	0.5420	26/08/2018	0.5824
10/07/2016	0.5470	06/08/2017	0.6857	02/09/2018	0.5913
17/07/2016	0.4431	13/08/2017	0.5474	09/09/2018	0.4755
24/07/2016	0.5070	20/08/2017	0.5715	16/09/2018	0.5500
31/07/2016	0.5060	27/08/2017	0.9022	23/09/2018	1.0789
07/08/2016	0.6583	03/09/2017	0.4668	30/09/2018	0.5327
14/08/2016	0.5233	10/09/2017	0.5047	07/10/2018	1.1093
21/08/2016	0.5347	17/09/2017	0.5151	14/10/2018	2.7078
28/08/2016	0.4894	24/09/2017	0.4515	21/10/2018	2.4240
04/09/2016	0.4793	01/10/2017	0.6058	28/10/2018	0.9273
11/09/2016	0.4790	08/10/2017	0.4723	04/11/2018	0.4960
18/09/2016	0.4915	15/10/2017	0.5047	11/11/2018	0.5123
25/09/2016	0.4837	22/10/2017	0.5217	18/11/2018	0.6086
02/10/2016	0.5802	29/10/2017	0.9931	25/11/2018	0.4628
09/10/2016	0.4515	05/11/2017	0.8749	02/12/2018	0.5229
16/10/2016	0.3883	12/11/2017	0.5863	09/12/2018	0.4530
23/10/2016	0.4740	19/11/2017	0.4920	16/12/2018	0.5877
30/10/2016	0.4250	26/11/2017	0.4599	23/12/2018	0.5187

Appendix 3

Appendix 3 goes through the procedure of getting forecasted hedge ratios in order to evaluate the CCC-GARCH out-of-sample.

A3.1 Forecasting Procedure

To test the strategy out-of-sample we need to forecast the conditional variances from the GARCH (1,1), both on spot and futures returns. The procedure takes previous information and tries to predict the conditional variances ahead of time. The forecast is a one step ahead forecast meaning that the model only predicts one estimation at the time and at each point take new information into account (Brooks, 2019). We then use the forecasted conditional variances to compute the forecasted hedge ratios.

$$\sigma_{t+1}^2 = \alpha_0 + \alpha_1 u_t^2 + \beta \sigma_t^2$$

Table A3.1: Forecasted conditional variances on weekly spot and futures returns and forecasted betas

Dates	Spot	Futures	Beta
13/01/2019	0.01071	0.00428	0.58230
20/01/2019	0.01655	0.00469	0.62337
27/01/2019	0.02037	0.00504	0.64200
03/02/2019	0.02288	0.00534	0.64951
10/02/2019	0.02451	0.00559	0.65128
17/02/2019	0.02559	0.00580	0.65011
24/02/2019	0.02629	0.00598	0.64752
03/03/2019	0.02675	0.00613	0.64435
10/03/2019	0.02705	0.00626	0.64107
17/03/2019	0.02725	0.00638	0.63791
24/03/2019	0.02737	0.00647	0.63500
31/03/2019	0.02746	0.00655	0.63239
07/04/2019	0.02751	0.00662	0.63008
14/04/2019	0.02755	0.00667	0.62807
21/04/2019	0.02757	0.00672	0.62633
28/04/2019	0.02759	0.00676	0.62483
05/05/2019	0.02760	0.00680	0.62354
12/05/2019	0.02761	0.00683	0.62244
19/05/2019	0.02761	0.00685	0.62150
26/05/2019	0.02761	0.00687	0.62070
02/06/2019	0.02762	0.00689	0.62003
09/06/2019	0.02762	0.00691	0.61945
16/06/2019	0.02762	0.00692	0.61896
23/06/2019	0.02762	0.00693	0.61854

30/06/2019	0.02762	0.00694	0.61819
07/07/2019	0.02762	0.00695	0.61789
14/07/2019	0.02762	0.00696	0.61763
21/07/2019	0.02762	0.00696	0.61742
28/07/2019	0.02762	0.00697	0.61723
04/08/2019	0.02762	0.00697	0.61708
11/08/2019	0.02762	0.00697	0.61695
18/08/2019	0.02762	0.00698	0.61684
25/08/2019	0.02762	0.00698	0.61674
01/09/2019	0.02762	0.00698	0.61666
08/09/2019	0.02762	0.00698	0.61659
15/09/2019	0.02762	0.00699	0.61653
22/09/2019	0.02762	0.00699	0.61648
29/09/2019	0.02762	0.00699	0.61644
06/10/2019	0.02762	0.00699	0.61641
13/10/2019	0.02762	0.00699	0.61638
20/10/2019	0.02762	0.00699	0.61635
27/10/2019	0.02762	0.00699	0.61633
03/11/2019	0.02762	0.00699	0.61631
10/11/2019	0.02762	0.00699	0.61630
17/11/2019	0.02762	0.00699	0.61628
24/11/2019	0.02762	0.00699	0.61627
01/12/2019	0.02762	0.00699	0.61626
08/12/2019	0.02762	0.00699	0.61625
15/12/2019	0.02762	0.00699	0.61625
22/12/2019	0.02762	0.00699	0.61624

Appendix 4

Table A4.1: Standard deviations and correlations for spot and futures returns out-of-sample

	Spot	Futures	Correlation
Monthly contracts			
Weekly	0.187	0.065	0.5314
Monthly	0.294	0.155	0.8558
Quarterly contracts			
Monthly	0.294	0.166	0.9649
Quarterly	0.466	0.245	0.9532