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Contents

Summary

Given the recent volatility of electricity prices, this thesis aims to determine if the findings on electricity price hedging using futures are consistent with previous research. This paper will study the effectiveness of futures contracts in the Nordic electricity market in reducing variance and compare the in-sample and out-of-sample hedging ability of the minimum variance hedge computed using naïve, ordinary least squares regression (OLS) and rolling OLS hedge ratios. The empirical results in this paper suggest significant differences between hedging performance, volatility characteristics, and optimal hedge ratios in the Nordic electricity market. Hedging effectiveness varies over time due to unstable correlations between changes in spot and future prices. The out-of-sample hedging effectiveness is limited compared to the in-sample performance; this may be attributed to the high volatility of electricity prices in 2021 and 2022, which resulted in low correlations between spot and future prices. In contrast with previous literature in various other energy markets, we found that static hedge approaches were more effective than a dynamic hedge.

1.0 Introduction

Research topic and background

The free electricity market refers to a system in which electricity is bought and sold on an open market rather than provided by a government-owned utility. This type of market encourages competition among electricity producers and gives consumers a choice of electricity providers. Although electricity is considered a commodity, it inhibits distinct characteristics that differentiate it from other commodities. Electricity is entirely interchangeable. One megawatt hour of electricity produced from coal or natural gas contains the same amount of energy. Electricity must also be created and used simultaneously. The storage of electricity is still costly; supply must meet demand precisely in the power grid (CME Group Inc, 2023); these characteristics also contribute to higher volatility than other commodities. The Nordic electricity market is divided into a physical and financial market, where trade occurs on separate exchanges (Norwegian Ministry of Petroleum and Energy, 2023). Financial trading occurs on Nasdaq commodities, while physical electricity trading happens mostly through Nord Pool. The financial power market enables buyers and sellers to manage the risks associated with physical market prices; however, technical conditions such as grid congestion and access to capacity are not considered when entering these financial contracts.

The continuous development of the electricity market, combined with its unique characteristics, makes further research on the effectiveness of various hedging strategies in this market a vital topic. Much like the rest of Europe, the Nordics are currently grappling with a severe energy crisis resulting in recent exaggerated price fluctuations; it is an appropriate time to examine potential ways to reduce the risk for producers. In addition, climate policy and regulation mean that an increasing share of the total energy production comes from renewable sources; therefore, price risk management will be increasingly important as this evolves. While much of the existing research on hedging in the electricity market dates to the early 2000s, this thesis aims to examine the changes in the market and determine if the findings on electricity price hedging using futures are consistent with previous research. The primary contribution of this thesis is the examination of the evolving electricity market and the use of futures for hedging purposes.

Research question, aims, and approach

The scope of our thesis is to analyze if hedging with futures contracts at Nasdaq Commodities results in reducing the volatility that electricity producers face when selling electricity in the spot market. Following the recent increased volatility in the electricity spot market due to the energy crisis, we can observe if the results from earlier studies differ from those under a stressed environment, for example, whether we observe more tail protection than earlier anticipated. We also want to observe how hedging effectiveness with futures has changed over time and how the market has developed. We apply three methods, naïve one-to-one, static OLS, and rolling OLS hedging approaches. We also analyze the effects of different contracts with various holding periods. We use the hedge effectiveness metric (Ederington, 1979) to compare the different hedging approaches and the minimum variance method to estimate the optimal hedge ratios.

We expect that the volatility of returns in the Nordic electricity market will be reduced by hedging with electricity futures; however, the effectiveness will vary depending on the hedging strategy applied, the type of contract, and the duration of the hedge. Testing for ARCH effects may help us determine whether dynamic hedge ratios are more efficient than static hedge ratios, and we will test the hypothesis that longer hedging durations drive superior performance. The persistence of strong volatility in electricity prices may result in a stronger incentive to manage the risk.

The following section of this paper will first address the history and essential background information about the Nordic electricity market, characteristics of electricity prices, and risk factors of the electricity market. Section 3 provides a review of the relevant literature. Section 4 explains the empirical methods and models, including statistical tests, the minimum variance method, the various hedging strategies, the measurement for hedge effectiveness, and backtesting. Section 5 is an overview of how the data is collected and transformed, and we perform a preliminary analysis of the data and discuss the expected results. In section 6, we discuss the results. Lastly, section 7 concludes with the performance of the various hedging strategies, the impact of contracts with different maturity and holding periods, and the development of the market.

2.0 Background

History

In 1991, following the Law of Energy Act the previous year, the Norwegian parliament deregulated the market for trading electrical energy (Nord Pool group, 2023). The power price was set centrally before, causing inefficient production due to a lack of incentives for power producers to be cost-efficient (Bye, 2005). Price regions with oversupply created lower prices for local customers by charging higher prices in regions with undersupply, and the creation of a spot market in which anyone could purchase power rectified these problems. Nord Pool was established in 1992 following the liberalization of electricity markets in the Nordic countries. Prior to this, the electricity sectors were mostly government controlled. Nord Pool is a wholesale electricity market that covers much of the Nordic region, including Denmark, Finland, Sweden, and Norway. Electricity producers sell their electricity directly to consumers on an open market rather than being limited to selling to a government-owned utility. It is one of the world's oldest and largest electricity markets, and it is known for its high levels of transparency and efficiency.

The shift in price determination naturally led to increased price volatility. Electricity producers in the new market face volatile spot prices, which can leave them at risk if these prices do not cover their production costs. As a result, all market participants have an incentive to manage the risk of price uncertainty, spurring interest in electricity derivatives as a risk management tool. The liberalization of the electricity market has created this need for risk management among all market participants.

Risk Management

Risk management involves identifying risks, assessing future uncertainty, and controlling threats to a firm's capital and earnings to improve decision-making value. Risk cannot be eliminated, but understanding how it may affect a firm and managing it can help to minimize losses and volatility, exploit opportunities, and maximize gains.

Derivatives manage risk either through hedging or speculating. Hedging is combined with derivatives to reduce differing price risks. Power suppliers and energy-intensive industries share a common price risk due to fluctuations in the power market. An energy-intensive firm may manage risk by using derivatives to hedge its expenses, thereby securing a fixed price at which it purchases power. Alternatively, the firm could speculate on the movement of electricity prices and use derivatives to capitalize on expectations about the movement.

Volatility is a statistical measure of the dispersion of returns for a given security and is a signal of risk; the higher the volatility of an asset, the higher the risk associated with that particular asset (Corporate Finance Institute, 2023). High volatility means that the price is spread over a large range and may change quickly over a short time. Factors that drive the volatility of electricity prices include the price of other commodities, macroeconomic climate, weather, and supply.

Risk Factors in The Electricity Market

Participants in the electricity market face both quantity and price risks hourly, primarily due to the inherent characteristics of electricity (Souhir, Heni, & Lotfi, 2019). Electricity prices exhibit seasonal variations, with higher prices typically observed during winter than summer (Ek & Thorbjørnsen, 2014). Moreover, the limited storage capacity for electricity leads to price spikes caused by extreme weather conditions and other factors contributing to price volatility (Geman, 2008). Consequently, electricity prices are significantly more volatile than other commodities (Souhir, Heni, & Lotfi, 2019). Physical restrictions in the transmission grid, affecting the transfer of electricity, also contribute to price fluctuations and supply disturbances (Saakvitne & Bjønnes, 2015). However, due to the limited storage abilities of electricity, electricity producers relies more on derivatives to hedge against price volatility and secure future prices.

The Nordic electricity market relies heavily on renewable energy sources, particularly hydropower and wind, which account for a significant portion of electricity production (Veie, et al., 2019). Hydropower alone generates over half of the electricity production in the region (Nordic Energy Regulators, 2019). This dependence on renewables introduces a substantial quantity risk, as variations in water inflow to storage reservoirs and wind strength near turbines impact the electricity supply. Higher inflows increase supply and lower prices, while lower inflows lead to rising prices. Electricity production capacity is categorized into flexible and intermittent sources (Norwegian Ministry of Petroleum and Energy, 2021). Flexible production allows plants to adjust production based on market conditions, whereas intermittent production is limited to the availability of energy sources. Hydropower producers benefit from storing electricity using storage reservoirs, allowing them to scale down production during periods of low prices and up when prices are higher.

Given the ongoing global climate challenge, significant uncertainty surrounds the future development of the electricity market. More electricity production must come from renewable sources to meet climate policies and achieve climate goals. While hydropower will remain dominant in the Nordic electricity market in the coming years, there will be an increase in highly variable and intermittent sources such as solar and wind power (Veie, et al., 2019). Consequently, during periods of abundant sunshine and wind, production may exceed consumption, leading to lower prices due to the non-storability of electricity. This anticipated increase will likely amplify price volatility, making price risk management even more crucial.

Hedging Electricity Price Risk

From spring 2022, there was a significant withdrawal of fixed-price tariffs due to extreme volatility in the price of financial contracts used to hedge power price risk. Price volatility was so significant that retailers could not assemble a portfolio of customers before prices changed; many retailers stopped offering them altogether rather than risk losing money on fixed-price tariffs.

Power Purchase Agreements, or 'PPAs' are renewable energy supply contracts for plant operators, project developers, and investors. In addition to matching individual procurement strategies, PPAs are excellent hedging instruments and can mitigate portfolio risk (Statkraft, 2023). PPAs help reduce the challenge of the energy market where owners of renewable energy plants and power consumers do not have the same needs, offering predictability and security of supply to consumers and financial predictability and security for plant owners through the ability to generate stable, predictable revenues.

The Nordic Electricity Market

The Nordic electricity market operates with 15 bidding areas at Nord Pool, each with its own area price. These prices vary due to differences in transmission capacity, leading to congestion between areas and higher prices in areas with supply deficits. Area price determination considers orders on the day-ahead market and available transmission capacity. Market participants pay or receive the area price when trading on Nord Pool, while the day-ahead market balances supply and demand. The intraday market corrects discrepancies between consumption, production, and day-ahead positions. Nordic Transmission System Operators employ balancing markets to regulate consumption or production during external disruptions.

The system price, which represents the theoretical equilibrium price for the entire system, is the reference price for financial contracts in the Nordic electricity market. Grid congestions, capacity access, and area price risk are not considered in financial contracts. Nordic financial electricity trading takes place at Nasdaq Commodities through the Nasdaq Oslo ASA Exchange. Contracts are priced in euros per MWh and can have various durations. Trading these contracts without physical electricity delivery is a form of speculation.

Financial products in the market include futures, forwards, options, and electricity price area differential (EPAD) contracts. These products serve as contingent claims or forward commitments, providing the right to purchase or sell at a predefined price or a locked-in price in the future (CFA Institute, 2023). The system price is the reference for most financial contracts, while EPADs hedge against price area risk caused by transmission grid constraints (Nasdaq, 2023).

Power supplied to the grid follows the path of least resistance and cannot be differentiated by source or distance. Grid companies monitor power production and consumption for settlement purposes. The power market consists of wholesale and end-user markets, with the day-ahead market being the primary market for power trading in the Nordic region. The intraday market allows continuous trading to balance supply and demand, while the balancing market regulates production or consumption to maintain balance together with reserves.

The power exchange calculates the system price, which serves as the reference price. Bids from producers and end users determine the equilibrium price. Market-based price formation ensures cost efficiency and area prices reflect grid congestion. Areas with power deficits have higher prices, while areas with surpluses have lower prices. Power flows from low-price to high-price areas to meet demand. Area prices inform generation and consumption adjustments while bidding zones indicate the need for long-term measures in the power system.

Following the Ukraine conflict, Russia's energy weaponization was a significant awakening regarding the security of the energy supply and the need to address dependencies. Companies have suffered significant damage to their competitiveness due to soaring energy prices and disruptions in various supply chains, especially energy-intensive industries. In response to the high energy costs and the desire to replace costly fuels with more affordable renewables, the EU has taken significant measures aligned with the REPowerEU plan. In 2022, the EU witnessed a 25% growth in wind and solar renewable energy production capacity from 2020, surpassing 400 GW. The goal is to consolidate gas demand, coordinate infrastructure utilization, negotiate with international partners, achieve savings, enhance storage capabilities, and establish a cap on short-term markets. The EU Commission will present a reform of the electricity market design, including an increasing role of long-term price contracts to ensure predictable and more affordable renewable power costs for electricity consumers. Industrial competitiveness will need to improve through transforming industrial processes, accelerating, and expanding renewable energy deployment, intensifying efforts towards energy efficiency and demand reduction, and providing workforce reskilling and upskilling initiatives (European Commission, 2023). A Green Alliance was established between Norway and the EU; it is not a legally binding agreement, but it represents a common understanding of the priority areas for the green transition moving forward and enhances cooperation (Office of the Prime Minister of Norway, 2023).

3.0 Literature Review

(Modigliani & H. Miller, 1958) stated that in the absence of market imperfections, financial policy, including hedging, does not increase firm value. However, (Smith & Stulz, 1985) argue that firms may use hedging to ease risk exposure, and the insurance theory by (Keynes) proposes that producers use commodity futures markets for insurance by locking in prices and making revenues more predictable. The naïve (or one-to-one) hedge assumes that futures and cash prices are closely together, where the hedging position in equal numbers of futures contracts as the position in the underlying asset, meaning the hedge ratio is always one. However, an impartial correlation between spot and future prices led to proposing a minimum variance hedge ratio (Johnson, 1960).

The Hedging Performance of New Futures Markets (Ederington, 1979) addresses the economic rationale for futures markets, which is to facilitate the transfer of risk of price changes in the underlying commodity to speculators willing to bear such risks. Ederington formalized the approach to estimating the optimal hedge ratio by using Ordinary Least Squares (OLS) to regress spot on future prices and proposed a measure of the risk reduction effect of the OLS hedge ratio. (Byström)'s widely cited study of the Nordic electricity market finds that the OLS hedging strategy reduces the variance of the hedged portfolio. (Madaleno & Pinho)'s paper on optimal hedge ratios and hedging effectiveness for the German electricity market finds that the OLS hedge outperforms the naïve hedge. (Torro) finds that the characteristics of electricity prices generate ineffective performance.

Despite previous success hedging with OLS, it has limitations as the hedge ratio assumes that the variance-covariance matrix of returns is constant over time, which is unlikely in a volatile electricity market. Time-varying hedge ratios may have a better result; the conditional Heteroskedastic AutoRegressive Specification (ARCH) was presented by Engle (1982) and further extended by Bollerslev (1986) to the Generalized AutoRegressive Conditional Heteroskedastic specification (GARCH). According to research from Baillie & Myers (1991) and Kroner & Sultan (1993), bivariate GARCH models result in improved hedge performance compared to the OLS approach, mainly using a bivariate Constant Conditional Correlation GARCH (CCC-GARCH) model proposed by Bollerslev. This research was further improved to consider how correlations change over time by introducing the multivariate Dynamic Conditional Correlations GARCH (DCC-GARCH) model (Engle, 2001).

The choice of a multivariate volatility model can lead to varying conclusions in an application involving estimating the optimal hedge ratio (Kroner & Ng, 1998). In contrast, other research (Malo & Kanto, 2005) found few differences in hedging performance when implementing different GARCH specifications. Bystrom's paper (2003) demonstrates that GARCH approaches do not perform better than the original OLS approach in reducing portfolio variance despite reducing the volatility of returns. GARCH models obtain the maximum hedging effectiveness when volatility is relatively high in the Nordic electricity market (Zanotti, Gabbi, & Geranio, 2010); the results are dependent on the estimation data being kept up-to-date for the re-estimation of the hedge ratios. The OLS hedge ratio performs better than the VGARCH hedge ratio due to the variability of the VGARCH models (Lien, Tse, & Tsui, 2002).

One of the most recent papers published on the hedging effectiveness of future contracts (Peña, 2023), finds that unstable correlations between spot price changes and future price changes are the reason for the variance in hedging effectiveness over time.

4.0 Theory and Methodology

Required Data

To test the strategies, we need both spot and future prices on electricity. We obtained the ENWSSPAV Index's prices from Nasdaq and its corresponding monthly and quarterly traded futures prices.

Statistical Tests

We run the Jarque-Bera test for normality, where the null hypothesis states that skewness and excess kurtosis are jointly zero to determine whether the data shows a normal distribution. The Ljung Box test checks for linear dependence in time series and tests the joint hypothesis that all the maximum length lags of autocorrelation are simultaneously equal to zero to test for autocorrelation. To check for ARCH effects (heteroscedasticity), we use Engles' ARCH test and the Ljung Box test with squared residuals. If we find significant evidence for heteroscedasticity, the standard errors could be wrong, and it may be appropriate for us to use a model that does not assume constant variance. Lastly, we perform an ADF unit root test for stationarity and a KPSS stationarity test to confirm the results of the ADF test.

Minimum Variance Hedge

In this paper, the minimum variance approach determines the most effective hedge ratio for an electricity producer who holds a long position in an asset and hedges their position by selling futures contracts (Brooks, 2019). This approach seeks to minimize the variance of the value of the hedged position for the producer. The return on the portfolio, consisting of a long position in the spot market and a short position in the futures market at the following time period, is represented as follows:

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

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 β_t is the optimal hedge ratio. The conditional variance of this portfolio is computed as follows:

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

The hedge ratio shows how many futures contracts must be sold to hedge the underlying position to minimize the portfolio variance. To obtain the conditional minimum variance hedge ratio, we minimize the variance of the hedged portfolio with respect to β_t:

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

Hedging Strategies

Naïve one to one

The 'naive' hedge is a strategy that takes one short futures contract for every spot unit but does not allow the hedge to vary with time (Brooks, 2019). This strategy assumes that the covariance between futures and spot returns equals the variance of futures returns.

Static OLS

The static ordinary least squares (OLS) estimated hedge ratio was popularized by Ederington (1979). This hedge ratio is also referred to as the minimum-variance hedge ratio as it minimizes the variance of a spot futures portfolio (Hull, 2012) and is the single hedge ratio that, on average, reduces the most variance over the sample when considering in-sample analysis. This strategy assumes that the R^2 represents the proportion of the sample variance in a spot portfolio that can be eliminated by hedging with futures. A higher R^2 implies a greater potential variance reduction.

Rolling OLS

The rolling OLS method estimates the hedge ratio over time, allowing for changes in the relationship between the two assets. It involves fitting a linear regression model to a rolling window of historical data, where the dependent variable is the returns of one asset, and the independent variable is the returns of the other asset. The hedge ratio is re-estimated at each step by sliding the window over the data, capturing the evolving relationship between the assets. One of the pioneering studies that introduced the concept of rolling OLS for hedging purposes is a paper focused on foreign exchange rates by (Engle & Granger, 1987) which laid the foundation for applying rolling OLS in the context of estimating hedge ratios.

Hedging Effectiveness

To compare the performance of the different hedging strategies, we implement the hedge effectiveness (HE) metric (Ederington, 1979). This metric measures the percentage of variance reduction of the hedged position compared to the unhedged position.

$$HE = 1 - \frac{Variance_{Hedged}}{Variance_{Unhedged}}$$

If the HE is positive, this indicates that the hedge is effective, and the hedging strategy that gives the highest percentage variance reduction is considered the best. If the HE is zero or negative, the hedging is considered inefficient since it can increase variance in the worst case.

Backtesting

Backtesting is performed to analyze how effective a hedging strategy performs ex-post and to analyze its viability by discovering how it performs using historical data and potential changes that can optimize the strategy (Chen, 2021). In-sample testing is the testing of a strategy on the data set used to develop and optimize the strategy. In contrast, the out-of-sample testing enables us to test how the model performs using a different time period, a more realistic measure of hedging effectiveness.

5.0 Data

Data Description

We take the point of view of an electricity producer and assume one spot per timeframe and that they sell at the end of the timeframe. We use Nord Pool Day-ahead and Nord Pool Intraday market data, volumes, capacities, and flow. Futures prices will be collected from Bloomberg as traded at Nasdaq Commodities. We observe monthly spot and futures prices for monthly futures contracts and monthly and quarterly spot and futures prices for quarterly contracts. These are denoted EUR/MWh, and the spot price refers to the Nordic system price.

It is essential to consider that when we are hedging with Nordic electricity futures, a perfect hedge is only possible when there are no transmission grid congestions in the market area; otherwise, additional basis risk is implied. The hedge is not against area price risk as we do not divide the spot prices in the different geographical systems but just take the Nordic system price, leaving us with a basis risk equal to the difference between the area price and the producer's physical location and the system price, due to possible transmission grid congestions in the market area.

In some of the hedging strategies, we apply a hedge ratio that will not add up to a round number of contracts. We assume that the futures contract can be partly shorted or that the results can be scaled to a volume that is possible to purchase from the marketplace. The results would be more challenging to replicate in the real world due to this problem.

We use a significant enough sample period to get generalized and valid results, especially given that we want to observe how the effectiveness of hedging with futures has changed over time and how the market has developed. We were able to access 5 years of data for the in-sample period (01.01.2017 – 31.12.2021) and a one-year out-of-sample period (01.01.2022 – 31.12.2022). It may have been beneficial to test our hedge strategies on weekly futures contracts to get a larger amount of observations; however, this data was not available at Bloomberg.

Data Transformation

We transform the spot and future prices into log returns. Since log returns can be interpreted as continuously compounded returns, the frequency of compounding is not a factor affecting the returns. Therefore we can compare returns across different assets. In addition, logarithmic returns are symmetric, meaning logarithmic returns of equal magnitude but opposite signs will cancel each other out. Taking logarithms of the prices may result in a more constant variance, a positively skewed distribution turning closer to a normal distribution, and they are unit-free, so should avoid the problem of non-stationary time series. The equation for continuously compounding returns where r_t are the continuously compounded returns at time t, p_t denotes the asset price at time t, and ln denotes the natural logarithm.

$$r_t = 100\% \cdot \ln\left(\frac{p_t}{p_{t-1}}\right) = 100\% \cdot (\ln \; p_t - ln\, p_{t-1})$$

Time series of returns

We examined the time series of returns (Appendix 4) as an initial step in analyzing the data, as this can provide valuable insights into the behavior and characteristics of the underlying data. We examine close to a normal distribution of returns up until 2020 and mean reversion, where the data reverts to its long-term average over time, and the magnitude of fluctuations in the returns is greater since 2020. The data exhibits seasonality in the return; regular fluctuations occur at fixed intervals in yearly cycles, with higher prices in the winter and lower in the summer. The extreme outliers in recent years demonstrate structural changes and increased variance in the market.

Descriptive Statistics

The following table below shows the results of the statistical tests previously mentioned.

Table 1: Descriptive Statistics

	Monthly contracts traded monthly		Quarterly contracts traded monthly		Quarterly contracts traded quarterly	
	Spot	Futures	Spot	Futures	Spot	Futures
Mean	1.66	2	1.66	1.73	4.98	5.2
Std dev.	57.57	36.52	57.57	24.87	63.79	52.72
Skewness	2.22	0.53	2.22	-0.53	-0.48	-2.03
Kurtosis	11.64	5.88	11.64	5.47	4.89	8.49
Jarque Bera	235.9416	23.4689	235.9416	18.0179	3.7316	38.861
ADF						
Price levels	0	0.9	0	0	-1.31	-0.18
First diff.	-3.65	-2.87	-3.65	-3.81	-2.02	-2.26
KPSS						
Price levels	0.87	0.24	0.87	0.23	0.33	0.17
First diff.	0.1	0.22	0.1	0.18	0.12	0.2
Ljung-box test on Standardized Residuals						
LB 1 Lag[1]	0.6698	0.001024	0.6698	0.1551	0.02245	0.2161
LB 2 Lag[5]	4.4577	2.884020	4.4577	0.4055	1.38313	1.1206
LB 3 Lag[9]	6.3486	5.087154	6.3486	1.6059	2.31758	4.5392
Ljung-box test on Standardized Squared Residuals						
LB 4 Lag[1]	0.08066	0.05901	0.08066	0.3691	0.2222	0.1477
LB 5 Lag[5]	1.23275	1.49888	1.23275	1.4709	4.1386	0.3739
LB 6 Lag[9]	2.66322	2.62197	2.66322	2.4684	5.3178	0.5988
Weighted ARCH LM Tests						
ARCH Lag[3]	0.4309	0.001021	0.4309	0.7212	0.001435	0.1474
ARCH Lag[5]	2.0103	1.684023	2.0103	0.8870	0.604656	0.2695
ARCH Lag[7]	2.8987	2.115035	2.8987	1.6651	1.017522	0.3561
Correlation	0.2844		0.443		0.7232	

The 99% critical value for the Jarque Bera is 9.2103. The null hypothesis of the ADF test is that the series contains a unit root, and for the KPSS test, the null hypothesis is that the time series is stationary. The ADF 99% critical values for price levels and first differences are 1.7656 for contracts traded monthly and 2.0073 for contracts traded quarterly. The KPSS 99% critical values for price levels and first differences are 2.8799 for all contracts. The null hypothesis of the weighted Ljung-Box test on standardized Residuals *and standardized squared residuals* is that there is no serial correlation. The null hypothesis for the Engle's arch test *is* "series exibhits no conditional heteroscedasticity (ARCH effects)". 99% CV for the most restrictions on the LB tests and ARCH test for the monthly contracts are approxematly 81.72 and 43.19 and for the quarterly contracts 19.06 and 6.61.

The monthly and quarterly spot contracts traded monthly exhibit means of 1.66, are positively skewed to a degree of 2.22, and exhibit high excess kurtosis. The futures have slightly higher means of 2 and 1.73, respectively, and the monthly contracts are positively skewed, while the quarterly contracts are negatively skewed, both exhibiting low excess kurtosis. The standard deviations of the spot and futures are different in the same market, the spot volatility (57.57) is higher than that of the futures, and the monthly contracts are more volatile than the quarterly contracts, both traded monthly. The Jarque Bera test shows that the monthly and quarterly spot returns have a non-normal distribution of residuals. The futures are also not normally distributed but not by as great of a degree. The issue of non-normality is likely caused by outliers or heteroscedasticity in the time series (Brooks, 2019). Outliers can be removed, or dummy variables can be introduced, but due to the volatility of electricity prices in this period, we argue that every data point contains valuable information. Given that the monthly and quarterly spot contracts both exhibit a non-normal distribution of residuals, this may result in inefficient estimates. The heteroscedasticity in the time series means GARCH models may be appropriate.

The quarterly contracts traded quarterly spot and future returns exhibit a mean of 4.98 and 5.2, respectively. Both are negatively skewed, the futures to a greater extent than the spot returns. The spot returns exhibit a lower excess kurtosis than the futures, indicating that the distribution of quarterly spot returns has relatively heavy tails and potentially some outliers. The Jarque Bera test statistic for spot returns suggests that it is normally distributed; the p-value is greater than the significance level of 1%, indicating insufficient evidence to reject the null hypothesis of normality. The distribution of quarterly spot returns is likely normal despite the slight left-skewness and heavy tails. In contrast, the futures exhibit heavy tails, a potentially large number of outliers, and a significant left skewness. The Jarque Bera test shows that the quarterly future returns traded quarterly significantly deviate from the normal distribution.

Spot returns in quarterly returns traded quarterly are appropriately normal but there is evidence of non-normality in future contracts for the same period, suggesting systemic factors or dynamics may be at play, causing the distribution of future returns to deviate formality. This can be attributed to various reasons, including market inefficiencies, structural changes or specific events impacting the market. It is essential to consider the non-normality in future returns, because if it is caused by occasional extreme events such as heavy tails, a standard hedging approach that assumes normality may not protect against such events. Alternative hedging techniques that account for this, for example, tail-risk hedging, could be more appropriate. The quarterly future returns traded quarterly have significant left skewness, this could be incorporated into hedging techniques, or the hedge ratio could be dynamically adjusted based on observed asymmetries in the market.

The ADF test on price levels rejects the null hypothesis in all cases, and the test statistic is smaller than the critical value in all cases, indicating that the time series is stationary. However, it presents high p-values indicating that we cannot reject the null hypothesis that there is a unit root. The ADF test has a high degree of Type I error, meaning it often rejects a true null hypothesis. Hence the results of this test are inconclusive, we cannot reject the null hypothesis based on the p-values, and there may be a unit root (non-stationarity) present in the data. For the KPSS test on price levels, the test statistic for all values is smaller than the critical value; we fail to reject the null hypothesis of stationarity. The p-values are greater than the significance level, reinforcing that stationarity may be present in all cases. When taking the first differences in the ADF test, we cannot reject the null that there is a unit root based on the p-values. However, the test statistic suggests that we reject the null, again potential evidence of a Type I error. The values of the test statistic for the first difference in the KPSS test mean we fail to reject the null that the data is stationary; the p-values reinforce this answer. The overall results suggest that the data is stationary; hence it would be beneficial to transform the series into returns before implementing the hedging strategies.

In the Ljung Box test on standardized residuals for all lag lengths, the test statistics are below the critical values; we fail to reject that the time series has no serial correlation for all values. The p-value is also smaller than the significance level of 1% in all of the lag lengths, which strengthens our findings of no serial correlation. If the time series had exhibited presence of autocorrelation in the residuals, it may have led to inefficient OLS coefficients, and the standard errors could be wrong (Brooks, 2019). The Ljung Box test with squared residuals fails to reject the null hypothesis that there are no serial correlation effects present in the time series. The p-values suggest that we should reject the null hypothesis; the time series does not contain serial correlation.

We performed Engle's ARCH test for residual heteroscedasticity with 3, 5, and 7 lags. Under the null hypothesis, the series exhibits no conditional heteroscedasticity (ARCH effects). We fail to reject the null and ascertain that there are no ARCH effects present in the data. The p-value reinforces our conclusion against an alpha of 1%. These results suggest that implementing time-varying variances in the hedging model may not be as beneficial as we previously anticipated.

Expected Results

The expected result is that the uncertainty of the hedged portfolio will be reduced by hedging the spot prices in the Nordic electricity market. The expected outcome of employing a simple one-to-one hedging strategy can vary depending on market conditions and the effectiveness of the hedging approach. However, before implementing this strategy, there are several expectations we typically have. Firstly, we anticipate better price stability. By utilizing futures contracts for hedging, we can secure a predetermined price for future electricity sales, which is advantageous during periods of anticipated price volatility. Secondly, we expect to achieve enhanced income certainty. Producers can better understand their electricity income by hedging with futures contracts, facilitating improved budgeting, and reducing the risk of unexpected price fluctuations. In the event of a decline in spot prices, the hedge can help mitigate the loss by offsetting the decline and minimizing income reduction. Generally, we expect the hedge effectiveness to increase along with the holding period.

It is important to note that this strategy assumes a perfect linear relationship between spot and futures price returns, which may not be applicable in the real world. Factors such as energy transportation costs, limited storage capabilities, and overall market production uncertainty introduce complexities. Consequently, the strategy is exposed to basis risk, where the connection between spot and futures prices deviates. If the basis widens or narrows significantly, the hedging strategy may not align perfectly with spot price movements, leading to potential gains or losses.

A static OLS hedge recognizes that there may be imperfect correlation; however, the imposition of a restriction of a constant joint distribution between spot and future returns may result in suboptimal performance in periods with high basis volatility. A naïve hedge performs similarly to an OLS hedge when the OLS hedge ratio is close to one. A rolling-OLS hedge strategy is a dynamic hedge strategy;

hence it should enhance the risk reduction properties of the hedge compared to the naïve and OLS hedge, which are both static hedges. It can be advantageous in volatile markets where the relationship between spot and future prices or returns is not constant; hence we assume that it will perform best in the out-of-sample period (2022), given that the standard deviation of spot returns was high compared to futures.

6.0 Hedging Results

We present the results of the in- and out-of-sample hedge performances and analyze the naïve, static OLS and rolling OLS hedging approaches. This section will also discuss the development of spot- and futures price volatility and hedging effectiveness. We examine the hedge performance by looking at each strategy's variance and hedge effectiveness metric. We calculate the hedge effectiveness for both in- and out-of-sample periods.

In-Sample Performance

Table 2: Variances & Hedge Effectiveness in-sample

2017-01-01 - 2021-12-31	**No hedge**	**Naive**	**OLS**	**Rolling Regression**
Monthly contracts traded monthly				
Variance	0.3314	0.3452	0.3046	0.3592
Hedge effectiveness		-4.16%	8.09%	-8.39%
Quarterly contracts traded monthly				
Variance	0.3314	0.2664	0.2663	0.2838
Hedge effectiveness		19.62%	19.63%	14.36%
Quarterly contracts traded quarterly				
Variance	0.4069	0.1941	0.1941	0.2862
Hedge effectiveness		51.24%	52.3%	29.67%

The hedge effectiveness for the monthly contracts traded monthly is -4.16% for Naïve, 8.09% for OLS, and -8.39% for rolling regression. The naïve and rolling regression are inefficient and result in slightly increased variance compared to the unhedged, whereas the OLS hedge reduces variance. Both the Naïve and OLS hedge strategies for quarterly contracts traded monthly result in reduced variance compared to the unhedged variance, with almost equal hedge effectiveness of 19.62% and 19.63%. The rolling regression hedge is also effective in reducing variance for that time period; however, it is not as effective as the other two hedging strategies. The hedge ratio starts at one, and the OLS regression is applied for each data point, therefore it takes some time for the hedge ratio to catch up, which may be why it was not as effective as anticipated. A longer period may reduce the impact of this factor.

For the quarterly contracts traded quarterly, variance is reduced by using both the Naïve and OLS hedge, the OLS outperforming with a hedge effectiveness of 52.3% while the Naïve hedge results in a hedge effectiveness of 51.24%. The rolling regression hedge also reduces variance, but again, it is not as effective as the other two hedging strategies.

The OLS hedge is the most effective overall, reducing variance in all three cases. The Naïve hedge is almost identically as effective as the OLS hedge for quarterly contracts traded monthly and quarterly, however it shows inefficient results for monthly contracts. These variable results can be explained by the high volatility of electricity prices and the low correlation between spot and future returns for monthly contracts traded monthly.

The correlation coefficient for spot and future results are highest for quarterly contracts traded quarterly (0.7232), which help explain why hedging these contracts is most efficient. All of the hedging strategies perform best when correlation is higher due to lower basis risk, which is the risk that the spot and future prices diverge over time. A higher correlation indicates that the price movements in the spot prices are closely correlated to those in the future market. As a result, the hedge position in the spot market is more likely to offset losses or gains in the futures market.

The naïve hedge is ineffective for monthly contracts traded monthly; this may be because the hedge ratio is far from one, meaning the spot position is not utilized effectively to hedge the risk of a futures position. In contrast, the naïve hedge is more effective in reducing variance for quarterly contracts traded monthly and quarterly as the hedge ratio is closer to one. The hedge ratio for rolling OLS is closest to one for the quarterly contracts traded monthly and quarterly; these are the contract lengths where the hedge is most effective.

Out-of-Sample Performance

The out-of-sample performance of the naïve and OLS hedge is tested by applying the static hedge ratios from the in-sample data to the out-of-sample data. The hedge ratios obtained are reported in the appendix, along with the conditional variances from the out-of-sample data which are used to compute the hedged variance and hedge effectiveness, the results of which are presented below.

Table 3: Variances & Hedge Effectiveness out-of-sample

2021-12-31 - 2022-12-31	**No hedge**	**Naive**	**OLS**	**Rolling Regression**
Monthly contracts traded monthly				
Variance	1.2788	1.5293	1.3141	1.3522
Hedge effectiveness		-19.59%	-2.76%	-5.74%
Quarterly contracts traded monthly				
Variance	1.2788	0.8298	0.823	0.8258
Hedge effectiveness		35.11%	35.64%	35.43%
Quarterly contracts traded quarterly				
Variance	0.6126	1.0383	0.9556	0.9404
Hedge effectiveness		-69.51%	-56%	-53.52%

All hedging strategies reduce variance compared to the unhedged for quarterly contracts traded monthly and are all close to equally effective. The hedging strategies for all the other contract lengths and trading periods are ineffective and increase variance. From record low levels in 2020, the electricity price increased substantially in 2021 and 2022. Electricity prices were at record highs in 2022. Given that our hedging strategy is based on the in-sample period, where electricity prices were less variable overall, this might cause lower hedge effectiveness in the out-of-sample period.

The highest hedge ratio for the out-of-sample period is for the quarterly contracts traded monthly; this contract length performs best with the highest hedge effectiveness. The correlation between the spot and futures is highest for the quarterly contracts traded monthly (0.6596), hence why the hedging strategies reduced the volatility of this contract length and the hedges were effective. The correlation for the monthly contracts traded monthly and quarterly contracts traded quarterly are 0.0489 and -0.1832 respectively. The hedging strategies were ineffective for contracts with low correlation as this implies that the spot and future returns are not moving close together or by similar magnitudes; hence the hedge cannot reduce the volatility or risk exposure of the underlying position. The naïve hedge assumes perfect correlation and that the futures position completely offsets the spot position.

The out-of-sample analysis has an overall lower variance reduction compared to the in-sample results. The spot standard deviations are significantly higher than the futures for the out-of-sample period. This means that the futures do not capture the variance in the spot returns as much as in the in-sample period, hence are less effective in hedging the risk. The unhedged spot portfolio is more volatile than the hedged futures portfolio for the in-sample period; the opposite is true for the out-of-sample period.

Overall Performance and Market Development

The OLS hedge performs best overall for the in-sample hedging. The out-of-sample hedging performance is highly variable and only performs well for quarterly contracts traded monthly. There is no significant outperformance by any of the hedging strategies in particular.

The rolling-OLS hedge is a dynamic hedge strategy, meaning it takes advantage of time-varying correlations, trends or other patterns in the market. By adjusting the hedge ratio dynamically, a rolling-OLS hedge should enhance the risk reduction properties of the hedge compared to the naïve and OLS hedge, which are both static hedges. However, the dynamic model does not perform better than the static hedges overall.

In the in-sample hedging, the rolling OLS performs worse than the static hedging strategies for all contracts. In contrast, the in-sample hedging, the rolling-OLS performs about the same as the static hedging strategies for all contract lengths. Previous literature finds that static hedge ratios are inefficient in markets characterized by high inefficiency, and introducing dynamic volatility- and correlation approaches can reduce hedging errors (Byström, 2003) and (Zanotti, Gabbi, & Geranio, 2010). Our findings on dynamic hedging strategies being more effective at reducing variance are inconsistent with previous literature. The rolling

OLS may have performed slightly better in the out-of-sample hedging due to the higher volatility of returns. Suppose we had implemented a more extended period for the out-of-sample testing. In that case, we might have seen more of a pattern of volatility clustering, therefore exhibiting more gains from taking time-varying variances into account.

Hedging with quarterly frequency performs better than the monthly frequency in the in-sample period. The correlation coefficients between spot and futures are higher for these contracts. In contrast, in the in-sample period, hedging with monthly frequency for quarterly contracts performs best as it has a longer hedging duration but is adjusted more frequently.

The naïve hedging strategy involves taking a hedge ratio, determined by the OLS regression, which is maintained throughout the hedging ratio. Any deviation in spot and futures prices over time may lead to a mismatch in the hedge and the underlying position. Periodic rebalancing is necessary to bring it back in line with the desired hedge ratio. Therefore, the naïve hedge is likely to be more costly due to transaction costs and also requires more time, effort and resources for frequent monitoring and administrative tasks.

The OLS hedge strategy determines a single hedge ratio and does not require frequent rebalancing; the hedge ratio remains constant, and adjustments are only made if significant changes occur in the underlying relationship between spot and future prices. The hedge ratio for the rolling OLS strategy is rebalanced monthly or quarterly, depending on the trading frequency. Hence, the rolling OLS strategy will be more costly than the regular OLS hedge.

Hedging with electricity futures has become less effective over the time period examined, as the correlation between spot and future returns is lower in the out-of-sample period.

(Byström)' s findings for the hedging of weekly futures from 1996 to 1999 result in spot and future returns with standard deviations of 0.0655 and 0.0418, respectively. (Zanotti, Gabbi, & Geranio) observe standard deviations of 0.0531 and 0.0239 from 2004 to 2006. These observations vary significantly from the period we analyzed.

While we only observed monthly and quarterly spot and futures, the standard deviation was significantly higher from 2017 to 2023. These changes demonstrate that the Nordic electricity market has become more volatile over the period examined. A recent study in a different market (Peña, 2023) found unstable correlations between spot and future price changes and limited out-of-sample performance; this is more consistent with our findings.

Research on California electricity futures (Moulton, 2005) finds that hedge ratio analysis can be erratic at matching prices. Our research supports this statement as hedge ratios for the out-of-sample period were ineffective at hedging electricity price risk, and the correlation between future and spot prices is low for the out-of-sample period except for quarterly contracts traded monthly. Hedging with more frequent rebalancing than the contract length may result in more effective hedging.

The success of futures contracts depends on the commodity's attributes or the contract's structure according to theory and empirical evidence (Black, 1986). Such attributes may include the size and riskiness of a cash market, the futures contract's specifications and the existence of close substitutes contracts. Given that electricity markets have been volatile, and this volatility may increase with the increase in renewable energy production, together with the lack of substitute contracts and the inherent characteristics of electricity, we expect futures contracts to be less effective in reducing risk over time unless the design of the electricity market is reformed.

Our results contrast those obtained in previous research in various other energy markets where futures contracts increase hedging efficiencies by up to 90% (Li, Huang, & Li, 2021). The Nordic market was the best performer in hedging electricity risk out of the most actively traded European electricity markets (APXUK and Phelix) between 2005-2014 in this paper.

The sample period we analyze contains two crisis periods, the Covid pandemic from March 2020 and the Ukraine crisis, which started at the end of the pandemic in February 2022. The significant changes in the MV hedge ratio over time in the rolling regression suggest structural changes in the market. For the monthly contracts traded monthly, the hedge ratio was negative for most of 2017. Then it was stable primarily around 0.5 until the Covid pandemic in March 2020, where it rose to around 0.8 for a couple of months then stabilizing close around 0.5 until the end of the sample period. The quarterly contracts traded monthly show a similar trend, except the hedge ratio remains close to 1 after the Covid pandemic. The quarterly contracts traded quarterly are low, between 0.1 and 0.25 until after the Covid pandemic where it stays around 0.8 until the end of the sample period. This reinforces our hypothesis of structural changes in the market.

Uncertainty

One of the hedging strategies we considered testing is the CCC-GARCH model hedge. This was developed from (Engle R. F.) 's ARCH model (1982) by (Bollerslev T. , 1986) and the strategy estimates the conditional variance as a function of both the lagged squared errors and lagged estimates of conditional variances. The coefficients on the lagged conditional variances must be non-negative to ensure positive variance estimates. (Zanotti, Gabbi, & Geranio, 2010) found that the CCC-GARCH has historically been the best-performing model for the Nordic electricity market as it captures the time-varying nature of spot and futures returns.

A CCC-GARCH model is appropriate when observing ARCH effects in the time series, and hedge effectiveness increases in the case of futures with ARCH effects. It is appropriate in the case of heteroscedasticity as it allows for the volatility to be time-varying and captures the persistence of volatility shocks. However, the absence of ARCH effects in our model means that despite GARCH models historically performing well in the Nordic electricity market, they are unsuitable for our dataset. We also tested an exponentially weighted moving average model, however, it performed poorly. Therefore, we decided to test an alternative dynamic hedging strategy, the rolling-OLS regression.

One uncertainty we discovered in our data is that the results of the ADF test on price levels were inconclusive. The test statistic indicated that the time series was stationary; however, it also presented high p-values indicating we could not reject the null hypothesis that there is a unit root. The ADF test has a high degree of type I error, often rejecting a null hypothesis. However, the KPSS test results on price levels indicated that the data may be stationary. These conflicting results led us to transform the series into returns before implementing the hedging strategies.

In this thesis, we have used the last prices for the spot price and mid prices for the future prices due to the difficulty of obtaining the correct data. It is essential to acknowledge that utilizing different types of prices for spot and futures contracts introduces uncertainty in the research findings. This uncertainty can arise from various factors, such as market dynamics, liquidity variations, and trading activities, which may affect the results' reliability and accuracy. It also increases the chance of outliers in the data having a more significant impact on the results than initially expected. This problem also increases with the increasing timeframe, seeing as the monthly and quarterly spot prices are computed from the daily last price on those dates.

7.0 Conclusion

Our motivation for exploring this topic stemmed from an interest in the impact of increasing renewable energy generation on the electricity market. The power sector will bear the most considerable burden of emissions reduction in the energy transition and can contribute to the decarbonization of other polluting sectors. The design of the market will face increasing challenges from the growing generation share of non-dispatchable, zero-marginal cost technologies (Peña, 2023) and the consequent importance of the forward and futures markets and auctions of long-term contracts (Fabra, Rapson, Reguant, & Wang, 2021). Hence, understanding to which extent exchange-traded futures can mitigate electricity price risk and the effectiveness of different hedging strategies is crucial, particularly given the recent volatility in the market.

The deployment of renewables and the phase-out of gas requires the improvement of conditions in the electricity system for the use of flexibility solutions such as demand response, storage, and other weather-independent renewable and low-carbon sources (European Commission, 2023). This can be achieved through incentivizing longer-term contracts, in particular increasing the market of power purchase agreements (PPAs), stabilizing the prices of electricity, and curbing excessive revenues of energy producers by requiring the use of two-way contracts for difference (CFDs) for new investments in low carbon generation where public funding is needed, and improving the forward electricity markets. The proposal revising the EU's internal electricity market demand covers all of these topics, and it will make further research on the development of hedging with electricity futures all the more critical.

The empirical results in this paper suggest significant differences between hedging performance, volatility characteristics, and optimal hedge ratios in the Nordic electricity market. The duration of time and volatility attributes also significantly influence the hedging effectiveness; notably, hedging is more effective for contracts with longer time periods. This suggests that participants in the electricity market may encounter difficulties in mitigating their exposure through short-term futures hedging. The comparatively inadequate performance of electricity futures as risk management instruments raise concerns as to the purpose and usefulness of electricity futures markets.

Most methods present significant in-sample hedging effectiveness from 2017 to 2021, the quarterly contracts are the most effective for reducing volatility, and the OLS hedge strategy outperforms all contracts with 8.09%, 19.63% and 52.3% hedge effectiveness. In contrast, the out-of-sample evaluation shows that all hedging strategies are ineffective except in the case of the quarterly contracts traded monthly. The hedge ratio estimates indicate a volatile hedge position due to unstable correlations between spot and future price changes.

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Appendices

Appendix 1

Appendix 1 shows an overview of the number of observations for the two different contracts with the two different hedging durations. The in-sample period is 01.01.2017 - 31.12.2022, and the out-of-sample period is 01.01.2022 – 31.12.2022.

Table A1.01 Number of observations

	In-sample	Out-of-sample
Monthly contracts		
Traded monthly	60	12
Quarterly contracts		
Traded monthly	60	12
Traded quarterly	20	4

Appendix 2

Appendix 2 contains the hedge ratios used in this paper.

Table A2.1: Hedge ratios for OLS-hedge for in- and out-of-sample period

	Monthly contracts traded monthly	Quarterly contracts traded monthly	Quarterly contracts traded quarterly
Beta	0.4494271	1.025366	0.8759604

Table A2.2: Hedge ratios for Rolling OLS for in- and out-of-sample period

	Monthly contracts traded monthly	Quarterly contracts traded monthly	Quarterly contracts traded quarterly
2017-01-31	1	1	
2017-02-28	-0.4586	-0.2768	
2017-03-31	-0.4519	-0.2776	1
2017-04-30	-0.3013	-0.2359	
2017-05-31	-0.2958	-0.2356	
2017-06-30	-0.2971	-0.2305	0.0918
2017-07-31	-0.0146	-0.2363	
2017-08-31	0.0777	-0.085	
2017-09-30	0.1871	-0.0251	0.0717

	Monthly contracts traded monthly	Quarterly contracts traded monthly	Quarterly contracts traded quarterly
2017-10-31	-0.1292	0.0629	
2017-11-30	-0.1695	0.0845	
2017-12-31	0.1169	0.1365	0.1629
2018-01-31	0.2599	0.1647	
2018-02-28	0.3375	-0.0489	
2018-03-31	1.1085	0.3796	0.1324
2018-04-30	0.9644	0.2143	
2018-05-31	1.0573	0.201	
2018-06-30	0.5798	0.4684	0.1652
2018-07-31	0.4156	0.4583	
2018-08-31	0.466	0.4822	
2018-09-30	0.4594	0.4826	0.263
2018-10-31	0.4982	0.525	
2018-11-30	0.4963	0.5168	
2018-12-31	0.4789	0.5163	0.255
2019-01-31	0.4645	0.4777	
2019-02-28	0.4969	0.3354	
2019-03-31	0.5445	0.3708	0.1454
2019-04-30	0.5625	0.3866	
2019-05-31	0.5421	0.2981	
2019-06-30	0.5203	0.2591	0.1365
2019-07-31	0.5112	0.2852	
2019-08-31	0.6218	0.2852	
2019-09-30	0.634	0.2852	0.2456
2019-10-31	0.6258	0.2852	
2019-11-30	0.6326	0.2918	
2019-12-31	0.6312	0.2941	0.2456
2020-01-31	0.684	0.3623	
2020-02-29	0.8958	0.5923	
2020-03-31	0.8357	0.6391	0.2048
2020-04-30	0.887	0.6684	
2020-05-31	0.7885	0.6215	
2020-06-30	0.541	0.6174	0.8223
2020-07-31	0.507	0.6218	
2020-08-31	0.5136	0.4269	
2020-09-30	1.1404	0.7959	0.6904
2020-10-31	0.8522	0.8745	
2020-11-30	0.8608	0.8766	
2020-12-31	0.455	0.8766	0.8361
2021-01-31	0.3836	0.8692	
2021-02-28	0.4632	0.906	

	Monthly contracts traded monthly	Quarterly contracts traded monthly	Quarterly contracts traded quarterly
2021-03-31	0.4636	0.9601	0.8899
2021-04-30	0.4619	0.9414	
2021-05-31	0.4666	0.9456	
2021-06-30	0.4656	0.9163	0.8901
2021-07-31	0.4656	0.9162	
2021-08-31	0.4641	0.9081	
2021-09-30	0.4704	0.9162	0.9036
2021-10-31	0.4528	0.9214	
2021-11-30	0.4616	0.9304	
2021-12-31	0.4846	1.038	0.8842
2022-01-31	0.4494	1.0254	
2022-02-28	0.4549	0.9634	
2022-03-31	0.4507	1.0005	0.876
2022-04-30	0.4584	1.0016	
2022-05-31	0.4599	1.0034	
2022-06-30	0.4471	0.9957	0.879
2022-07-31	0.4464	0.988	
2022-08-31	0.4458	0.8968	
2022-09-30	0.4953	0.9238	0.8629
2022-10-31	0.4977	0.965	
2022-11-30	0.4558	0.9666	
2022-12-31	0.5368	1.0757	0.6787

Appendix 3

Appendix 3 contains more decriptive statistics for the data used.

Table A3.1 Descriptive statistics out-of-sample period

	Monthly contracts traded monthly		Quarterly contracts traded monthly		Quarterly contracts traded quarterly	
	Spot	**Futures**	**Spot**	**Futures**	**Spot**	**Futures**
Mean	-6.59	5.4	-6.59	3.76	-19.76	11.28
Standard deviation	113.09	55.88	113.09	41.81	78.27	52.47
Skewness	-0.5	-0.51	-0.5	-0.62	0.54	-0.21
Kurtosis	3.18	3.11	3.18	1.86	1.81	1.86
Correlation	0.0489		0.6596		-0.1832	

Table A3.02 Descriptive statistics p-values

	Monthly contracts traded monthly		Quarterly contracts traded monthly		Quarterly contracts traded Quarterly	
	Spot	**Futures**	**Spot**	**Futures**	**Spot**	**Futures**
Mean	1.66	2	1.66	1.73	4.98	5.2
Standard deviation	57.57	36.52	57.57	24.87	63.79	52.72
Skewness	2.22	0.53	2.22	-0.53	-0.48	-2.03
Kurtosis	11.64	5.88	11.64	5.47	4.89	8.49
Jarque Bera	0	0	0	1e-04	0.1548	0
ADF						
Price levels	0.99	0.99	0.99	0.99	0.8335	0.9888
1st diff.	0.0368	0.2224	0.0368	0.0241	0.5653	0.4717
KPSS						
Price levels	0.01	0.1	0.01	0.1	0.1	0.1
1st diff.	0.1	0.1	0.1	0.1	0.1	0.1
Ljung-box test on Standardized Residuals						
LB Lag[1]	0.41312	0.9745	0.41312	0.6938	0.8809	0.6420
LB Lag[5]	0.01881	0.5459	0.01881	1.0000	0.9993	1.0000
LB Lag[9]	0.20393	0.4341	0.20393	0.9956	0.9666	0.5618
Ljung-box test on Standardized Squared Residuals						
LB Lag[1]	0.7764	0.8081	0.7764	0.5435	0.6374	0.7008
LB Lag[5]	0.8051	0.7402	0.8051	0.7471	0.2373	0.9753
LB Lag[9]	0.8130	0.8193	0.8130	0.8424	0.3842	0.9972
Weighted ARCH LM Tests						
ARCH Lag[3]	0.5116	0.9745	0.5116	0.3957	0.9698	0.7010
ARCH Lag[5]	0.4690	0.5453	0.4690	0.7667	0.8523	0.9483
ARCH Lag[7]	0.5329	0.6930	0.5329	0.7877	0.9107	0.9895
Correlation	0.2844	0.443		0.7232		

The null hypothesis for JB test is that skewness and excess kurtosis are jointly zero The null hypothesis of the ADF test is that the series contains a unit root, and for the KPSS test the null hypothesis is that the time series are stationary.

Appendix 4

Appendix 4 contains plots for visualization of the dataset.

Table A4.01 Time series of returns

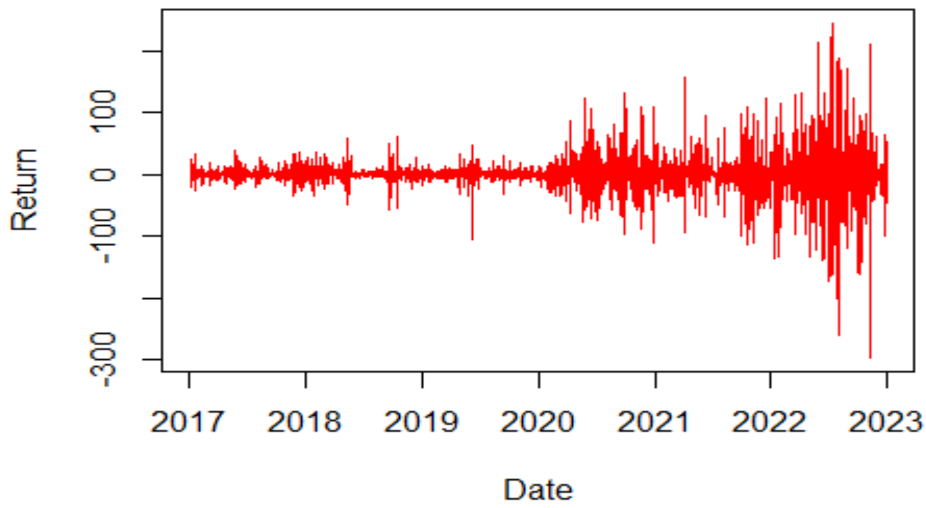

Table A4.02 Time series of prices

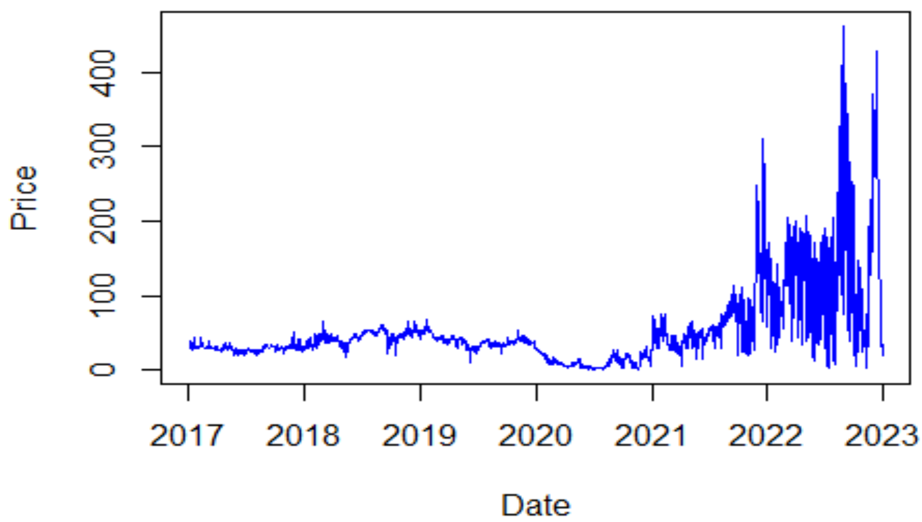

Table A4.03 Histogram of returns