PERFORMANCE OF SEASONALLY OPTIMIZED HEDGE RATIOS FOR THE NORDIC ELECTRICITY MARKETS

Lappeenranta–Lahti University of Technology LUT

Master’s Programme in Strategic Finance and Analytics, Master's thesis

2022

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ABSTRACT

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Master's thesis

2022

81 pages, 17 figures, 22 tables and 3 appendices

Examiners: Associate Professor Jan Stoklasa and Associate Professor Sheraz Ahmed

Keywords: electricity markets, Nord Pool, seasonality, future, hedge ratio, variance, lower partial moment, optimization

This thesis fills a gap in the literature on futures hedging by investigating the hedging performance of the bidding areas of the Nordic Power Exchange (Nord Pool). EPADs are futures with which it is possible to protect oneself against the difference between a bidding area's spot price and the Nord Pool system price. This thesis presents a novel way to optimize hedge ratios seasonally so that the hedge ratio remains the same within a season but changes when a new season begins. The length of a season can be three or six months. Optimization has been carried out by minimizing return variance or losses. Hedging was investigated by studying the years 2008–2020.

There are performance differences between long and short hedgers, but these differences don't appear to be systematic in any way. Because the seasonally optimized hedge ratios manifest superior performance in comparison to the constant static hedge ratios, there is seasonality present in the Nord Pool bidding areas. For both long and short hedgers, there is especially strong evidence for the presence of four three-months-long periods. Hedging strategies based on the minimization of losses constantly outperform hedging strategies based on the minimization of return variance. Hedging strategies that minimize the magnitude of losses do not necessarily reduce the number of losses. Thus, the magnitude of losses and the number of losses are clearly two different optimization criteria. Generally hedging performance is rather limited. Only the Oslo bidding area distinguishes itself from others with exceptionally high hedging performance.

TIIVISTELMÄ

Lappeenrannan–Lahden teknillinen yliopisto LUT

LUT-kauppakorkeakoulu

Kauppatieteet

Tuomas Lankinen

Kausivaihtelun mukaan optimoitujen suojausasteiden suorituskyky Pohjoismaisilla sähkömarkkinoilla

Kauppatieteiden pro gradu -tutkielma

2022

81 sivua, 17 kuvaa, 22 taulukkoa ja 3 liitettä

Tarkastajat: Tutkijaopettaja Jan Stoklasa ja tutkijaopettaja Sheraz Ahmed

Avainsanat: sähkömarkkinat, Nord Pool, kausivaihtelu, futuuri, suojausaste, varianssi, alaosamomentti, optimointi

Tämä tutkielma täyttää aukon futuurisuojausta käsittelevässä kirjallisuudessa käsittelemällä suojauksen suorituskykyä Pohjoismaisen sähköpörssin (Nord Pool) tarjousalueilla. EPAD-futuureilla on mahdollista suojautua tarjousalueen spot-hinnan ja Nord Pool -pörssin systeemihinnan väliseltä erolta. Tutkielma esittelee uuden tavan optimoida suojausasteita kausivaihtelun mukaan siten, että suojausaste pysyy samana yhtenä vuodenaikana mutta muuttuu uuden vuodenajan alkaessa. Vuodenajan pituus voi olla joko kolme tai kuusi kuukautta. Optimointi on tehty minimoimalla tuottojen varianssi tai tappiot. Suojausta tarkasteltiin tutkimalla vuosia 2008–2020.

Lyhyiden ja pitkien suojaajien välillä on suorituskykyeroja, mutta nämä erot eivät vaikuta olevan millään tavoin systemaattisia. Koska vuodenajan mukaan optimoidut suojausasteet suoriutuvat paremmin kuin vakioidut staattiset suojausasteet, Nord Pool -pörssin tarjousalueilla esiintyy kausivaihtelua. Sekä pitkien että lyhyiden suojaajien tapauksessa havaitaan erityisen vahvaa evidenssiä neljästä kolmen kuukauden pituisesta jaksosta. Tappioiden minimointiin perustuvat suojausstrategiat suoriutuvat toistuvasti paremmin kuin tuottojen varianssin minimointiin perustuvat suojausstrategiat. Suojausstrategiat, jotka minimoivat tappioiden koon, eivät välttämättä minimoi tappioiden lukumäärää. Näin ollen tappioiden koko ja tappioiden lukumäärä ovat selvästi kaksi erillistä optimointikriteeriä. Yleisesti ottaen suojauksen suorituskyky on varsin rajallinen. Ainoastaan Oslon tarjousalue erottuu muista poikkeuksellisen suurella suojauksen suosituskyvyllä.

Table of contents

Appendices

Figures

Tables

1. Introduction

This thesis compares different static hedging models with the electricity futures that are traded in the Nordic Power Exchange (Nord Pool) for different Nordic countries (Finland, Sweden, Norway and Denmark). Nord Pool, the first multinational exchange for electricity trading, has existed since January 1996 (Byström 2003, 1). Spot and futures contracts are traded on this exchange and the typical characteristics of the exchange are very high volatilities as well as non-normally distributed returns (Byström 2003, 1, Torró 2011, 58-59). Two characteristics of electricity markets explain the difficulty in obtaining good performance of hedging spot price risk with futures: Because electricity is not storable, there is not the cash-and-carry connection between spot and futures, and thus spot and futures prices follow each other less tightly simultaneously. Thus, there is a low correlation between spot and futures prices and therefore hedging strategies generally perform poorly. (Torró 2011, 59)

For those who are uninformed, the basics of the futures markets are explained in the following sentences. A futures contract is an agreement between two parties for the delivery of physical asset (like electricity) at a certain time in the future, for a certain price fixed at the inception of the contract (Kolb & Overdahl 2006, 1). The buyer of a futures contract is said to have a long position and the seller has a short position (Kolb & Overdahl 2006, 2). Futures contracts generally require margin payments and daily settlement (Kolb & Overdahl 2006, 4). A hedger is a trader who enters the futures market in order to reduce a pre-existing risk (Kolb & Overdahl 2006, 169). In a long/short hedge the hedger buys/sells a futures contract (Kolb & Overdahl 2006, 171). In many cases, a hedger has a certain hedging horizon, i.e., the future date when the hedge will terminate (Kolb & Overdahl 2006, 170). A company which produces electricity might want to avoid a risk that the electricity spot price falls within the next week by selling futures contracts on electricity. Because at the inception of the contract the price for the delivery period has been fixed, an electricity producer engaging in short hedging is able to profit if the spot market price falls below this fixed price. (Kolb & Overdahl 2006, 171) The hedge ratio is the number of futures contracts to buy or sell for a given position in the commodity in question (Kolb & Overdahl 2006, 175). If a hedge ratio is 1, the hedge is called “naïve” as one future is bought/sold for one spot unit (in the case of electricity, for 1 MWh) (Torró 2011, 38, Nasdaq Oslo ASA and Nasdaq Clearing AB 2021, 87, 112). If a hedge ratio is, for instance, 0.45 = 45/100, this means that 45 futures are bought/sold for 100 MWh of electricity that is bought/sold. If, for instance, 50 MWh of electricity is bought/sold, then 45/100 * 50 = 22.5 ≈ 23 futures are bought/sold. (Kolb & Overdahl 2006, 177)

In the Nordic power market, the different bidding areas help to indicate constraints in the transmission systems and ensure that regional market conditions are reflected in the spot price (Nord Pool 2020a). A transmission system operator (abbreviated as TSO) is responsible for the security of electricity supply in its bidding area (Nord Pool 2020b). For each Nordic country, the local TSO decides which bidding areas the country is divided into. Today there are five Norwegian bidding areas. Eastern Denmark and Western Denmark are always treated as two different bidding areas. Finland, Estonia, Lithuania and Latvia constitute one bidding area each. Sweden was divided into four bidding areas in 2011. The Nord Pool system price is calculated based on sale and purchase orders disregarding available transmission capacity between bidding areas in the Nordic market. The system price is the Nordic reference price for trading and clearing of most financial contracts. Due to bottlenecks in the transmission system, bidding areas may get different prices called area prices. Power will always go from the low-price area to the high-price area if there are constraints in transmission capacity between two bidding areas. (Nord Pool 2020a) The spot price is the electricity price that is formulated in the Nord Pool Elspot markets for each bidding area in the Nordic countries. The spot price is determined by the intersection between the supply and demand of electricity. Futures on the electricity price area difference (abbreviated as EPAD, previously CfD) are derivatives with which it is possible to protect oneself against the difference between a bidding area’s spot price and the system price. The price of the EPAD is the difference between the bidding area’s futures price and the system futures price. Thus, the electricity futures price of an area is then the sum of the system futures price and the EPAD price. (Nordic Green Energy 2021) In this thesis the electricity spot prices of five different bidding areas (Helsinki, Stockholm, Oslo, Copenhagen, Aarhus) are hedged with system price futures and the EPADs of their own bidding areas.

For both the system price futures and EPADs the contract base size is 1 MWh, and the contract price is expressed as €/MWh (Nasdaq Oslo ASA and Nasdaq Clearing AB 2021, 87, 112). The settlement involves both a daily mark-to-market settlement and a final cash settlement for those positions which remain open at maturity (Torró 2011, 43). The mark-to-market settlement means that a trader is required to realize any losses in cash on the day they occur. Let’s suppose that, for instance, an electricity producer sells 1000 futures for 50 €/MWh and a day after the sale the electricity futures price rises to 53€/MWh. This means that the producer has incurred a loss of 1000 MWh * (53-50) €/MWh = 3000 €, which is deducted from the margin deposited with the broker (Kolb & Overdahl 2006, 12-13). Cash settlement implies that the physical delivery of electricity doesn’t take place (Kolb & Overdahl 2006, 16). The Nord Pool electricity futures have a delivery period, which means that the futures price predicts the electricity spot price in a particular period (for instance, in one month like January) (Fleten, Bråthen & Nissen-Meyer 2010, 11). The final settlement covers the difference between the last closing price of the futures contract and the system price in the delivery period (Torró 2011, 43).

There may exist seasonality in electric power markets, e. g. due to weather and demand. Seasons with high demand and adverse weather conditions increase price volatility and the probability of price jumps. (Furió & Torró 2020, 1) In order to study seasonality, the studied period can be divided into annually recurring subperiods like two 6-month-long periods (e.g., spring-summer/autumn-winter) or four 3-month-long periods (spring/summer/autumn/ winter). After this division a static hedge ratio is optimized separately for each subperiod. Currently there are no published articles which optimize static hedge ratios seasonally, so that only the data of certain months is utilized in the hedge ratio optimization when this ratio is then utilized in hedging that takes place in those respective months in the future. Therefore, this thesis tests the hedging efficiency of seasonal static hedge ratios in the local Nord Pool markets. The main assumption behind this research is that the optimal hedge ratio remains roughly the same always when the same season takes place.

A hedge ratio is static when it remains constant and thus there is no need to rebalance it (Madaleno & Pinho 2010, 40). In the case of dynamic hedging the hedge ratio changes so that the futures position is changed periodically (Hull 2010, 518). Dynamic hedging traditionally means that the futures position must be updated very often (like weekly). Although in this thesis the hedge ratio changes when a new season begins, the studied seasonal hedging strategies can be described as static because the hedge ratio remains constant for a very long time (at least for three months). Additionally, the hedge ratio always remains completely static for a particular period (e.g., it is always the same for the autumn period).

This thesis only considers static hedging without comparing it to dynamic hedging. The reasons this decision have been explained in this and the following paragraph. In this paragraph the word “ideal” refers to the currently unknown hedging strategy that can produce as high hedging performance as possible (according to the preferred measure) from all the knowable hedging strategies (that are just waiting to be discovered). The current published hedging strategies are either completely static or completely dynamic and there is no unambiguous evidence that would indicate whether hedge ratios should static or dynamic. The current juxtaposition of static and dynamic hedging strategies can result from the immaturity of research on futures hedging. Good hedging performance of static strategies cannot be used to prove that dynamic hedging is completely dysfunctional as there is a possibility that ideal hedge ratios can have both a static and dynamic component. For instance, the average optimal hedge ratio for the summer season may be constant in a long term but the ideal hedge ratio for a particular summer period may vary around this mean (so that values follow some probability distribution). The deviations of these hedge ratios from the long-term mean may be explained by the events in the recent history. If the results of this thesis indicate that optimized seasonal hedge ratios outperform the naïve hedge ratio of 1 and other constant (i.e., non-seasonal) static hedge ratios, this provides evidence for the presence of the seasonal static component in the ideal hedge ratios but doesn’t exclude the possibility for the existence of the dynamic component. In other words, although this study examines static hedging it doesn’t claim that the ideal hedging strategies are completely static (i.e., without a dynamic component).

One could make the static strategies dynamic by estimating their hedge ratios with a rolling window (the estimation period whose length remains fixed but for which the start date and end date successively increase by one observation (Brooks 2014, 28)). However, the length of the rolling window affects the estimation results and there are no clear criteria for the selection of the rolling window length. Therefore, the study of rolling windows would extend the scope of this thesis too much. Additionally, because the estimation period of the rolling window changes all the time while the estimation period of a static hedge remains constant, there can be problems in comparing the hedging performances of the strategies as hedging performance can be dependent on the period that is studied (as the statistical features of a time series can change with time). If the estimation (and testing) periods differ between strategies it may not be possible to make generalizations about their relative superiority outside the studied period. But when all hedge ratios are estimated for some specific period (in this research, from June 2008 to May 2014) and then tested with other two specific periods (the subperiod 1 from June 2014 to May 2017 and the subperiod 2 from June 2017 to May 2020), conclusions about their relative superiority can be made. The temporal locations (start dates and end dates) of the estimation (i.e., in-sample) and testing (i.e., out-of-sample) periods of course affect the obtained hedging performances, but they should not affect their relative superiority as all strategies are subject to same market conditions (that are realized in the statistical features of the utilized data) in each of the examined periods. Two separate periods are utilized to test the performance of the optimized strategies to see whether these studied strategies retain their performance in different periods. Thus, it can be observed whether there are serious reasons to make generalizations outside the studied period.

This thesis studies both long and short hedging. A long hedger is a party who buys electricity from the power market (e. g. an electricity retailer) and thus wants to reduce positive spot returns that imply rises in the electricity spot price. A short hedger is a party who sells electricity to the power market (e. g. electricity producer) and thus wants to reduce negative spot returns that imply falls in the electricity spot price. In order to make the language of this thesis unambiguous to the reader, some terminology must be clarified. The terms “negative return” and “positive return” are “objective” expressions which describe increases and decreases in spot and futures prices. The terms “loss” and “profit” are “subjective” expressions that describe whether a hedger's net cashflow is decreased or increased. For a long hedger a negative return is a profit and a positive return a loss. For a short hedger a negative return is a loss and a positive return a profit.

In this thesis the optimization of static hedge ratios is carried out by minimizing the variance of returns and the 1st lower partial moment of returns (abbreviated from now on as the 1st LPM). Lower partial moments measure the variability of returns below some target return (Cotter & Hanly 2006, 682). Thus, when they are utilized, the optimization minimizes downside risk which is the chance of returns falling below a critical level (Cotter & Hanly 2006, 681, Grootveld & Hallerbach 1999, 306). Because the LPM target return that is utilized in optimization is 0 in this thesis, the losses are minimized. There are two main justifications for using reduction in an LPM instead of reduction in variance to optimize hedge ratios and measure hedging performance: 1. LPMs measure only reduction in the losses of a hedger which corresponds to the goal of hedging which is to reduce losses. In addition to loss reduction, variance also measures reduction in profits which is at odds with the hedging's goal and detrimental for the hedger's net cashflow. 2. Because LPMs measure the one-sided dispersion of a return distribution they can take into account asymmetry in the distribution. Thus, LPMs reveal differences in hedging performance for short and long hedgers. Because variance is a two-sided measure that presupposes a symmetrical distribution it is the same for short and long hedgers. Thus, it cannot reveal differences in short and long hedging performance or provide accurate reduction values for short and long hedgers. Because of its presupposition of symmetry, variance won't provide meaningful information if the distribution of returns is asymmetrical in reality.

The reductions of the 1st and 0th LPMs are used to measure hedging performance. The 1st LPM reduction measures reduction in the magnitude of losses whereas the 0th LPM reduction measures reduction in the number of losses (Eftekhari 1998, 646-647). Both these are important criteria for evaluating hedging performance. By comparing the values of the 1st and 0th LPM reductions, one can determine whether these two criteria are usually met simultaneously, in other words, whether the optimal hedging strategy usually reduces both the magnitude and number of losses.

The research questions of this thesis have been given below:

1. Which of the two types of hedgers, long or short, obtains better hedging performance in the Nord Pool bidding areas?
2. Is the hedging performance of seasonally optimized hedge ratios sometimes so high that it indicates that some particular seasonality phenomenon is taking place recurringly?
3. Do the hedging strategies based on the minimization of the 1st lower partial moment outperform the strategies based on the minimization of variance?
4. Do the strategies that are optimal in reducing the magnitude of losses also reduce the number of losses?

These questions are answered by modelling hedging performance with the spot and futures prices for the five examined bidding areas (Helsinki, Stockholm, Oslo, Copenhagen and Aarhus) in the period June 2008– May 2020. Although the four research questions are presented separately, their answers are obtained from the results of a single model which provides the 1st and 0th LPM reductions.

There are some limitations to this research. The most important one is that because LPMs examine only losses, minimizing them in the hedge ratio optimization uses only about half of the return observations. Minimizing variance utilizes all return observations and thus LPM-minimizing hedge ratios can be less precise than variance-minimizing hedge ratios (when they are both calculated for the same period). Additionally, hedge ratios that are optimized for shorter seasonal periods are less precise because these hedge ratios utilize less observations in their optimization than the hedge ratios of longer periods. Of all studied strategies a 3-month-specific hedge ratio that is optimized by minimizing the 1st LPM utilizes the smallest number of observations, about 39 weekly returns. This is still enough for reliable optimization, especially because weekly returns contain less non-seasonal variation than daily returns. The study also doesn’t take into account transaction and clearing costs that are incurred when trading futures in the Nord Pool markets. Additionally, it is assumed that the same hedge ratio applies both for system price futures and for EPAD futures. This means that one EPAD future is always bought for one system price future. This is justified because the price of one EPAD future is determined in relation to one system price future. However, it could be possible to estimate two separate hedge ratios, one for system price futures and another for EPAD futures.

Another important limitation is that the contracts are held till expiration and thus the thin market and expiration effects (Byström 2003, 3) are ignored. The thin market effect refers to the ability of any activity to cause a big rise or fall in the futures price when the market has only few traders who are buying and selling futures (Cambridge University Press 2021). The expiration effects refer to large price swings on the expiration day which originate from large buying and selling orders carried out by arbitrageurs (Chow, Yung & Zhang 2003, 68). These effects are ignored because this thesis analyzes continuous futures price time series that have been provided in the Datastream information service and which have been formulated by taking futures contracts which generally have no more than a month till their expiration and then providing the daily prices for these contracts until their expiration.

If a time series which takes the thin market and expiration effects into account were formulated, for instance, by following the same procedure as Byström (2003, 3) and rolling over to the next contract one week prior to the expiration of the current contract, the prices of each individual futures contract should be downloaded separately and then merged into one single continuous time series. Because the time series should be downloaded for the system price and EPAD prices of five different bidding areas and for each month of the studied 12-year period, about (5 + 1) * 12 * 12 = 864 contracts should be downloaded and merged. Additionally, it is not guaranteed that all available contracts have long enough lives (of about one month) to be included in a continuous series and therefore each contract should be checked individually before making the decision to use it. This would simply be a too time-consuming task to be carried out within the scope of this thesis. Because this thesis is a pilot study in examining the optimization of seasonal hedge ratios, the utilization of the pre-existing continuous time series for the sake of faster practical implementation is justified.

Additionally, Byström (2003, 3) states that there is a drawback from closing out the futures positions before expiration because this practice introduces some basis risk to the hedge since the futures price is not directly tied to the underlying spot price prior to the maturity date. Torró (2011, 59) also discovered that maintaining futures positions as near as possible to their final settlement improved hedging effectiveness in the Nord Pool market and this indicates that rolling to the next contract before the expiration of the current contract may not be necessary or beneficial. If the analysis of this thesis provides indications of substantial results, a later study can carry out a similar analysis with a continuous time series in which the impact of the aforementioned effects has been eliminated. Because the studied period is very long (12 years) the impact of the thin market and expiration effects is not as big as in a smaller sample because an individual highly volatile period just before the contract maturity date is not able to distort the data unreasonably.

The structure of the thesis is the following: After this introduction, the second chapter reviews current literature on the topics relevant to the scope of the thesis. These topics include electricity spot price hedging with futures and lower partial moments in futures hedging. At the end of the second chapter research gaps are identified in the reviewed literature and these gaps then become the focus of the empirical research of the thesis. In the third chapter, the design of the empirical research on the Nord Pool bidding areas is explained and the mathematics behind the methods that are utilized to implement this design in practice is explained in detail. The presented methods are variance, lower partial moments and the Nelder-Mead optimization algorithm. In the fourth chapter, the important characteristics of the data on the prices of different electricity futures and their underlying electricity spot prices are explained. The fifth chapter presents and analyses the results that are obtained by implementing the research design with the data on the Nord Pool spot and futures prices. In the sixth and final chapter, the research questions presented in this introductory chapter are answered and future research perspectives are outlined.

2. Literature review

This review examines literature on two topics that are relevant for the research design of the empirical part of the thesis: electricity spot price hedging with futures and lower partial moments in futures hedging. The articles that have been covered in this review were found by performing searches on these two topics in the LUT Primo and Google Scholar services. The utilized search phrases were the topics: “electricity spot price hedging with futures” and “lower partial moments in futures hedging”. The obtained pool of articles was extended by examining studies in the lists of references of the already found articles and by finding out studies that referred to found articles with Google Scholar. This search was continued until it was no more possible to find new relevant articles which were either used as references for the selected studies or which referred to these studies. Only the articles that conformed strictly to the aforementioned two topics were selected. For instance, studies that discussed forwards (and not futures) were omitted. Because there weren’t many articles available about either of the two topics, no restriction on the publication year was imposed. Both topics are discussed in their own subchapters. The literature review ends with a conclusion which justifies the implementation of the research design that is carried out in the empirical part of the thesis. The methods that are used to implement this design in practice are then explained in the methodology chapter.

2.1. Electricity spot price hedging with futures

While almost all published studies have tried to identify the optimal hedging strategies for electricity by performing optimization on historical price data, one study has examined the actual hedging strategies implemented by electricity producers. Sanda, Olsen and Fleten (2013, 326) investigated risk management practices of 12 Norwegian hydropower companies that hedge physical electricity production by using the power derivatives available at NASDAQ OMX Commodities. These power derivatives included futures, forwards, European-style options and Contracts for Difference (CfDs) (Sanda et al. 2013, 330). The companies used a Cashflow at Risk (C-FaR) approach or a hedge ratio approach or followed no explicitly stated approach (Sanda et al. 2013, 326). The cashflow at Risk (C-

FaR) approach means a hedging practice which aims to securing an acceptable income while preserving upside income potential (Sanda et al. 2013, 336). The majority of these companies earned a substantial share of their total profit from hedging transactions, but they did not manage to reduce cashflow volatility. Theoretically hedging should lead to opposite results with a zero expected value and smoothed income. The most common hedging strategy was to apply predefined hedge ratio boundaries and to use views on market development in hedging decisions inside these boundaries. Most companies had different hedge ratios for summer and winter production. (Sanda et al. 2013, 337)

The Nord Pool market has been the focus of some studies. Byström (2003, 1,11) compared the hedging effectiveness of static and dynamic hedges in the Nord Pool market by using one-week hedging horizon. The studied period was 1996-1999 (Byström 2003, 2). It was found out that static minimum-variance hedge ratio (abbreviated from now on as the static MV hedge) was slightly more successful in reducing portfolio variance than other models (which included the naïve hedge, constant conditional correlation GARCH and Orthogonal GARCH) (Byström 2003, 5-6, 11). When the weekly returns calculated from the spot and futures prices for Friday were utilized, the obtained out-of-sample variance reductions varied from 11.18 % (for the OGARCH hedge) to 19.50 % (for the naïve hedge) (Byström 2003, 9). Torró (2011, 31, 58) studied the utilization of the expected change in spot prices in the Nord Pool electricity market when calculating MV hedge ratios. The studied period was 1998–2008 (Torró 2011, 43). The use of the expected spot price change led to a significant improvement in the hedging effectiveness (Torró 2011, 58). Torró (2011, 35-36) utilized a predictability-adjusted variance reduction measure which is not directly comparable to traditional variance reduction. The obtained out-of-sample reductions on the weekly hedging horizon ranged from 19.45 % (for the standard naïve hedge) to 57.69 % (for the asymmetric dynamic covariance with the Ederington and Salas approach) (Torró 2011, 39-40, 55). Hedging performance was significantly improved by increasing hedging duration and maintaining futures positions as near as possible to their final settlement (Torró 2011, 59).

Liu, Jian and Wang (2010, 2498) studied the dynamic hedging of electricity futures using copula-GARCH models. The Student's-t, Gumbel and time-varying normal copulas were utilized to capture the dependence structure between the spot and futures prices of electricity (Liu et al. 2010, 2498). The Nord Pool market was investigated in the period 1996-1999 on the weekly horizon (Liu et al. 2010, 2501). The obtained variance reductions varied between -2.44 % (for the naïve hedge) and 8.16 % (for the T copula) (Liu et al. 2010, 2502).

There has also been a study that has tried to find the optimal hedging strategy through simulation. Vehviläinen and Keppo (2003, 136, 146) presented a framework for the Monte Carlo performance simulation and optimization of a combined physical and financial power portfolio. The simulation and optimization were implemented in the Nordic electricity market in the period 1996-2000 (Vehviläinen & Keppo 2003, 136, 142). The stochastic processes that were used to model the uncertainties in the market were for example electricity spot price, marginal production cost, and consumption processes. It was assumed that there are electricity futures for each future spot quote. Market frictions, such as the transaction costs and taxation, were ignored. (Vehviläinen & Keppo 2003, 137) There were not enough historical data to provide reliable estimates on model parameters at the moment of the study (Vehviläinen & Keppo 2003, 146).

Some articles have compared hedging performance in the Nord Pool market and other electricity markets. Hanly, Morales and Cassells (2018, 29, 39) studied futures hedging in the three of the most actively traded European electricity markets: Nord Pool, APXUK and Phelix in the period 2005-2014. They discovered that electricity futures can effectively manage risk only for specific time periods (Hanly et al. 2018, 29). The Nord Pool market performed the best out of the studied markets (Hanly et al. 2018, 29). For the Nord Pool market, the obtained out-of-sample variance reduction on the weekly hedging horizon was -0.45 % for the static MV hedge (Hanly et al. 2018, 39). The time period and underlying volatility characteristics of the electricity market in question impacted the hedging efficacy very significantly (Hanly et al. 2018, 39). Zanotti, Gabbi and Geranio (2010, 142) also studied hedging in three European electricity markets: Nord Pool, Phelix and Powernext. The studied period was from January 2004 to February 2006 for Nord Pool, from July 2002 to February 2006 for Phelix and from June 2004 to February 2006 for Powernext and the daily hedging horizon was utilized (Zanotti et al. 2010, 142). The studied models were the naïve hedge, the static MV hedge ratio, the dynamic MV hedge ratio estimated by continuously updating the moving averages, a constant correlation model and two dynamic time varying correlation models: GARCH dynamic conditional correlation and exponential smoothing conditional correlation (Zanotti et al. 2010, 136, 144). In the Nord Pool market, the variance reductions were between -7.35 % (for the naïve hedge) and 3.12 % (for the constant conditional correlation). In the Phelix market, the reductions were between -3.93 % (for the dynamic MV hedge) and 3.63 % (for the GARCH dynamic conditional correlation). In the Powernext market, the reductions were between -4.05 % (for the dynamic MV hedge) and 0.02 % (for the constant conditional correlation). (Zanotti et al. 2010, 145) The results provided evidence for the capability of time-varying hedge ratios to generate superior hedging performance (Zanotti et al. 2010, 147).

In addition to Hanly et al. and Zanotti et al., also Madaleno and Pinho (2010, 26, 42, 56) examined hedge ratio optimization and the hedging effectiveness in the German Phelix electricity futures market. The studied period was from June 2004 to July 2008 and the weekly hedging horizon was utilized (Madaleno & Pinho 2010, 43-44). Three static hedging strategies (MV, naïve and multiscale wavelet analysis) and a dynamic hedging strategy (using the multivariate GARCH model) were utilized (Madaleno & Pinho 2010, 57). Wavelet analysis (the continuous Morlet wavelet and the discrete MODWT technique) was used to access the relation between spot and futures electricity prices at different time scales (Madaleno & Pinho 2010, 56). The dynamic multivariate GARCH hedging provided the highest (although small) hedging effectiveness of all the studied models. The wavelet analysis didn’t lead to substantial hedging effectiveness in the electricity markets. A likely reason for this was a weak relation between spot and futures prices. (Madaleno & Pinho 2010, 57) The obtained variance reductions varied between -3.16% (for the naïve hedge) and 19.79% (for the diagonal-BEKK) (Madaleno & Pinho 2010, 53).

There appears to be only one published study that examines cross hedging with futures in the electric power market. Tanlapco, Lawarrée and Liu (2002, 577-579) investigated cross-hedging in California–Oregon Border, Palo Verde, Cinergy and Entergy electricity markets in the period from July 1998 to October 2000. Cross hedging refers to using the futures of one commodity to hedge the spot price of another commodity (Tanlapco et al. 2002, 577). Several stock indices and commodity futures were used in cross hedging (Tanlapco et al. 2002, 581). In all studied spot markets, the MV hedging using electricity futures contracts lowered risk more than MV cross hedging, naïve hedging, or no hedging at all (Tanlapco et al. 2002, 582). Thus, the use of electricity futures contracts was superior to using other related futures contracts such as crude oil (Tanlapco et al. 2002, 577).

Only two articles have examined hedging specifically from the perspective of an electricity retailer. Aber and Santini (2003, 7) studied the long-term cost effectiveness of different methods to purchase large quantities of electricity. Two separate contracts that were traded at the New York Mercantile Exchange were studied. The first one had a delivery location at the California-Oregon Border and the second one at Palo Verde, Arizona. (Aber & Santini 2003, 8) The studied period was from May 1996 to January 2000 (Aber & Santini 2003, 11). Four strategies for buying electricity were considered: buying at spot, buying and taking delivery via futures, buying and taking delivery via the forward market and buying at spot and hedging with futures (Aber & Santini 2003, 25). Both using futures to take the delivery of electricity and using futures to hedge the purchase of electricity in the spot market resulted in average prices higher than would be paid on average by purchasing at the current spot price. In the absence of any consideration of counterparty credit risk, the used of forward contracts yielded the lowest average price and had the lowest variance. (Aber & Santini 2003, 7)

Dupuis, Gauthier and Godin (2016, 31) developed a dynamic global futures hedging procedure for a retailer of the electricity market facing price, load and basis risk in the Nord Pool market. More common local hedging procedures minimize the risk associated with the portfolio until the next rebalancing whereas global hedging procedures minimize the risk related to the terminal cash flow (Dupuis et al. 2016, 32, 56). The developed hedging algorithm accounted for transaction fees (Dupuis et al. 2016, 31). Analysis with the actual market data revealed that the global hedging procedure provided considerable risk reduction in comparison to benchmarks strategies (delta hedging, local MV hedging, static hedging)

(Dupuis et al. 2016, 31, 50-52). The utilized data was from January 2007 to July 2012 and the weekly hedging horizon was used (Dupuis et al. 2016, 34, 36).

One study complements the observations of Aber and Santini about the poor performance of the futures of California-Oregon Border and Palo Verde. Moulton (2005, 181, 194) investigated reasons for the collapse of the futures market on California electricity which led to the discontinuation of trading in 2002. He found out that speculators left the market, leaving hedgers to meet hedgers, and thus the market was less active (Moulton 2005, 194). Additionally, the correlations between spot and futures price changes were low and thus hedging was not successful (Moulton 2005, 194).

One study has also investigated the hedging of both electricity and the fuel that is used to produce it. Martínez and Torró (2018, 745) studied the management of spark spread risk with futures contracts. The spark spread is the gross profit margin earned by buying and burning natural gas to produce electricity (Martínez & Torró 2018, 731). Three European markets were investigated: Germany, the United Kingdom and the Netherlands (Martínez & Torró 2018, 745). The studied periods varied between the markets but always took place between January 2004 and April 2016 (Martínez & Torró 2018, 736). Dynamic MV hedging with the extension by Ederington and Salas was utilized (Martínez & Torró 2018, 733, 744). Martínez and Torró (2018, 735) didn't use traditional hedging performance measures (like variance reduction) but formulated their own performance measure. Spark spread risk reduction for monthly periods attained values ranging between 20.05 % and 48.90 %, whereas electricity price risk reductions ranged between 48.69 % and 69.06 % for base load prices and between 31.22 % and 55.89 % for peak load prices. Optimal strategies for natural gas prices for monthly periods led to risk reductions that ranged between 56.54 % and 61.77 %. (Martínez & Torró 2018, 745)

The variance reductions of the Nord Pool system price that have been presented in the preceding paragraphs are summarized in the table 1. The hedging performance of the strategies tested in this thesis can be compared to the values of this table.

Table 1. Variance reductions of the Nord Pool system price

Article	**Variance reduction**
Byström 2003	11.18 % – 19.50 %
Hanly, Morales and Cassells 2018	0.45 %
Liu, Jian and Wang 2010	-2.44 % – 8.16 %
Zanotti, Gabbi and Geranio 2010	-7.35 % – 3.12 %

2.2. Lower partial moments in futures hedging

Lower partial moments are a group of downside risk measures which consider negative deviations from some predefined level of return (Cotter & Hanly 2006, 681-682). Using LPMs may help an investor to minimize the probability of falling below this target return (Cotter & Hanly 2006, 681). The lower partial moments have been defined mathematically in the subchapter 3.3. LPMs can be utilized both to examine hedging performance and as the objective function that is minimized in hedge ratio optimization. There are several advantages of using LPMs to examine hedging performance. First, because an LPM is estimated as a function of the underlying distribution, it has been shown to be robust to nonnormality. Thus, the LPM framework can estimate tail probabilities for assets whose return distributions are not normal. Second, information regarding the asymmetry of the joint distribution of spot and futures returns may be revealed. Therefore, a downside risk approach using LPMs addresses the primary shortcoming of the traditional variance-based hedging performance measure (which has been described mathematically in the subchapter 3.2). (Cotter & Hanly 2006, 682)

Several studies utilize LPMs in the hedge ratio optimization as an alternative to MV hedging. The problem point of the MV hedge is that it assumes that hedgers are willing to forego profits to reduce total variance (Turvey & Nayak 2003, 112) and the minimization of an LPM avoids this problem. When an LPM is minimized in the hedge ratio optimization, returns increase, since only the unattractive portion (the downside) of deviation is minimized (Eftekhari 1998, 651). LPM hedge ratios tend to be lower than MW hedge ratios, and thus when they are used, the volume of futures trading will be reduced (Eftekhari 1998, 652).

Many articles have investigated the utilization of LPM-minimizing hedge ratios with stock indices. Eftekhari (1998, 645, 647) found out that static and dynamic LPM hedge ratios are effective in reducing downside risk and increasing returns when calculated for the FTSE-100 index in the period 1985-1994. Lien and Tse (2000, 163, 166) examined the optimization of static LPM hedge ratios for the Nikkei Stock Average (NSA) index. The studied period was from January 1988 to August 1996 (Lien & Tse 2000, 166). For a hedger who was very cautious about large losses, the hedge ratio that minimizes LPMs was sharply different from the MV hedge ratio. The conventional MV hedge ratio was inappropriate for a hedger who cared only for downside risk. (Lien & Tse 2000, 169) In their other study Lien and Tse (1998, 711, 719) constructed dynamic LPM hedge ratios on the NSA index in the period from January 1989 to August 1996. Because the resulting LPM hedge ratios exhibited strong variations, the assumption of a static LPM hedge ratio couldn't be accepted (Lien & Tse 1998, 719). Demirer, Lien and Shaffer (2005, 51, 57) discovered that in the period from July 1998 to April 2002 long hedgers achieved better hedging performance with the static LPM-minimizing hedge ratio than with the MV hedge ratio when using four stock index futures traded at the Taiwan futures exchange.

Dai, Zhou and Zhao (2017, 502, 509-510) combined wavelet decomposition with static LPM-minimizing hedge ratios to generate a multi-scale hedging model. This model was tested with the spot and futures prices for the CSI 300 index in the period from April 2010 to October 2015 (Dai et al. 2017, 506). Dai et al. (2017, 510) found out that the appropriate multi-scale hedge ratio depended on the hedging horizon. Ubukata (2018, 270) studied the performance of dynamic futures hedging models which minimize downside risk measures and compared these dynamic models to static hedging approaches. The utilized downside risk measures included an LPM and other measures (Ubukata 2018, 270). The Nikkei 225 index spot and futures prices were studied in the period from March 1996 to March 2013 (Ubukata 2018, 275). The out-of-sample results indicated that when the order of an LPM was higher, the dynamic hedge ratios outperformed static ones (Ubukata 2018, 279).

Mattos, Garcia and Nelson (2008, 78) analyzed how the utilization of LPMs and less restrictive assumptions in the hedge ratio optimization affected the optimal hedging position and the opportunity costs of not hedging. The commonly used restrictive assumptions include the absence of both transaction costs and possibility of investments in assets other than cash and futures positions (Mattos et al. 2008, 79). Empirical simulations were conducted by using spot and futures returns for soybeans and the S&P500 index from January 1990 to June 2004 (Mattos et al. 2008, 83). The findings indicated that the optimal hedge ratio changes considerably when a one-sided risk measure is adopted and standard assumptions are relaxed (Mattos et al. 2008, 78). The introduction of transaction costs appeared to have the largest effect on the optimal hedge ratio, particularly when the LPM target return was lower. Increases in transaction costs quickly reduced the optimal static hedge ratios to zero. (Mattos et al. 2008, 86, 90)

Two studies have also examined the estimation of LPM-minimizing hedge ratios with currencies. When comparing hedging performance for short versus long hedgers across three currencies, five commodities and two stock indices in the period from January 1988 to June 1998 Demirer and Lien (2003, 25, 28, 30-31, 36) discovered that the performance of static hedging declined if the order of an LPM or the target return increased. A long hedger benefited more from futures trading than a short hedger in reducing the downside risk (Demirer & Lien 2003, 36). Lien and Tse (2001, 159, 166) estimated static hedge ratios that minimize LPMs to compare the hedging effectiveness of currency futures and currency options in the case of three currencies: the British pound, the Deutsche mark, and the Japanese yen. The studied period was from August 1983 to January 1997 (Lien & Tse 2001, 163-164). They discovered that currency futures were almost always better hedging instruments than currency options (Lien & Tse 2001, 168).

There have also been studies that have investigated the estimation of LPM-minimizing hedge ratios with commodities. Semivariance is one of the lower partial moments and measures the variability of returns below the mean (Cotter & Hanly 2006, 681-682). Turvey and Nayak (2003, 100, 106, 110-111) presented an algorithm for solving a static semivariance-minimizing hedge ratio and applied it to hedge Kansas City wheat (in the period 1980-2000) and Texas steers (in the period 1989-2000). They discovered that the hedge ratio was lower when semivariance was minimized instead of variance and thus the number of required futures contracts was reduced (Turvey & Nayak 2003, 112-114).

There have been a couple of studies that have examined the use of LPMs in hedging oil. Cotter and Hanly (2012, 259, 265) examined the impact of asymmetry on the hedging effectiveness of the NYMEX West Texas Light Sweet Crude oil futures. Two data sets were studied. The first one had an asymmetric return distribution and ran from January 2001 to December 2001. The second one had a symmetric return distribution and ran from January 2002 to December 2002. (Cotter & Hanly 2012, 266) The studied hedge ratio estimation methods were the naïve hedge, the rolling-window MV hedge and two bivariate GARCH models (Cotter & Hanly 2012, 260-261). The utilized hedging performance measures were variance reduction and the reductions of three downside risk measures: the 3rd lower partial moment, value at risk and conditional value at risk (Cotter & Hanly 2012, 262-265). It was discovered that hedging may not be as effective during the periods of asymmetric returns (Cotter & Hanly 2012, 277). Larger differences in hedging performance were found between the short and long hedgers for the asymmetric distribution in comparison to a symmetric distribution. Thus, Cotter and Hanly recommended the use of one-sided hedging performance measures instead of the traditional variance reduction criterion. The best method for hedge ratio estimation for both short and long hedgers was the MV model. (Cotter & Hanly 2012, 278)

Yu, Wang, Zhang and Li (2021, 14777, 14781) proposed an improved kernel density estimation for the optimal LPM hedge ratio of WTI crude oil futures. Due to the correlation between spot and futures returns, the kernel method was extended to the bivariate case (Yu et al. 2021, 14781). The studied period was from January 2015 to October 2019 (Yu et al. 2021, 14777). Empirical results revealed that the hedging strategy based on the kernel density estimation method achieved better performance (smaller hedged ratios and higher effectiveness) than the hedging strategy based on the traditional parametric method. The results of the static hedging strategy were better and more stable than the results of the dynamic hedging strategy due to the incorporation of more sample points. (Yu et al. 2021, 14782)

There have also been studies that have applied LPMs to the hedging of both the final product and its raw material. Liu, Vedenov and Power (2017, 31) studied hedging the crack spread, i.e., the price difference between crude oil and refined products which is very important for the profit margin of an oil refinery. It is commonly thought that three barrels of crude oil can be cracked into two barrels of gasoline and one barrel of heating oil (Liu et al. 2017, 31). Two cases were examined: hedging all three commodities (crude oil, gasoline, and heating oil) in a fixed 3:2:1 proportion and allowing for separate hedge ratios for each commodity (Liu et al. 2017, 39-40). A rolling window was used to calculate the optimal hedge ratios implied by the 2^{nd} LPM and variance minimization hedging objectives. The studied period was from January 2012 to December 2015. (Liu et al. 2017, 39) The commonly used way of hedging the crack spread at the fixed 3:2:1 proportion was found to be generally less effective in reducing price risk than a strategy that allows for hedging individual commodities separately. Using the 2^{nd} LPM as a hedging criterion helped hedgers to better track downside risk and led to higher expected profit and a lower expected shortfall (Liu et al. 2017, 40).

Another study which investigated the hedging of both a product and its raw material is by Power and Vedenov (2010, 290, 300-301) who compared static LPM-minimizing hedge ratios with conventional static MV hedging for a typical Texas panhandle feedlot operator. The spot and futures prices for live cattle and corn were obtained for the period from January 2000 to June 2005 (Power & Vedenov 2010, 297). In this case the raw material was the corn which was used to feed the cattle (which is the final product). Although the main topic of their study was multi-commodity hedging, Power and Vedenov (2010, 290) discovered that the MV hedge leads to over-hedging relative to the LPM hedge also in the single-commodity case.

2.3. Gaps in the literature

Current literature hasn't yet applied LPMs in the study of electricity spot price hedging with futures although measuring hedging performance with reduction in LPM values would enable to find out performance differences between long and short hedgers. This is not possible with the most commonly used measure, variance reduction, because variance assumes the return distribution to be symmetrical. Because LPMs don't require distributional symmetry, they are able to differentiate between short and long hedgers. Consequently, any study hasn't yet compared the performances of an LPM and variance as criteria that are minimized in hedge ratio optimization for the electricity spot price. The studies using LPMs in futures hedging also haven't examined whether the magnitude of losses (measured by the 1^{st} LPM) and the number of losses (measured by the 0^{th} LPM) are usually reduced simultaneously when hedge ratios are optimized. Both the magnitude of losses and the number of losses are important criteria in judging hedging performance. If magnitude of losses is reduced but the number of losses is increased, this means that hedging can make new small losses to take place. If the number of losses is reduced but the magnitude of losses is increased, this means that hedging can make remaining losses become greater. If hedging doesn't systematically reduce both the magnitude of losses and the number of losses, hedge ratio optimization should be based on the simultaneous and separate minimization of these two criteria in order to achieve true improvement in real-life hedging performance.

Although there are several studies on static LPM- and variance-minimizing hedge ratios, there are no articles investigating seasonally varying static hedge ratios, i.e., the case in which the hedge ratio remains the same within a season but changes when a new season begins. The assumption behind the concept of seasonal static hedge ratios is that the same hedge ratio is always capable to generate successful hedging performance when a particular season (e.g., spring) takes place. According to Lien and Tse (1998, 719) LPM hedge ratios cannot be static, but their finding doesn't exclude the possibility of this kind of seasonally varying hedge ratios. By testing different ways to divide a year into seasons it can be defined whether seasonality exists, how many seasons there are and when seasons begin and end. The division which leads to best hedging performance (when the hedge ratio of each season is optimized) is the one which best describes the seasonality present in the Nord Pool electricity spot and futures markets. One could assume that seasonal hedge ratios estimated for shorter periods capture the features of the data in more detail but on the other hand there exists a risk that the hedge ratios of shorter periods lead to overfitting in the in-sample period and thus to worse hedging performance in the out-of-sample period.

The Nord Pool electricity market has been examined in several studies, but there seem to be no studies that would have investigated the hedging performance of the Nord Pool bidding areas. By now, all published articles have examined hedging the Nord Pool system price. Studying the hedging of the bidding area prices has lot more practical utility than studying the hedging of the system price because each Nordic company operating in the power market buys or sells electricity at the price of the bidding area in which it is located and not at the system price.

Thus, this thesis fills five research gaps: hedging performance in the Nord Pool bidding areas, performance comparison between long and short hedgers in the electricity spot markets, the performance of static hedge ratios that are optimized for different seasons by minimizing variance or lower partial moments, performance comparison between variance- and LPM-minimizing hedge ratios in the electricity spot markets and the simultaneity of reductions in the magnitude of losses and the number of losses.

For the reasons stated in the introduction of this thesis, variance can be argued to be an inferior measure for hedging purposes (in comparison to LPMs), but it is utilized because variance is the most common optimization criterion found in the literature. The naïve one-to-one static hedge is used as a benchmark strategy because it is the simplest of the hedging methods. In the case of all studied hedging strategies hedging performance is measured with the 1st LPM reduction. Because GARCH models have been widely covered in the existing literature on electricity futures hedging, they are not discussed in this research.

3. Methodology

The first subchapter explains the general setup of the research whose outcomes are presented in the Results-chapter. The subchapters 2-4 explain in detail the mathematics behind those methods that are utilized to carry out this empirical research.

3.1. General setup

The hedging horizon is the future date when the hedge will terminate (Kolb & Overdahl 2006, 170). It can be supposed that the longer a hedging horizon is, the better hedging performance is achieved. This is because long-term changes in spot and futures prices are more likely to be correlated with each other than short-term price changes. The reason for this is that in the longer term more information from the spot market is incorporated to the futures prices. The monthly hedging horizon cannot not be examined in this thesis, because with the monthly data frequency there are too few observations (only 144 in the period June 2008 – May 2020) left to be analysed as the data on futures prices is not long enough. Thus, the weekly hedging horizon is studied in this thesis. Additionally, in literature on electricity futures hedging the hedging horizon is most commonly one week and thus using this horizon makes it possible to compare the results of this thesis to the variance reductions obtained in the earlier literature.

In this thesis logarithmic returns are used instead of simple returns because logarithmic returns can be interpreted to be continuously compounded which means that the frequency of compounding of the return does not matter and thus returns across assets can be more easily compared than when using simple returns (Brooks 2014, 8). It is assumed that within the hedging horizon the compounding frequency is insignificant. A continuously compounded spot/futures return is calculated with the following equation:

$$r_t = 100\ \% \times \ln\left(\frac{p_t}{p_{t-1}}\right) \qquad (1)$$

where p_t is the spot/futures price at time t and p_{t-1} is the spot/futures price at time $t-1$ (Brooks 2014, 7-8). The weekly data is formulated from the original daily time series by always taking the price for Friday. This means that in practice every fifth price value is selected to be included in the weekly data. The prices of Friday are analysed because the Friday prices don't contain negative values. If there were negative prices, they should be replaced with positive prices because logarithmic weekly returns used in the hedge ratio optimization cannot be calculated with negative values. All possible ways to replace negative values would make the time series unrealistic because the original negative values won't be used anymore.

The whole studied period is divided into two periods of equal length, the in-sample period and the out-of-sample period. The in-sample period is used to optimize the static hedge ratios by minimizing variance or the 1st LPM. Using variance minimizes both profits and losses whereas using the 1st LPM minimizes only losses. The optimized static hedge ratios are then used in the two equally long subperiods of the out-of-sample period to discover whether these optimized values are still able to produce reasonably high 1st LPM reductions. Out of all possible LPMs, the 1st LPM is utilized because the 1st LPM doesn't emphasize the greatness of a loss but treats all losses equally. Also the 0th LPM reductions are calculated for the out-of-sample period to see whether those strategies that lead to highest reduction in the magnitude of losses (measured by the 1st LPM reduction) also lead to reduction in the number of losses.

Only the months that belong to a particular seasonal period are utilized in the optimization of a static hedge ratio. In the case of a constant hedge ratio this period includes all months and in the case of a 3-month (6-month) period three (six) consecutive months. The weekly returns that are included in a particular month in each year of the 6-year in-sample period are included in the dataset that is utilized to maximize the objective function (which is either variance reduction or the 1st LPM reduction). The starting point for the optimization is the naïve hedge ratio of 1. Other starting points (the hedge ratios -10 and 10) were also tested for the optimization, and they didn't impact the final resulting hedge ratios. In the cases where a seasonal period changes (as the first month of a new period begins) in the middle of a one-week hedge, the hedge ratio of the new season is optimized (in the in-sample period) or utilized (in the out-of-sample period). In other words, the hedge ratio of a new season is optimized/utilized for this hedge which is initiated at the end of the period that precedes this new season.

The three possible ways to divide a year into four three-month periods have been illustrated in the table 2 below. The first column of the table 2 presents the letter of a sample. The columns 2-13 present the twelve months of a year. The numbers tell which period a month belongs to (the first, second, third or fourth). One must understand that the numberings are just symbolic because the seasons take place again and again. In other words, the season which has been given the number 1 could as well have been given the number 2, 3 or 4.

Table 2. Divisions of the four 3-month periods

	Month											
Division	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
A	1	1	1	2	2	2	3	3	3	4	4	4
B	4	1	1	1	2	2	2	3	3	3	4	4
C	4	4	1	1	1	2	2	2	3	3	3	4

The six possible ways to divide a year into two six-month periods have been illustrated in the table 3 on the next page. The first column of the table 3 presents the letter of a sample. The columns 2-13 present the twelve months of a year. The numbers tell which period a month belongs to (the first or second).

Table 3. Divisions of the two 6-month periods

	Month											
Division	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
A	1	1	1	1	1	1	2	2	2	2	2	2
B	2	1	1	1	1	1	1	2	2	2	2	2
C	2	2	1	1	1	1	1	1	2	2	2	2
D	2	2	2	1	1	1	1	1	1	2	2	2
E	2	2	2	2	1	1	1	1	1	1	2	2
F	2	2	2	2	2	1	1	1	1	1	1	2

In the modelling of this thesis the spot and futures positions are completed via a reversing trade. This is also the most common way to complete positions in real life. At the beginning of hedging an electricity retailer has a short position in electricity, i.e., the retailer has sold electricity to the end user but hasn't yet bought electricity from the counterparty (an electricity producer). The electricity retailer has also initially taken a long position (obligation to buy) in electricity futures. The spot and futures position are then completed by performing offsetting transactions. This means buying electricity and taking the offsetting short futures position (obligation to sell). (Kolb & Overdahl 2006, 17) Taking the opposite position in the same futures contract brings the net position in that particular contract back to zero which absolves the party from the obligation for the physical delivery (Kolb & Overdahl 2006, 17-18). If a hedger initially takes h long positions of futures contracts for each unit of short positions held in electricity, the return, r_H, on the hedge portfolio is given by the equation

$$r_H = hr_F - r_S. \tag{2}$$

where r_S and r_F are the log returns of the spot and futures prices, respectively, and h is the hedge ratio (Byström 2003, 5). The equation 2 can be understood by considering that the rise of the electricity spot price decreases the hedge portfolio return r_H for the electricity retailer and thus the spot return r_S is preceded by a minus sign in the equation 2. However, the rise of the electricity futures price increases the hedge portfolio return because the selling price is higher than the initial buying price. Thus, the futures return r_F is preceded by a plus sign in the equation 2.

The hedging procedure for an electricity producer can be explained in the same way. At the beginning the electricity producer has a long position in electricity, i.e., ownership and will sell the electricity to the counterparty (an electricity retailer) in the future. The electricity producer has also initially taken a short position (obligation to sell) in electricity futures. The spot and futures positions are then completed by selling electricity and taking the offsetting long futures position (obligation to buy). If a hedger initially takes h short positions of futures contracts for each unit of long positions held in electricity, the return, r_H, on the hedge portfolio is given by the equation

$$r_H = r_S - hr_F \tag{3}$$

The equation 3 can be understood by considering that the rise of the electricity spot price increases the hedge portfolio return r_H for the electricity producer and thus the spot return r_S is preceded by a plus sign in the equation 3. However, the rise of the electricity futures price decreases the hedge portfolio return because the buying price is higher than the initial selling price. Thus, the futures return r_F is preceded by a minus sign in the equation 3.

Although this thesis examines the hedging performance of the weekly hedging horizon, in the case of a static hedge ratio the hedging horizon can be easily extended by simply performing offsetting transactions later than originally planned as there is no need to change the number of futures that are bought/sold initially. For instance, a retailer which originally had a hedging horizon of one week can extend its horizon to two weeks by taking a short futures position and buying electricity one week later than was originally planned. Thus, the retailer doesn’t need to change its original long futures position when a hedge ratio is static.

3.2. Variance

Because only a part of the whole studied period is utilized for the optimization of the minimum-variance hedge ratio, the sample variance (instead of population variance) should be utilized. The sample variance is given by the following equation:

$$s^2 = \frac{\sum_{t=1}^{T}(r_t - \bar{r}\,)^2}{T - 1} \tag{4}$$

r_t is one return observation, $\bar{r}$ is the sample mean of returns and T is the number of return observations. (Williams, Sweeney & Anderson 2009, 111-112) Variance is calculated both for the hedge portfolio returns given by the equation 2 (for a long hedger) or 3 (for a short hedger) and for the returns of the unhedged portfolio. The variance of the hedged portfolio is denoted by s_H^2 and the variance of the unhedged portfolio is denoted by s_S^2. Reduction in the variance of a hedge strategy over a no-hedge position can be then measured with the following metric:

$$\text{Variance reduction} = 100\ \% \times \left(1 - \frac{s_H^2}{s_S^2}\right) \tag{5}$$

(Cotter & Hanly 2006, 680)

3.3. Lower partial moments

Different sources define lower partial moments in a slightly different way. According to Eftekhari (1998, 647) and Cotter and Hanly (2006, 681) the lower partial moment of order n around τ can be defined as

$$LPM_n = \frac{1}{T}\sum_{t=1}^{T}(max[0, \tau - r_t])^n \tag{6}$$

where T is the number of return observations, r_t is a return and τ is the target return parameter. In practice, the value of τ will depend on an investor's minimum acceptable level of return. Some values of τ that may be considered are 0 or the risk-free rate of interest. (Cotter & Hanly 2006, 682) In this thesis, the target return utilized is set to be 0, because the hedging party benefits financially only if a return is positive. The parameter n reflects the amount of weight an investor will attach to the shortfall from the target return. An investor who is more concerned with extreme shortfalls would assign a higher weight, which would be represented by higher values of n. (Cotter & Hanly 2006, 682) If $n = 2$ and τ is set to the mean, then (6) is equivalent to the semivariance (Cotter & Hanly 2006, 681-682).

According to Eftekhari (1998, 646) when $n = 0$ and the target rate is equal to 0 %, an LPM is simply the probability of a loss. However, it can be observed that this is not true for the equation 6 for the reason that when x is any number, $x^0 = 1$ and thus according to the equation 6 it is always that $LPM_0 = 1$. In order to obtain the probability of a loss by using $n = 0$, a definition of an LPM used in this study is formulated. First, the target return is set to 0, because the goal of hedging is to eliminate losses. L_i is a loss and R_i is a logarithmic return computed from the original price time series. Because a long hedger wants to eliminate situations where the price rises, a return for the long hedger is $-R_i$. Thus, a loss for a long hedger can be expressed as $L_i = 0 - (-R_i) = R_i$. Because a short hedger wants to eliminate situations where the price falls, a return for the short hedger is R_i. For a short hedger a loss can then be expressed as $L_i = 0 - R_i = -R_i$. If only losses which are positive are selected (because negative losses imply profits), in other words $L_i > 0$, then a lower partial moment can be expressed as

$$LPM_n = \frac{1}{T}\sum_{t=1}^{T_+} L_{+,t}^n \tag{7}$$

where T_+ is the number of positive loss observations, T is the number of return observations, $L_{+,t}$ is one positive loss and n is the order of a lower partial moment.

The hedging performance metric is then the percentage reduction in the LPM of a hedge strategy over a no-hedge position. This metric can be expressed with the following equation:

$$\text{LPM}_n \text{ reduction} = 100\ \% \times \left(1 - \frac{\text{LPM}_{n,\text{H}}}{\text{LPM}_{n,\text{S}}}\right) \tag{8}$$

n is the order of the LPM (0 or 1 in this thesis), $\text{LPM}_{n,\text{H}}$ is the LPM of the hedged portfolio (which is calculated by using the returns given by the equation 2 or 3) and $\text{LPM}_{n,\text{S}}$ is the LPM of the unhedged portfolio. (Cotter & Hanly 2006, 683) When futures contracts completely eliminate downside risk, LPM reduction is 100%. When LPM reduction is 0 %, hedging with futures contracts does not reduce risk. Therefore, a larger number indicates better hedging performance. (Cotter & Hanly 2006, 680)

3.4. Nelder-Mead optimization algorithm

The Nelder-Mead optimization algorithm is utilized to find the best static hedge ratios. The variance reduction (equation 5) and LPM reduction (equation 8) are the objective functions which are maximized (by minimizing their negatives). This means that variance and the 1st LPM are minimized in the optimization. The Nelder-Mead algorithm is a direct search method which is implemented as a MATLAB function *fminsearch* (MathWorks 2021a). Direct search is a method for solving optimization problems and it doesn't require information about the gradient of the objective function. A direct search algorithm searches a set of points around a current point, looking for one where the value of the objective function is lower than the value at the current point. Direct search can be used to solve problems for which the objective function is not differentiable or even continuous. (MathWorks 2021b) The Nelder-Mead algorithm maintains at each step a nondegenerate simplex, a geometric figure in n dimensions of nonzero volume that is the convex hull of $n + 1$ vertices (Lagarias, Reeds, Wright & Wright 1998, 112). The general idea of the of the Nelder-Mead optimization algorithm is explained in the following paragraphs.

Four scalar parameters have to be specified to define a Nelder-Mead method: reflection ρ, expansion χ, contraction γ and shrinkage σ. These parameters should satisfy

$$\rho > 0, \chi > 1, \chi > \rho, 0 < \gamma < 1 \text{ and } 0 < \sigma < 1. \quad (9)$$

In the standard Nelder-Mead algorithm the parameters are given the following values:

$$\rho = 1, \chi = 2, \gamma = \frac{1}{2} \text{ and } \sigma = \frac{1}{2}. \quad (10)$$

(Lagarias et al. 1998, 115)

At the beginning of the kth iteration, $k \geq 0$, a nondegenerate simplex Δ_k is given, along with its $n + 1$ vertices, each of which is a point in $\mathcal{R}^n$. It is always assumed that iteration k begins by ordering and labeling these vertices as $\mathbf{x}_1^{(k)}, \dots, \mathbf{x}_{n+1}^{(k)}$, such that

$$f_1^{(k)} \leq f_2^{(k)} \leq \cdots \leq f_{n+1}^{(k)} \quad (11)$$

where $f_i^{(k)}$ denotes $f(\mathbf{x}_i^{(k)})$. The *k*th iteration generates a set of *n+1* vertices that define a different simplex for the next iteration, so that $\Delta_{k+1} \neq \Delta_k$. Because the goal is to minimize f, $\mathbf{x}_1^{(k)}$ is referred as the best point or vertex, $\mathbf{x}_{n+1}^{(k)}$ as the worst point, and $\mathbf{x}_n^{(k)}$ as the next-worst point. Similarly, $f_{n+1}^{(k)}$ is referred as the worst function value, and so on. A single generic iteration is specified, omitting the superscript *k* to avoid clutter. The result of each iteration is either a single new vertex – the accepted point – which replaces $\mathbf{x}_{n+1}$ in the set of vertices for the next iteration, or if a shrink is performed, a set of n new points that, together with $\mathbf{x}_1$, form the simplex at the next iteration. (Lagarias et al. 1998, 115)

One iteration of the Nelder-Mead algorithm:

1. Order: Order the $n+1$ vertices to satisfy $f(\mathbf{x}_1) \leq f(\mathbf{x}_2) \leq \cdots \leq f(\mathbf{x}_{n+1})$ using the tie-breaking rules given below.

2. Reflect: Compute the reflection point $\mathbf{x}_r$ from

$$\mathbf{x}_r = \bar{\mathbf{x}} + \rho(\bar{\mathbf{x}} - \mathbf{x}_{n+1}) = (1+\rho)\bar{\mathbf{x}} - \rho\mathbf{x}_{n+1} \tag{12}$$

where $\bar{\mathbf{x}} = \sum_{i=1}^{n} \mathbf{x}_i / n$ is the centroid of the n best points (all vertices except for $\mathbf{x}_{n+1}$). Evaluate $f_r = f(\mathbf{x}_r)$. If $f_1 \leq f_r < f_n$, accept the reflected point $\mathbf{x}_r$ and terminate the iteration.

3. Expand: If $f_r < f_1$, calculate the expansion point $\mathbf{x}_e$,

$$\mathbf{x}_e = \bar{\mathbf{x}} + \chi(\mathbf{x}_r - \bar{\mathbf{x}}) = \bar{\mathbf{x}} + \rho\chi(\bar{\mathbf{x}} - \mathbf{x}_{n+1}) = (1+\rho\chi)\bar{\mathbf{x}} - \rho\chi\mathbf{x}_{n+1} \tag{13}$$

and evaluate $f_e = f(\mathbf{x}_e)$. If $f_e < f_r$, accept $\mathbf{x}_e$ and terminate the iteration; otherwise (if $f_e \geq f_r$), accept $\mathbf{x}_r$ and terminate the iteration.

4. Contract: $f_r \geq f_n$, perform a contraction between $\bar{\mathbf{x}}$ and the better of $\mathbf{x}_{n+1}$ and $\mathbf{x}_r$.

a. Outside: If $f_n \leq f_r < f_{n+1}$ (i.e., $\mathbf{x}_r$ is strictly better than $\mathbf{x}_{n+1}$), perform an outside contraction: calculate

$$\mathbf{x}_c = \bar{\mathbf{x}} + \gamma(\mathbf{x}_r - \bar{\mathbf{x}}) = \bar{\mathbf{x}} + \gamma\rho(\bar{\mathbf{x}} - \mathbf{x}_{n+1}) = (1+\rho\gamma)\bar{\mathbf{x}} - \rho\gamma\mathbf{x}_{n+1} \tag{14}$$

and evaluate $f_c = f(\mathbf{x}_c)$. If $f_c < f_r$, accept $\mathbf{x}_c$ and terminate the iteration; otherwise, go to step 5 (perform a shrink).

b. Inside: If $f_r \geq f_{n+1}$, perform an inside contraction: calculate

$$\mathbf{x}_{cc} = \bar{\mathbf{x}} - \gamma(\bar{\mathbf{x}} - \mathbf{x}_{n+1}) = (1-\gamma)\bar{\mathbf{x}} + \gamma\mathbf{x}_{n+1} \tag{15}$$

and evaluate $f_{cc} = f(\mathbf{x}_{cc})$. If $f_{cc} < f_{n+1}$, accept $\mathbf{x}_{cc}$ and terminate the iteration; otherwise, go to step 5 (perform a shrink).

5. Perform a shrink step: Evaluate f at the n points $\mathbf{v}_i = \mathbf{x}_1 + \sigma(\mathbf{x}_i - \mathbf{x}_1)$, $i = 2, \dots, n+1$. The (unordered) vertices of the simplex at the next iteration consist of $\mathbf{x}_1, \mathbf{v}_2, \dots, \mathbf{v}_{n+1}$. (Lagarias et al. 1998, 115-116)

The article by Nelder and Mead did not describe how to order points in the case of equal function values. The following tie-breaking rules are adopted, and they assign to the new vertex the highest possible index consistent with the relation $f\left(\mathbf{x}_1^{(k+1)}\right) \leq f\left(\mathbf{x}_2^{(k+1)}\right) \leq \cdots \leq f\left(\mathbf{x}_{n+1}^{(k+1)}\right)$. The nonshrink ordering rule states that when a nonshrink step occurs, the worst vertex $\mathbf{x}_{n+1}^{(k)}$ is discarded. The accepted point created during iteration k, denoted by $\mathbf{v}^{(k)}$, becomes a new vertex and takes position $j+1$ in the vertices of Δ_{k+1}, where $j = \max_{0 \leq \ell \leq n}\left\{\ell \middle| f\left(\mathbf{v}^{(k)}\right) < f(\mathbf{x}_{\ell+1}^{(k)})\right\}$; all other vertices retain their relative ordering from iteration k. The shrink ordering rule states that if a shrink step occurs, the only vertex carried over from Δ_k to Δ_{k+1} is $\mathbf{x}_1^{(k)}$. (Lagarias et al. 1998, 116) Only one tie-breaking rule is specified, for the case in which $\mathbf{x}_1^{(k)}$ and one or more of the new points are tied as the best point: if $\min\left\{f\left(\mathbf{v}_2^{(k)}\right), \dots, f\left(\mathbf{v}_{n+1}^{(k)}\right)\right\} = f(\mathbf{x}_1^{(k)})$, then $\mathbf{x}_1^{(k+1)} = \mathbf{x}_1^{(k)}$ (Lagarias et al. 1998, 116-117). Beyond this, whatever rule is used to define the original ordering may be applied after a shrink (Lagarias et al. 1998, 117).

4. Data

In the Datastream information service the continuous spot and EPAD futures prices have been provided for five different Nord Pool bidding areas: Helsinki, Stockholm, Oslo, Copenhagen and Aarhus. The electricity spot price time series are named Nordpool-Electricity Average Helsinki (NPXAVHE), Nordpool-Electricity Average Stockholm (NPXAVST), Nordpool-Electricity Average Oslo (NPXAVOS), Nordpool-Electricity Average Copenhagen (NPXAVKO) and Nordpool-Electricity Average Arhus (NPXAVAR). The mnemonics of the series have been presented in the parentheses. The futures price time series for the system price is named Nordpool-ENO Continuous (NOMCS00). The futures price time series for the EPADs are named Nordpool-Helsinki ENO Continuous (NMECS00), Nordpool-Stockholm ENO Continuous (NMSCS00), Nordpool-Oslo ENO Continuous (NMOCS00), Nordpool-Copenhagen ENO Continuous (NMCCS00) and Nordpool-Arhus ENO Continuous (NMACS00). The electricity futures price of a bidding area is the sum of the system futures price and the EPAD price (Nordic Green Energy 2021). There are no missing values in any of the time series.

The figure 1 presents the geographical locations of the examined bidding areas. From the map of the figure 1, it can be reasoned that “Helsinki” refers to the bidding area FI which constitutes the whole Finnish market (as Helsinki is the capital of Finland). “Stockholm” refers to the bidding area SE3 because Stockholm is located within the borders of this bidding area of the Swedish market. “Oslo” refers to the bidding area NO1 because Oslo is located within the borders of this bidding area of the Norwegian market. “Copenhagen” refers to the bidding area DK2 because Copenhagen is located within the borders of this bidding area of the Danish market. Finally, “Aarhus” refers to the bidding area DK1 because Aarhus is located within the borders of this bidding area of the Danish market. The codes of the studied bidding areas have been marked with orange-bordered rectangles. Although one could refer to the bidding areas by using their codes (FI, SE3, NO1, DK2 and DK1) in this thesis their main cities (Helsinki, Stockholm, Oslo, Copenhagen, and Aarhus) are utilized because this way it is easier to remember the locations of the bidding areas.

Figure 1. Geographical locations of the studied Nord Pool bidding areas (Nord Pool 2020a)

All time series are downloaded up to 29/5/2020. The available EPAD price time series for Helsinki, Stockholm, Oslo, and Copenhagen start from 15/3/2004 whereas the EPAD price time series for Aarhus starts from 01/06/2007. The spot price and system futures price time series start before the starting dates of the EPAD price time series, so the latest starting date in the EPAD time series defines the studied period. The in-sample and out-of-sample periods will be of equal length, and both must have a length of full years in order that an equal number of all twelve different months is included in both samples. The equal number of months is necessary for the study of seasonality because if this is not the case some seasonal periods would contain less observations than other seasonal periods and thus their hedge ratios wouldn't be as precisely estimated as the hedge ratios of other periods. This would then distort the obtained 1st LPM reductions and weaken the comparability of different strategies. Thus, the final studied period spans from 02/06/2008 to 29/5/2020. The whole studied period has the length of 12 years (3130 days) and the in-sample and out-of-sample period both have the length of 6 years (3130 days/2 ≈ 1565 days). Weekly returns are studied which means using every fifth spot and futures price value in return calculation. Thus, the number of analysed returns is (3130/5) - 1 = 625. The in-sample period from June 2008 to May 2014 utilizes 312 returns, the out-of-sample subperiod 1 from June 2014 to May 2017 utilizes 157 returns and the out-of-sample subperiod 2 from June 2017 to May 2020 utilizes 156 returns. The in-sample period must be long enough because the estimation of seasonal hedge ratios utilizes only a fraction of the observations in the in-sample period. The smallest number of observations is utilized when hedge ratios that minimize the 1st LPM are optimized (because only losses, which constitute about ½ of the observations, are used) and when 3-month-specific hedge ratios are estimated (because only 3/12 = 1/4 of the losses are used). Because the in-sample period contains about ½ of the observations, about ½ * ½ * ¼ * 625 ≈ 39 observations are used in the optimization of a 3-month-specific hedge ratio which minimizes the 1st LPM. This still is a sufficient number of observations for reliable optimization but if the in-sample period was substantially shorter, the number of observations would be too small to lead to reliable results.

In addition to daily closing prices, Datastream also provides the time to maturity for each day of the futures time series. The figure 2 presents for the system and bidding areas the boxplots of the maturities of futures contracts at the moment when a new contract replaces a previous contract that has expired. In other words, the highest maturity for each contract is analysed. Because the weekly hedging horizon is examined only maturities on Friday are utilized. In a boxplot a red horizontal line represents the sample median. The bottom and top of each box represent the 25th and 75th percentiles of the sample, respectively (interquartile range). The lines extending above and below each box are called whiskers and they go from the end of the interquartile range to the furthest observation within the whisker length. Red crosses mark outliers which have values that are more than 1.5 times the interquartile range away from the bottom or top of the box. (MathWorks 2022a) From the figure we see that the most common maturity is somewhat less than 30 days. 50 % of the maturities take place in the range of about 25-28 days. The highest maturity is 60 days and smallest less than 5 days. Thus, the futures time series are constructed by selecting a contract which matures within a month to provide the daily prices for a continuous series. When this contract matures, a new contract is selected according to the same criterion. If there are no contracts which mature within a month, a contract with the shortest available maturity (that is longer than a month) is selected.

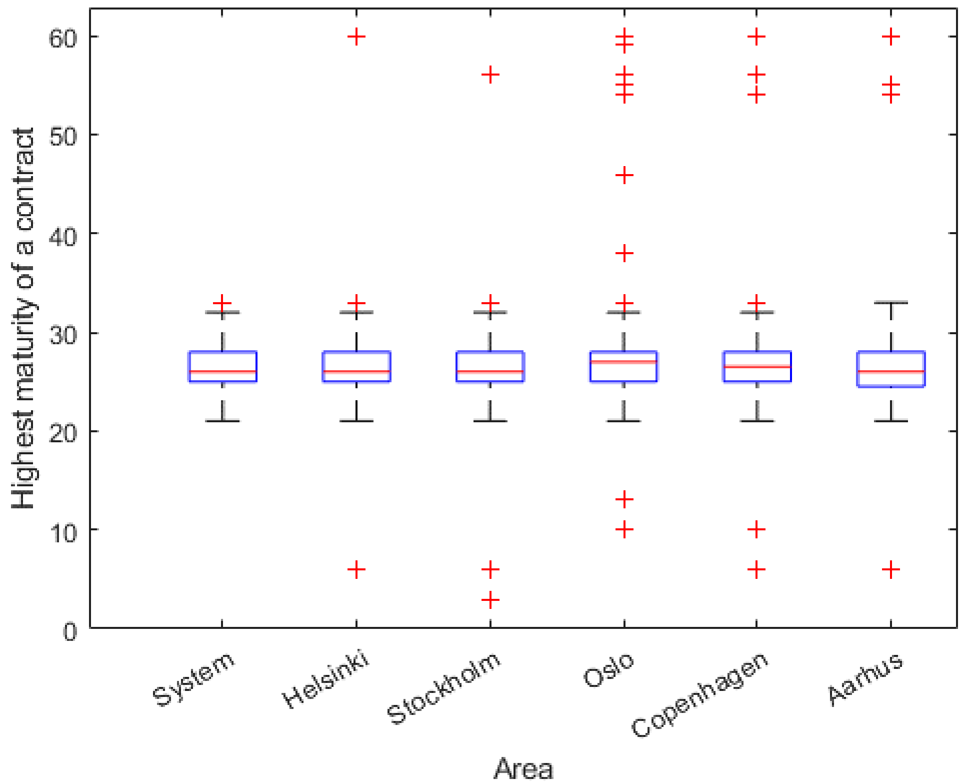

Figure 2. Highest maturities for the system price futures and EPAD futures

From Datastream one can observe that the delivery periods available for the system price futures and EPADs are a month, a quarter and a year. Because contracts which mature within a month are utilized to formulate the continuous time series, futures with a 1-month delivery period are obviously often selected as they are most frequently available. However, Datastream doesn't mention which delivery period lengths the contracts used in the continuous series have. It can be reasoned that for hedging purposes the delivery period should be as short as possible in order to make the hedging performance as high as possible. The reason for this is that the futures price predicts the average price for the delivery period. The longer this period is the less the futures price should react to the current events that supposedly have an impact only in the short term. Thus, the daily prices for the futures with a 1-month (or longer) delivery period are likely to underestimate the daily spot prices. The perfect hedging performance is achieved if the futures prices are exactly equal to the spot prices. This can be seen by examining the equations 2 and 3 (on the pages 32-33): if the spot and futures prices are equal all the time, their returns are also equal, and this always leads to the zero hedge portfolio return (when the naïve hedge is utilized) which implies that an LPM of any order n will be zero.

The table 4 presents the excess percentages of negative weekly spot returns and the table 5 presents the excess percentages of negative weekly futures returns which have been calculated from Friday prices. The calculation of these excess percentages is based on a notion that ideally there should be an equal number of positive and negative values in the spot returns and an equal number of positive and negative values in the futures returns. In other words, negative values should constitute 50 % of both spot and futures returns. In this ideal situation hedge ratios can be estimated reliably both for long hedgers and short hedgers. Thus, the excess percentage of negative spot/futures returns is the percentage of negative returns which exceeds 50 %. This means that if the excess percentage of negative returns is less than 0, less than 50 % of returns are negative. From the tables 4 and 5 we see that all excess percentages are rather close to zero and thus the percentages of negative spot and futures returns are very close to 50 % in both the in-sample period and out-of-sample periods. Thus, the distribution of returns enables to conduct the analysis both for long and short hedgers.

Table 4. Excess percentages of negative spot returns (%)

Helsinki	Stockholm	Oslo	Copenhagen	Aarhus
		In-sample		
1.60	2.56	-1.28	0.64	0.64
		Out-of-sample		
-0.80	0.16	-0.80	1.12	0.16

Table 5. Excess percentages of negative futures returns (%)

Helsinki	Stockholm	Oslo	Copenhagen	Aarhus
		In-sample		
1.92	2.56	0.96	-1.60	0.96
		Out-of-sample		
0.16	-1.76	-3.04	3.35	4.31

The figures 3-7 present the histograms of weekly spot and futures returns during the studied period. The weekly returns are logarithmic returns calculated by using prices for Friday. A long hedger wants to reduce positive returns because they imply increases in the electricity spot price. Correspondingly a short hedger wants to reduce negative returns because the imply decreases in the electricity spot price. From the histograms we see that in all bidding areas very large positive and negative spot returns take place frequently and that the futures markets continuously underestimate these returns. This observation is consistent with what was said above about the impact of a delivery period length and doesn't predict terribly high hedging performance, at least if naïve hedging is the utilized strategy. It appears that the futures market for Oslo is best (out of all the studied futures markets) at predicting the magnitude of spot returns.

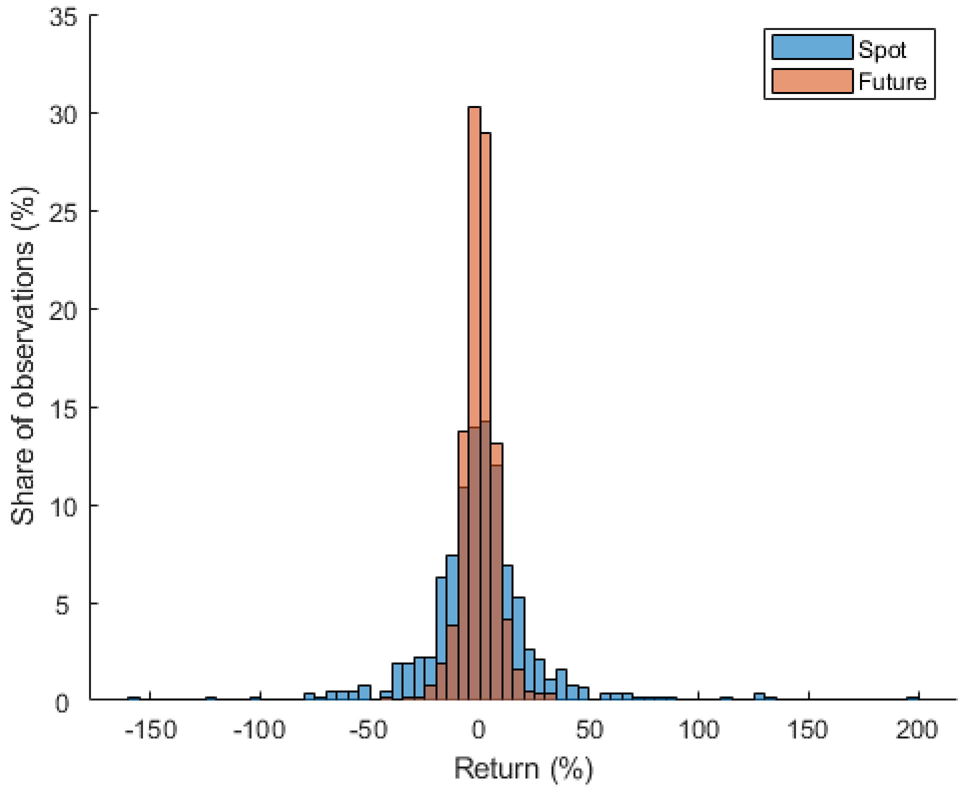

Figure 3. Weekly spot and futures returns for Helsinki

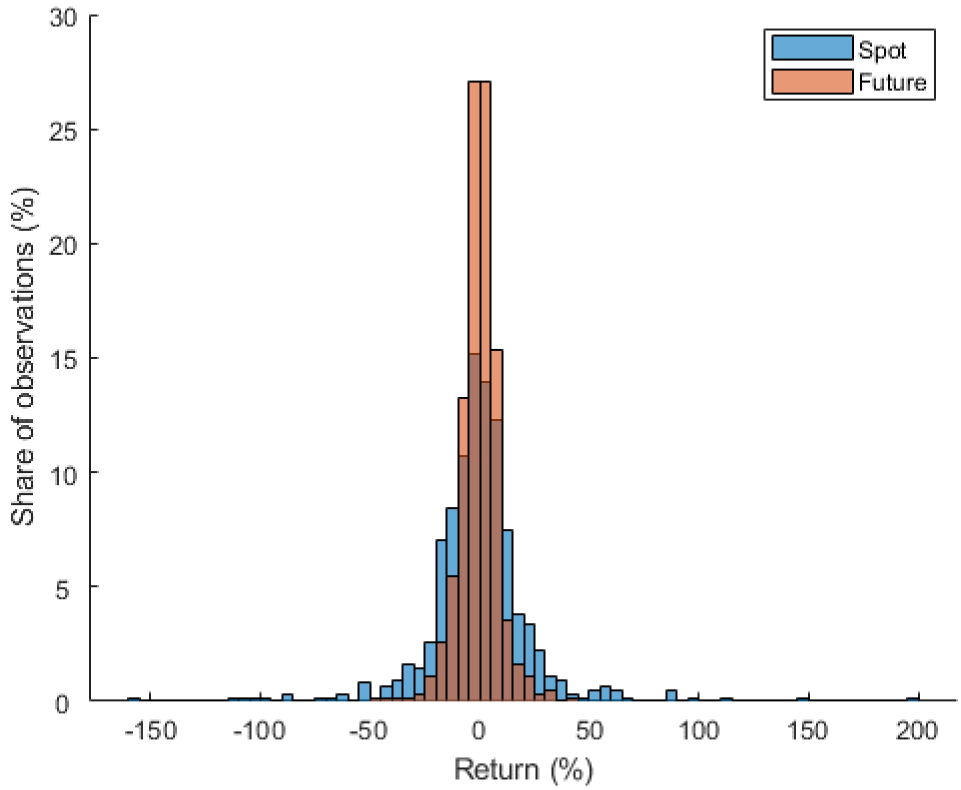

Figure 4. Weekly spot and futures returns for Stockholm

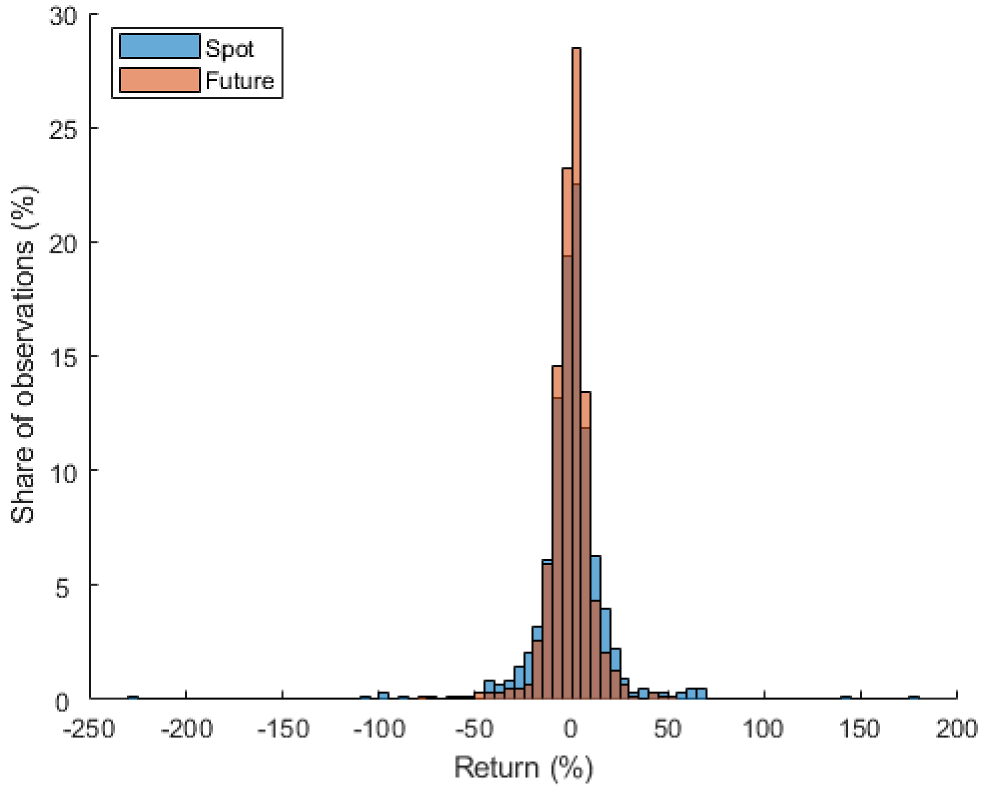

Figure 5. Weekly spot and futures returns for Oslo

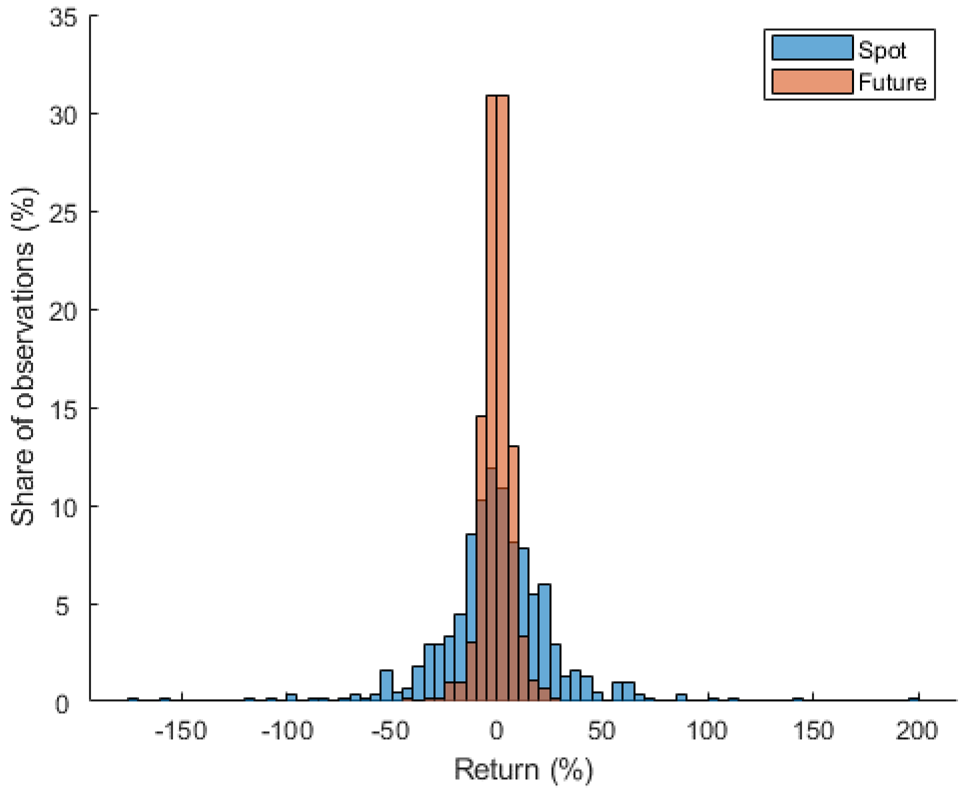

Figure 6. Weekly spot and futures returns for Copenhagen

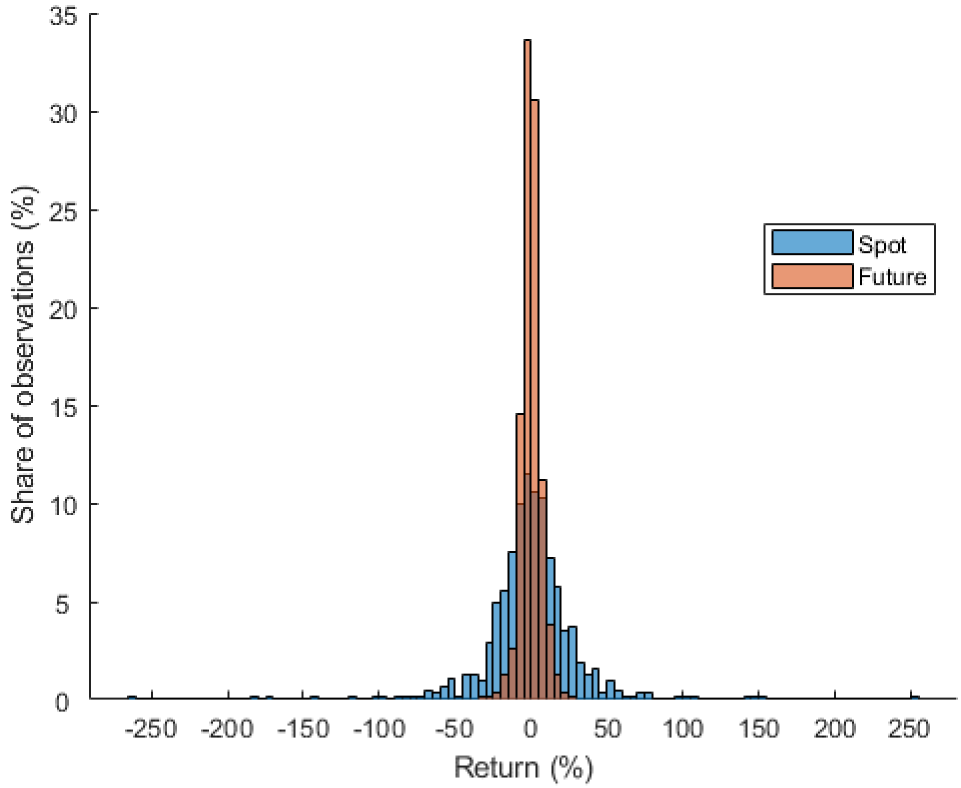

Figure 7. Weekly spot and futures returns for Aarhus

The following figures 8-12 present the histograms of weekly futures returns and the weekly 30-day average spot returns. The weekly 30-day average spot returns have been calculated with the following method: First, a daily moving average time series is created by calculating for each day the mean of the prices of the next 30 days in the future. After this, logarithmic weekly returns are calculated by using average prices for Friday. The idea behind this procedure is to compare the realized average spot returns for a 1-month delivery period to the futures returns for a 1-month (or longer) delivery period. Because we see from the histograms that the futures returns are often substantially larger than the 30-day spot returns we can propose that the futures prices in practice end up predicting the prices for lot shorter delivery periods than one month and are thus overly influenced by current events. For this reason, the utilization of futures with a 1-month (or longer) delivery period for hedging purposes is not completely unjustified.

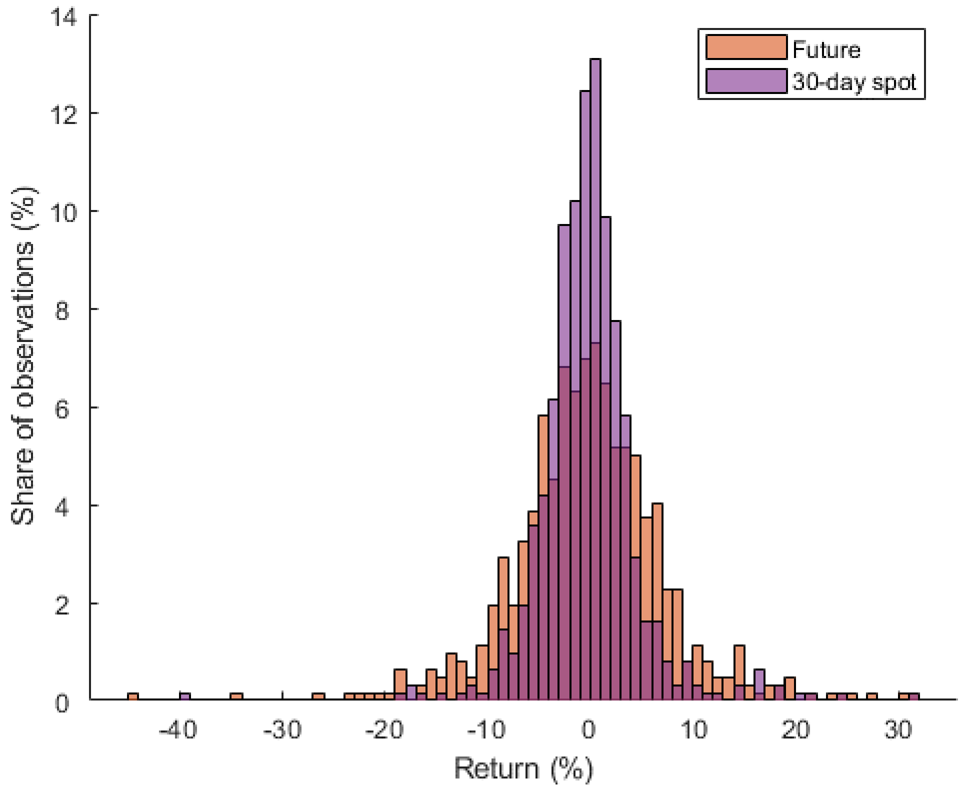

Figure 8. Weekly futures returns and weekly 30-day average spot returns for Helsinki

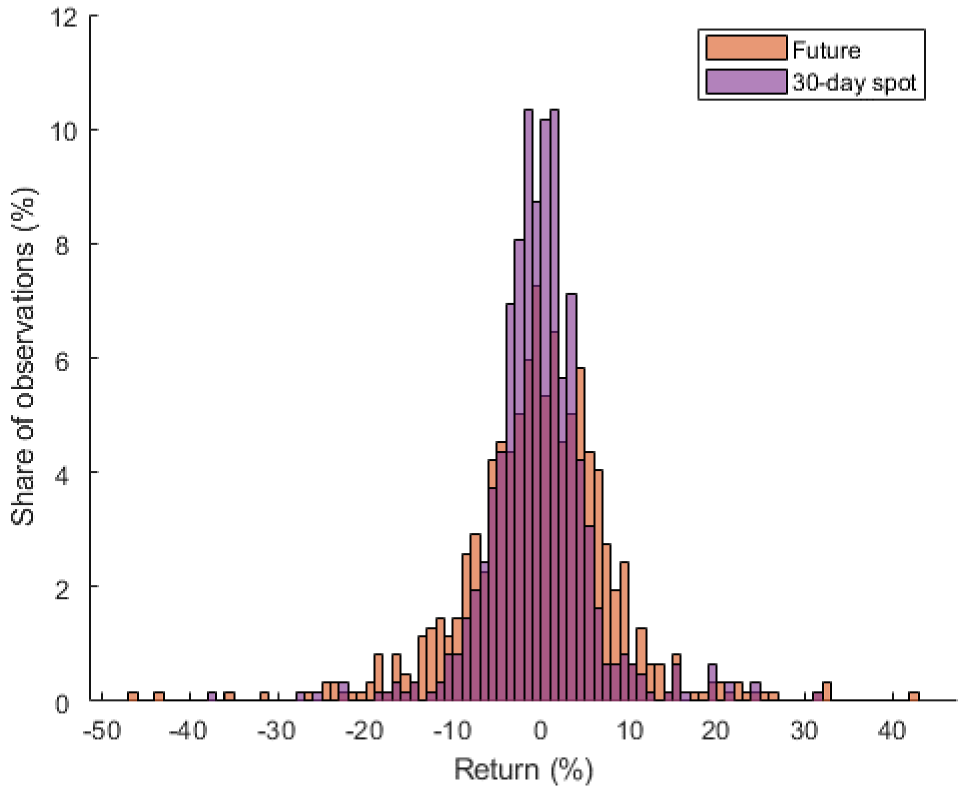

Figure 9. Weekly futures returns and weekly 30-day average spot returns for Stockholm

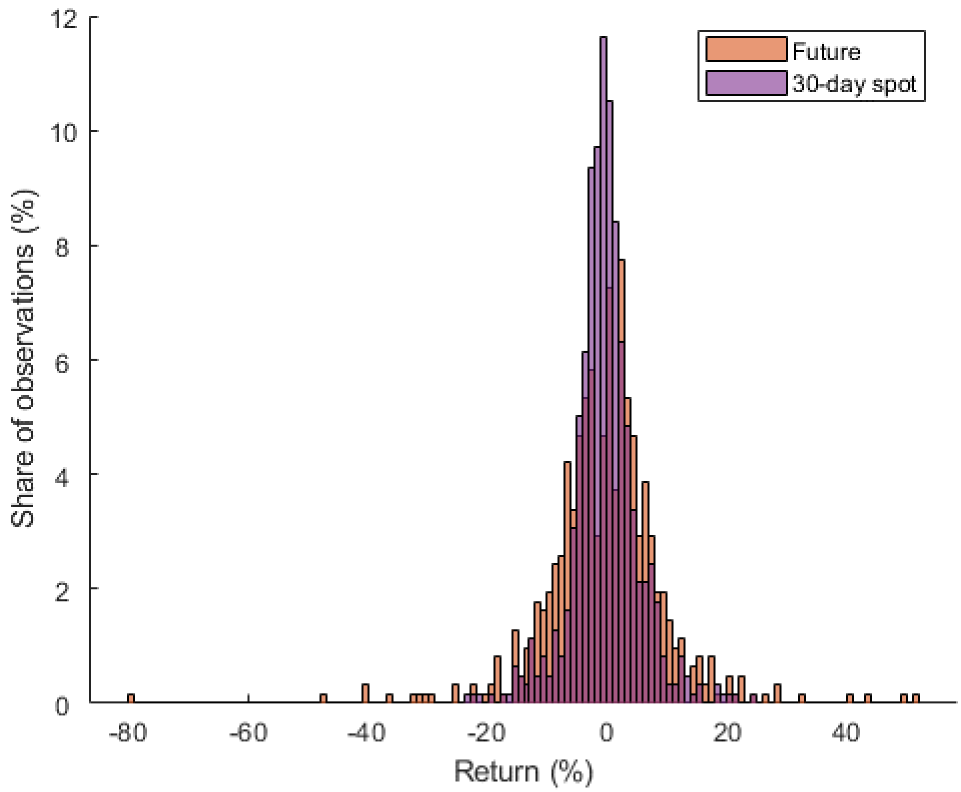

Figure 10. Weekly futures returns and weekly 30-day average spot returns for Oslo

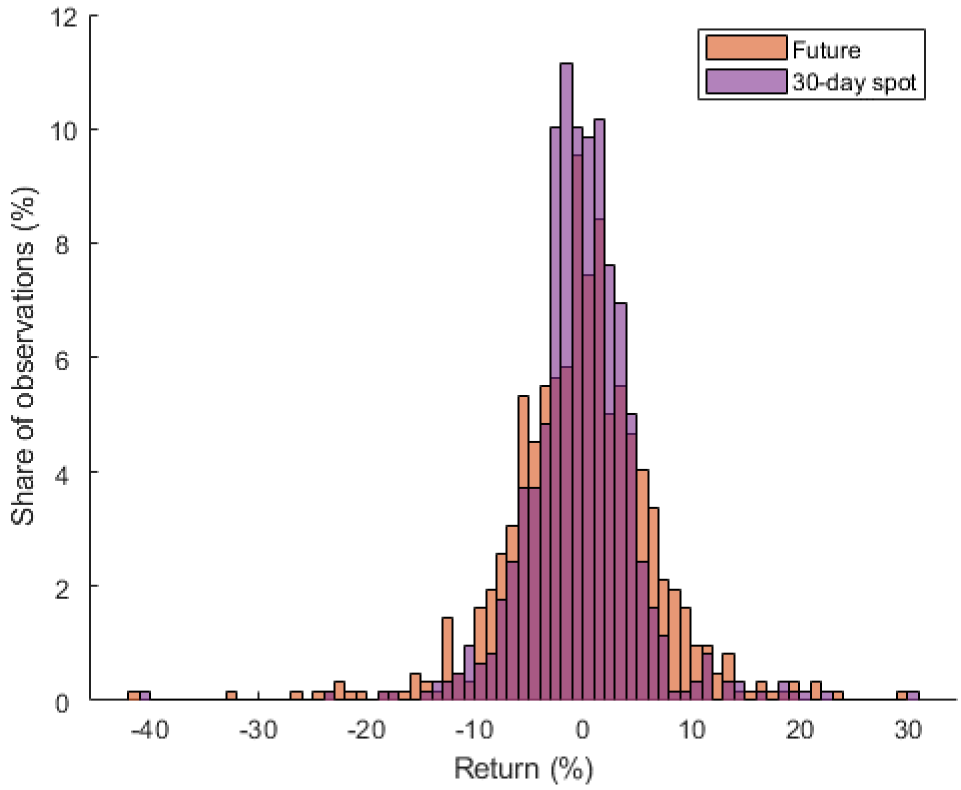

Figure 11. Weekly futures returns and weekly 30-day average spot returns for Copenhagen

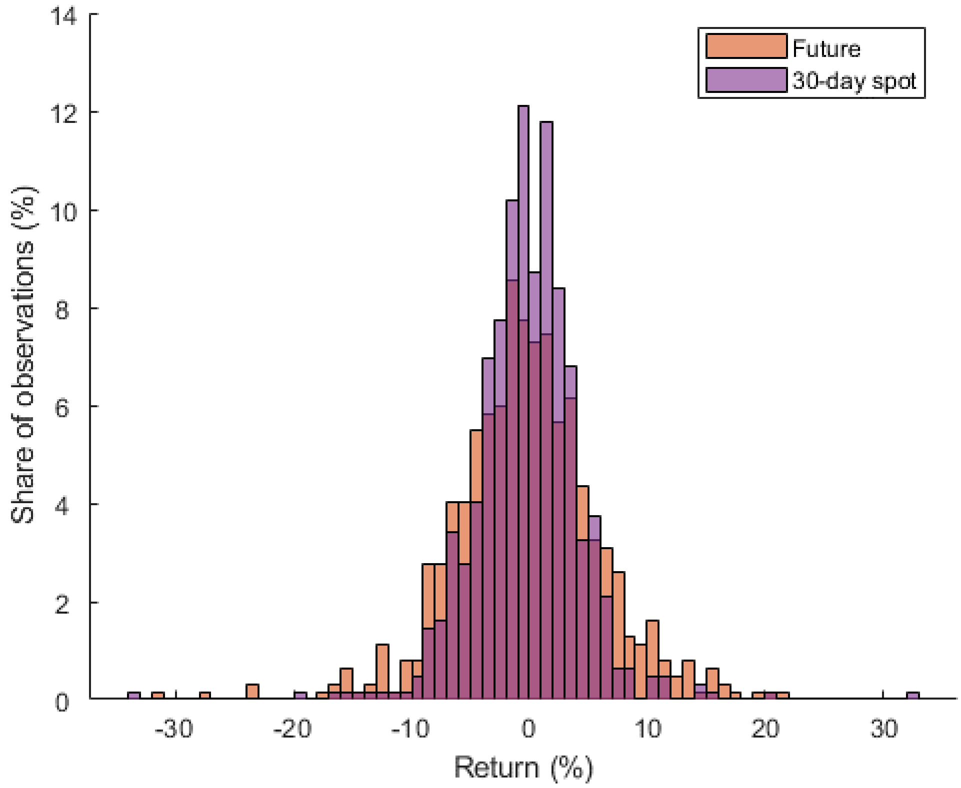

Figure 12. Weekly futures returns and weekly 30-day average spot returns for Aarhus

The capability of futures to successfully hedge the spot price of a bidding area can originate from two kinds of performance: Firstly, futures returns may accurately predict whether spot returns are positive or negative (i.e., the sign of returns). Secondly, for those spot returns for which futures correctly predict their sign, the futures may be able to accurately predict their magnitude. Ideally, these two kinds of performances would often take place. To study the first kind of performance, a table presenting the capability of different futures to successfully predict the signs of the spot prices of the bidding areas is constructed. The results are obtained both for the in-sample and out-of-sample periods.

Because there is a possibility that the local futures markets get the signs of returns right just by guessing randomly, this effect of random prediction must be eliminated. If the prediction of the futures markets is completely random, we can suppose that the markets predict a negative return 50 % of the time and a positive return 50 % of the time. Thus, the expected number of negative/positive sign predictions that are correct just by accident is 50 % * the number of negative/positive spot return observations. This expected number from random prediction (in the case of each bidding area) must be subtracted from the complete number of correct negative/positive sign predictions for each bidding area. After the numbers of correct negative/positive predictions that exceed the expected number from random prediction have been calculated, they are divided by the expected number of negative/positive predictions that are incorrect by random chance. This way a percentage is obtained with possible values in the range 0-100 %. 0 % means that the performance of the futures market in question is equal to the expected value from random prediction, i.e., the market doesn’t have any information on which it bases its sign predictions. 100 % means that the futures market in question always correctly predicts the sign of a return.

The percentages of the correct predictions of a spot return sign exceeding the expected value from random prediction have been presented in the table 6. The weekly returns calculated from Friday prices have been used. The bidding area of a spot price is indicated in the second row of the table. In the table H = Helsinki, S = Stockholm, O = Oslo, C = Copenhagen and A = Aarhus. The code that was used to generate the results of the table 6 has been provided in the appendices 1 and 2. By examining the table it can be seen that the majority of the values for the bidding areas are positive and thus in the case of bidding areas futures are generally better than random chance at predicting signs of spot returns. In the out-of-sample period the futures for Copenhagen and Aarhus are somewhat worse than random chance at predicting signs of positive spot returns because in these cases the values are slightly negative. For each bidding area the accuracy of sign predictions varies between the in-sample and out-of-sample periods.

Table 6. Correct predictions of a spot return sign exceeding the expected value from random prediction (%)

Negative returns (short)					**Positive returns (long)**				
H	**S**	**O**	**C**	**A**	**H**	**S**	**O**	**C**	**A**
In-sample									
26.71	31.71	36.84	18.99	22.78	17.88	20.27	26.25	25.97	16.88
Out-of-sample									
22.08	13.38	19.48	10.00	15.92	19.50	19.23	28.30	-3.27	-2.56

5. Results

This chapter contains two subchapters: The main analysis presents the results of hedge ratio optimization. Based on this main analysis additional clarifying investigations are conducted which illuminate the nature of spot and futures markets and the relationship between these markets.

5.1. Main analysis

Only the out-of-sample results have been provided in this thesis and analysed. The in-sample results, the maximum LPM reduction values obtained in the hedge ratio optimization, have been omitted. The main reason for this is that the out-of-sample results which test hedge ratios outside their estimation period are lot more important in judging the true hedging performance of different strategies. The mean hedge portfolio returns have not been presented because even if they were positive, they are not essential in evaluating hedging performance. The goal of hedging is to prevent undesirable losses, and this is measured by LPM reductions. Additionally, mean hedge portfolio returns don't necessarily describe the expected return of a single hedging position realistically, because few exceptionally high or low returns can distort mean return values. The MATLAB code that was used to produce the numerical results of this subchapter has been provided in the appendices 1 and 3.

The tables 7, 8, 12 and 13 present the 1^{st} and 0^{th} LPM reductions for all the examined hedging strategies when bidding area spot prices are hedged by using period divisions that are optimal according to the 1^{st} LPM reductions. The tables 7 and 8 present the subperiod results for long hedgers and the tables 12 and 13 the subperiod results for short hedgers. In the case of those static hedges where several alternative reductions are available because of several possible starting months of the yearly hedging periods, the period division which leads to the highest 1^{st} LPM reduction has been selected as the one whose value is included in the table. In the tables H = Helsinki, S = Stockholm, O = Oslo, C = Copenhagen and A = Aarhus. The row 2 tells the bidding area of the spot price that is hedged. For each bidding area the 1^{st} LPM reductions have also been ranked from the largest to the smallest with ordinal numbers 1.-7. in the tables 7, 8, 12 and 13. If two reductions have the same size, both are given the same ordinal number. The 1st and 0th LPM reduction values for the strategies with the ordinal number 1. have been underlined in the tables.

Next hedging performance is examined in the case of long hedging by studying the tables 7 and 8. By examining the values presented in the row 4 of the tables we see that the performance of naïve hedging is generally very poor as in the subperiod 1 all 1st LPM reductions are negative and in the subperiod 2 the highest 1st LPM reduction is slightly above 2 %. This means that naïve hedging can sometimes decrease the magnitude of losses but there is also a large risk that naïve hedging leads to increase in the magnitude of losses.

In comparison to the performance of naïve hedging, according to the 1st LPM reduction the performance improvement by the best hedge ratio optimization method is in the subperiod 1 for Helsinki (1.55 – (-1.40)) % = 2.95 %, for Stockholm (3.83 – (-4.90)) % = 8.73 %, for Oslo (8.04 – (-6.14)) % = 14.18 %, for Copenhagen (-0.51 – (-4.17)) % = 3.66 % and for Aarhus (1.52 – (-1.59)) % = 3.11 %. Performance improvement is greatest for Oslo and the Oslo spot price also has the best hedging performance. Decrease in the magnitude of losses is rather limited.

Table 7. Highest LPM reductions for different hedging strategies in the subperiod 1 (%, long)

1st LPM					0th LPM				
H	**S**	**O**	**C**	**A**	**H**	**S**	**O**	**C**	**A**
Naïve hedge									
7. -1.40	**7.** -4.90	**7.** -6.14	**7.** -4.17	**7.** -1.59	-2.47	3.80	6.98	11.54	8.86
Constant hedge (variance minimization)									
6. -1.10	**4.** -1.91	**6.** -4.51	**6.** -3.72	**6.** -0.52	-2.47	2.53	9.30	11.54	6.33
Constant hedge (1st LPM minimization)									
3. 0.25	**3.** -0.41	**4.** 3.41	**3.** -2.59	**5.** -0.16	-1.23	2.53	5.81	12.82	5.06
6-month-specific hedge (variance minimization)									
4. -0.71	**5.** -1.93	**5.** 2.40	**4.** -3.13	**4.** 0.59	-2.47	2.53	6.98	12.82	2.53
6-month-specific hedge (1st LPM minimization)									
1. 1.55	**2.** 2.20	**2.** 7.03	**2.** -0.82	**2.** 1.33	-2.47	7.59	3.49	8.97	6.33
3-month-specific hedge (variance minimization)									
5. -0.81	**6.** -3.63	**3.** 4.09	**5.** -3.22	**3.** 0.73	3.70	2.53	11.63	8.97	0.00
3-month-specific hedge (1st LPM minimization)									
2. 0.94	**1.** 3.83	**1.** 8.04	**1.** -0.51	**1.** 1.52	-1.23	6.33	5.81	10.26	7.59

According to the 1st LPM reduction, the performance improvement by the best hedge ratio optimization method is in the subperiod 2 for Helsinki (6.26 – 1.75) % = 4.51 %, for Stockholm (4.96 – 2.19) % = 2.77 %, for Oslo (11.30 – 2.10) % = 9.20 %, for Copenhagen (2.23 – (-5.03)) % = 7.26 % and for Aarhus (5.12 – 0.24) % = 4.88 %. Again, performance improvement is greatest for Oslo and the Oslo spot price also has the best hedging performance. Decrease in the magnitude of losses is limited but better than in the subperiod 1 because the highest 1st LPM reductions are higher for all locations in the subperiod 2.

Table 8. Highest LPM reductions for different hedging strategies in the subperiod 2 (%, long)

1st LPM					0th LPM				
H	**S**	**O**	**C**	**A**	**H**	**S**	**O**	**C**	**A**
Naïve hedge									
7.	**6.**	**7.**	**7.**	**7.**					
1.75	2.19	2.10	-5.03	0.24	1.28	0.00	-8.22	-6.67	-7.79
Constant hedge (variance minimization)									
6.	**5.**	**5.**	**6.**	**6.**					
2.04	3.81	4.11	-4.35	0.83	-1.28	-5.19	-8.22	-6.67	-2.60
Constant hedge (1st LPM minimization)									
4.	**4.**	**3.**	**4.**	**5.**					
2.43	4.01	8.91	-2.76	0.92	-3.85	-6.49	-5.48	-8.00	-1.30
6-month-specific hedge (variance minimization)									
5.	**3.**	**1.**	**5.**	**3.**					
2.39	4.34	11.30	-4.21	3.88	1.28	-3.90	-5.48	-5.33	5.19
6-month-specific hedge (1st LPM minimization)									
3.	**2.**	**2.**	**2.**	**4.**					
3.88	4.95	10.80	0.50	3.70	-2.56	-5.19	-2.74	-2.67	-5.19
3-month-specific hedge (variance minimization)									
2.	**7.**	**6.**	**3.**	**1.**					
4.48	2.13	3.84	-2.08	5.12	0.00	0.00	-5.48	-4.00	5.19
3-month-specific hedge (1st LPM minimization)									
1.	**1.**	**4.**	**1.**	**2.**					
6.26	4.96	7.15	2.23	5.07	2.56	-2.60	-8.22	-5.33	0.00

In order to evaluate the general performance level of different hedging strategies, in the table 9 the median ordinal numbers are shown for the hedging strategies in the case of long hedging. The table value for each strategy and each subperiod is obtained by first arranging the ordinal numbers for a particular hedging strategy in an ascending order (e.g., for the naïve static hedge in the subperiod 2 the sequence is 6, 7, 7, 7, 7) and selecting the median (the third ordinal number in the sequence) to be included in the table (for the naïve hedge it is 7). The median is utilized because it is not affected by exceptionally large or small values. Additionally, calculating the mean of ordinal numbers is not adequate as they are not continuous (as they can only take integer values). From the table 9 we see that naïve hedging has the worst 1st LPM reductions. The optimized static hedges that divide a year into seasonal periods clearly have better performance than the naïve hedge. In both subperiods, the best general performance is recorded for the 3-month-specific static hedge that is optimized with the 1st LPM minimization. In the case of all seasonal period lengths (constant, 3 and 6 months) the median ordinal numbers of the table 9 indicate that the 1st LPM works better as the minimization criterion for static hedges than variance. The obvious reason for this is that the 1st LPM doesn't assume distributional symmetry in the same way as variance and therefore cannot be erroneous because of a wrong assumption of symmetry.

Table 9. Median ordinal numbers for different hedging strategies (long)

	Median ordinal number	
Hedging strategy	**Subperiod 1**	**Subperiod 2**
Naïve hedge	7.	7.
Constant hedge (variance minimization)	6.	6.
Constant hedge (1st LPM minimization)	3.	4.
6-month-specific hedge (variance minimization)	4.	3.
6-month-specific hedge (1st LPM minimization)	2.	2.
3-month-specific hedge (variance minimization)	5.	3.
3-month-specific hedge (1st LPM minimization)	1.	1.

The optimal starting months of the first 3-month and 6-month periods of seasonal static hedges in the case of long hedging have been provided for both subperiods in the table 10. A starting month is optimal if it leads to the highest measured 1st LPM reduction. The starting months have been provided for the two utilized minimization criteria (variance and the 1st LPM). In the table Jan = January, Feb = February, Mar = March, Apr = April and Jun = June.

Table 10. Optimal starting months of the first periods (long)

Subperiod 1					Subperiod 2				
H	**S**	**O**	**C**	**A**	**H**	**S**	**O**	**C**	**A**
6-month-specific hedge (variance minimization)									
Feb	Mar	Feb	Feb	Jun	Apr	Apr	May	Jun	Jun
6-month-specific hedge (1st LPM minimization)									
Jun	Feb	Feb	Jan	Jan	May	Jan	May	May	Apr
3-month-specific hedge (variance minimization)									
Mar	Jan	Feb	Feb	Mar	Mar	Mar	Jan	Mar	Mar
3-month-specific hedge (1st LPM minimization)									
Jan	Feb	Feb	Jan	Jan	Mar	Mar	Feb	Mar	Jan

Next the values of the tables 7, 8 and 10 are combined in the table 11 to compare the characteristics of the hedging strategies that are optimal for long hedgers in the two studied subperiods. A strategy is optimal for the bidding area in question if it has the ordinal number 1. From the table we see that the most common length of a seasonal period is 3 months, and that the most common minimization criterion is the 1st LPM. Only in the case of Stockholm, Copenhagen, and Aarhus the optimal length of a seasonal period is the same in both subperiods. For Helsinki, Stockholm and Copenhagen the optimal minimization criterion is the same in both subperiods. However, the optimal starting month of the first seasonal period is always different for the subperiods 1 and 2 in the case of each location. In both subperiods the number of profits decreases in the case of some locations. Therefore, the minimization of the magnitude losses doesn't necessarily lead to decrease in the number of losses. These two optimization targets are clearly separate and won't be necessarily achieved at the same time. With the exception of Aarhus, in the case of all locations the change in the number of profits changes from negative to positive or vice versa when one transitions from the subperiod 1 to the subperiod 2. Thus, it seems that the change in the number of profits (as a result of hedging) in one period cannot be used to predict the change in the number of profits in another period.

Table 11. Characteristics of the best hedges (long)

Subperiod 1					Subperiod 2				
H	**S**	**O**	**C**	**A**	**H**	**S**	**O**	**C**	**A**
Length of a seasonal period (months)									
6	3	3	3	3	3	3	6	3	3
Starting month of the first period									
Jun	Feb	Feb	Jan	Jan	Mar	Mar	May	Mar	Mar
Minimization criterion									
LPM1	LPM1	LPM1	LPM1	LPM1	LPM1	LPM1	Var	LPM1	Var
Change in the number of profits									
–	+	+	+	+	+	–	–	–	+

Next the tables 12 and 13 presenting the results for short hedging are studied. By examining the values presented in the row 4 of the tables we see that the performance of naïve static hedging is often poor as all 1st LPM reductions in the subperiod 1 are negative. However, in the subperiod 2 high 1st LPM reductions are achieved for Stockholm and Oslo. Thus, naïve hedging can clearly reduce the magnitude of losses in favourable conditions, but the problem is that naïve hedging is not able to secure that loss reductions take place in all periods. In comparison to the performance of naïve hedging, according to the 1st LPM reduction measure the performance improvement by the best hedge ratio optimization method in the subperiod 1 is for Helsinki (2.67 – (-0.13)) % = 2.80 %, for Stockholm (1.94 – (-2.36)) % = 4.30 %, for Oslo (3.55 – (-6.45)) % = 10.00 %, for Copenhagen (-0.55 – (-2.79)) % = 2.24 % and for Aarhus (0.30 – (-0.57)) % = 0.87 %. Performance improvement is greatest for Oslo and the Oslo spot price also has the best hedging performance. Decrease in the magnitude of losses is rather limited.

Table 12. Highest LPM reductions for different hedging strategies in the subperiod 1 (%, short)

1st LPM					**0th LPM**				
H	**S**	**O**	**C**	**A**	**H**	**S**	**O**	**C**	**A**
Naïve hedge									
7. -0.13	**7.** -2.36	**6.** -6.45	**7.** -2.79	**6.** -0.57	2.63	-3.85	-8.45	-11.39	-8.97
Constant hedge (variance minimization)									
6. 0.10	**6.** -0.06	**5.** -4.72	**5.** -2.44	**2.** 0.25	2.63	-2.56	-11.27	-11.39	-6.41
Constant hedge (1st LPM minimization)									
3. 0.63	**5.** 0.53	**2.** 3.11	**6.** -2.52	**5.** -0.13	0.00	-2.56	-9.86	-11.39	-8.97
6-month-specific hedge (variance minimization)									
4. 0.32	**3.** 1.34	**4.** -4.64	**2.** -0.68	**4.** 0.19	1.32	1.28	-8.45	-11.39	-5.13
6-month-specific hedge (1st LPM minimization)									
2. 2.65	**2.** 1.86	**1.** 3.55	**4.** -1.26	**3.** 0.21	0.00	0.00	-9.86	-6.33	-8.97
3-month-specific hedge (variance minimization)									
5. 0.13	**4.** 1.17	**7.** -6.60	**1.** -0.55	**7.** -0.84	1.32	-1.28	-9.86	-8.86	2.56
3-month-specific hedge (1st LPM minimization)									
1. 2.67	**1.** 1.94	**3.** 2.90	**3.** -0.92	**1.** 0.30	1.32	0.00	-12.68	-6.33	-6.41

According to the 1st LPM reduction, the performance improvement by the best hedge ratio optimization method in the subperiod 2 is for Helsinki (5.87 - 4.47) % = 1.40 %, for Stockholm (10.22 – 7.65) % = 2.57 %, for Oslo (27.49 - 24.41) % = 3.08 %, for Copenhagen (-0.64 – (-2.99)) % = 2.35 % and for Aarhus (3.62 – 2.10) % = 1.52 %. Again, performance improvement is greatest for Oslo and the Oslo spot price also has the best hedging performance. Decrease in the magnitude of losses is generally limited but better than in the subperiod 1 because, except for Copenhagen, the highest 1st LPM reductions are higher for all locations in the subperiod 2.

Table 13. Highest LPM reductions for different hedging strategies in the subperiod 2 (%, short)

1st LPM					0th LPM				
H	**S**	**O**	**C**	**A**	**H**	**S**	**O**	**C**	**A**
Naïve hedge									
7. 4.47	**6.** 7.65	**4.** 24.41	**7.** -2.99	**5.** 2.10	-1.28	0.00	7.23	6.17	7.59
Constant hedge (variance minimization)									
5. 4.59	**5.** 7.66	**3.** 24.69	**5.** -2.47	**3.** 2.21	1.28	5.06	7.23	6.17	2.53
Constant hedge (1st LPM minimization)									
6. 4.51	**7.** 7.24	**6.** 20.09	**6.** -2.59	**3.** 2.21	2.56	3.80	3.61	7.41	3.80
6-month-specific hedge (variance minimization)									
4. 4.76	**2.** 10.15	**5.** 24.02	**1.** -0.64	**4.** 2.12	1.28	7.59	3.61	8.64	3.80
6-month-specific hedge (1st LPM minimization)									
2. 5.71	**3.** 10.03	**2.** 27.15	**3.** -0.87	**1.** 3.62	3.85	6.33	12.05	9.88	3.80
3-month-specific hedge (variance minimization)									
3. 5.63	**4.** 9.51	**7.** 16.59	**4.** -0.97	**6.** -2.09	-1.28	6.33	6.02	4.94	-5.06
3-month-specific hedge (1st LPM minimization)									
1. 5.87	**1.** 10.22	**1.** 27.49	**2.** -0.81	**2.** 2.87	3.85	6.33	13.25	7.41	-1.27

The general performance of different hedging strategies is illustrated in the table 14 which shows the median ordinal numbers for the hedging strategies in the case of short hedging. The table value for each strategy is obtained with the same method as the values in the table 9. From the table 14 we see that again naïve hedging has the worst LPM reductions. The 6-month-specific and 3-month-specific hedges generally perform better than constant hedges. In both subperiods, the best performance is again recorded for the 3-month-specific hedge that utilizes 1st LPM minimization. For the 6-month-specific and 3-month-specific hedges the 1st LPM seems to be a better minimization criterion than variance.

Table 14. Median ordinal numbers for different hedging strategies (short)

	Median ordinal number	
Hedging strategy	**Subperiod 1**	**Subperiod 2**
Naïve hedge	7.	6.
Constant hedge (variance minimization)	5.	5.
Constant hedge (1st LPM minimization)	5.	6.
6-month-specific hedge (variance minimization)	4.	4.
6-month-specific hedge (1st LPM minimization)	2.	2.
3-month-specific hedge (variance minimization)	5.	4.
3-month-specific hedge (1st LPM minimization)	1.	1.

The optimal starting months of the first 3-month and 6-month periods of seasonal static hedges in the case of short hedging have been provided in the table 15. The format of the table is similar to the table 10. January is clearly the most common starting month as it is utilized in 18 of the 40 possible hedges in the table.

Table 15. Optimal starting months of the first periods (short)

Subperiod 1					Subperiod 2				
H	**S**	**O**	**C**	**A**	**H**	**S**	**O**	**C**	**A**
6-month-specific hedge (variance minimization)									
Jan	Jan	Feb	May	Jan	Jan	Jun	Apr	Mar	Jan
6-month-specific hedge (1st LPM minimization)									
Jan	Jan	May	May	Mar	Jan	Jun	Jan	Mar	Mar
3-month-specific hedge (variance minimization)									
Feb	Feb	Jan	Feb	Feb	Jan	Jan	Feb	Jan	Mar
3-month-specific hedge (1st LPM minimization)									
Jan	Jan	Mar	Feb	Mar	Jan	Jan	Jan	Mar	Mar

Next the values of the tables 12, 13 and 15 are combined in the table 16 to compare the characteristics of the hedging strategies that are optimal for short hedgers in the two studied subperiods. The format of the table 16 is similar to the table 11. From the table we see that the most common length of a seasonal period is 3 months, and that the most common minimization criterion is the 1st LPM. Only in the case of Helsinki and Stockholm the optimal length of a seasonal period is the same in both subperiods. For all bidding areas the optimal minimization criterion is the same in both subperiods. For Helsinki, Stockholm and Aarhus the optimal starting month of the first seasonal period is the same in both subperiods. In the case of Helsinki and Stockholm the period division remains the same in both subperiods. For these two bidding areas there are four three-month periods which start in January, April, July and October. In the subperiod 1 the number of profits decreases in the case of some locations, which again illustrates that the minimization of the magnitude losses doesn't necessarily lead to decrease in the number of losses. In the case of Oslo, Copenhagen and Aarhus the change in the number of profits changes from negative to positive when one moves from the subperiod 1 to the subperiod 2. This again shows that the change in the number of profits (because of hedging) in one period cannot be used to predict the change in the number of profits in another period. In the case of Stockholm hedging doesn't change the number of profits in the subperiod 1 and thus its value is 0 in the table.

Table 16. Characteristics of the best hedges (short)

Subperiod 1					Subperiod 2				
H	**S**	**O**	**C**	**A**	**H**	**S**	**O**	**C**	**A**
Length of a seasonal period (months)									
3	3	6	3	3	3	3	3	6	6
Starting month of the first period									
Jan	Jan	May	Feb	Mar	Jan	Jan	Jan	Mar	Mar
Minimization criterion									
LPM1	LPM1	LPM1	Var	LPM1	LPM1	LPM1	LPM1	Var	LPM1
Change in the number of profits									
+	0	–	–	–	+	+	+	+	+

In the case of the subperiod 1 the subtraction of the highest 1st LPM reductions of long hedging (according to the table 7) from the highest LPM reductions of short hedging (according to the table 12) yields the following differentials: for Helsinki (2.67 – 1.55) % = 1.12 %, for Stockholm (1.94 – 3.83) % = -1.89 %, for Oslo (3.55 – 8.04) % = -4.49 %, for Copenhagen (-0.55 – (-0.51)) % = -0.04 % and for Aarhus (0.30 – 1.52) % = -1.22 %. Therefore, in the subperiod 1 short hedgers outperform long hedgers only in the case of Helsinki. Long hedgers outperform short hedgers in the case of Stockholm, Oslo, Copenhagen and Aarhus. In the case of the subperiod 2 the subtraction of the highest 1st LPM reductions of long hedging (according to the table 8) from the highest LPM reductions of short hedging (according to the table 13) yields the following differentials: for Helsinki (5.87 – 6.26) % = -0.39 %, for Stockholm (10.22 – 4.96) % = 5.26 %, for Oslo (27.49 – 11.30) % = 16.19 %, for Copenhagen (-0.64 – 2.23) % = -2.87 % and for Aarhus (3.62 – 5.12) % = -1.50 %. Therefore, in the subperiod 2 short hedgers outperform long hedgers in the case of Stockholm and Oslo. Long hedgers outperform short hedgers in the case of Helsinki, Copenhagen and Aarhus. In the case of Helsinki, Stockholm and Oslo the differentials calculated above have different signs in the two subperiods. This means that if long hedgers outperform short hedgers in the first period, short hedgers outperform long hedgers in the second period (and vice versa). However, for Copenhagen and Aarhus the signs are the same in both subperiods and thus the order of hedgers remains the same.

Therefore, it can be concluded that there are performance differences between short and long hedgers, but these differences don’t seem to be systematic in any way.

The figures 13-17 present the best optimized monthly hedge ratios for the studied bidding areas. The hedge ratios have been presented for the strategies that are optimal according to the tables 11 (long hedging) and 16 (short hedging). The general tendency which can be discerned from the figures 13-15 (of Helsinki, Stockholm and Oslo) is that for long hedgers the hedge ratios of the latter half of the year (from July to December) tend to be much larger than the hedge ratios of the first half (from January to June). For short hedgers, the situation is the opposite and the hedge ratios of the latter half of the year are much smaller than the hedge ratios of the first half. The first step to understand this phenomenon is to consider how long and short hedgers should incorporate their expectations on the electricity price development in their hedge ratios. In the following examples for long and short hedgers it is supposed that a hedger wants to ensure the positivity of hedge portfolio returns but to have as little as possible knowledge about market development. The higher a long hedger perceives the probability that the electricity price will rise to be, the higher its hedge ratio should be. This can be illustrated by examining the equation 2 on the page 32. If it is 100 % certain that the futures return r_F will be positive, the hedge ratio should be higher than 0. If it is 100 % certain that the spot return r_S will be negative, the optimal hedge ratio is 0. Because spot and futures prices are correlated, spot returns are likely to be positive when the hedge ratio is higher than 0 and the futures returns are likely to be negative when the hedge ratio is 0.

In the case of a short hedger the situation is the opposite. The higher a short hedger perceives the probability that the electricity price will rise to be, the smaller its hedge ratio should be. This can be illustrated by examining the equation 3 on the page 33. If it is 100 % certain that the spot return r_S will be positive, the optimal hedge ratio is 0. If it is 100 % certain that the futures return r_F will be negative, the hedge ratio should be higher than 0. Because spot and futures prices are correlated, futures returns are likely to be positive when the hedge ratio is 0 and spot returns are likely to be negative when the hedge ratio is higher than 0.

The most obvious reason for the fall and rise of the electricity spot prices of bidding areas is climate. Because the outside temperature increases during the first half of the year (as the summer approaches), the electricity price tends to go down (as the demand for electric heating decreases) and thus a short hedger needs a substantial degree of hedging (but not a long hedger). Because the outside temperature decreases during the second half of the year (as the winter is coming), the electricity price tends to go up (as the demand for electric heating increases) and thus a long hedger needs a large degree of hedging (but not a short hedger). The fact that the pattern is less clear for Copenhagen and Aarhus supports this interpretation because these bidding areas are located further south than Helsinki, Stockholm and Oslo and thus variation in their yearly temperatures is not as dramatic.

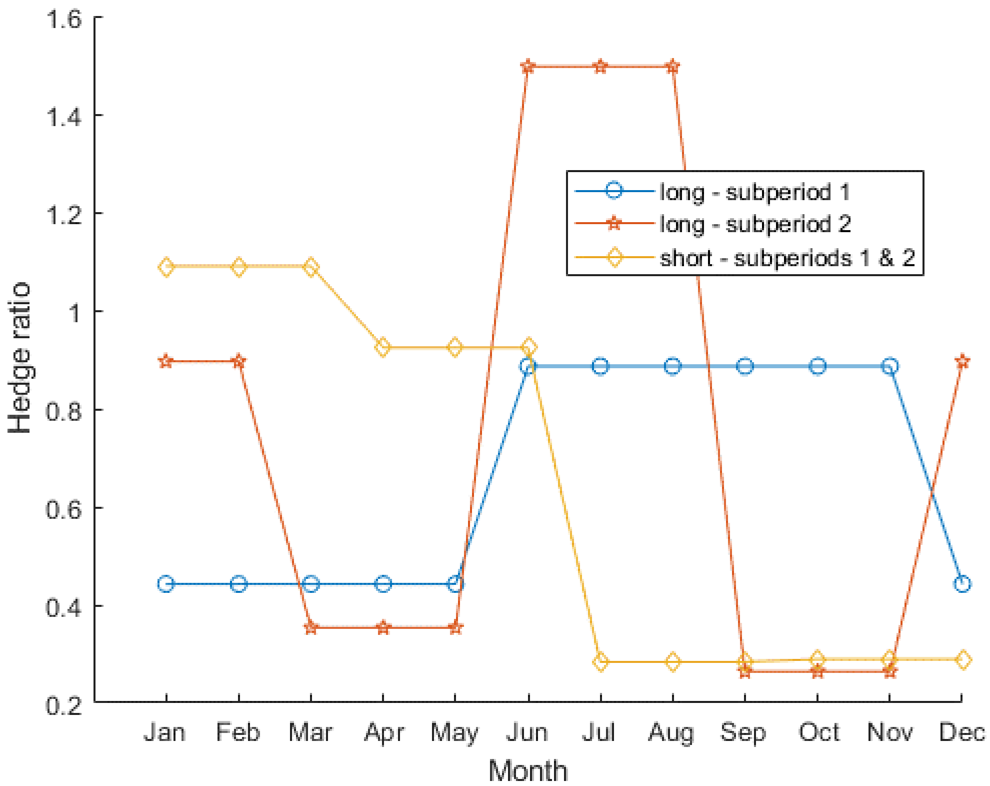

Figure 13. Optimized monthly hedge ratios for Helsinki

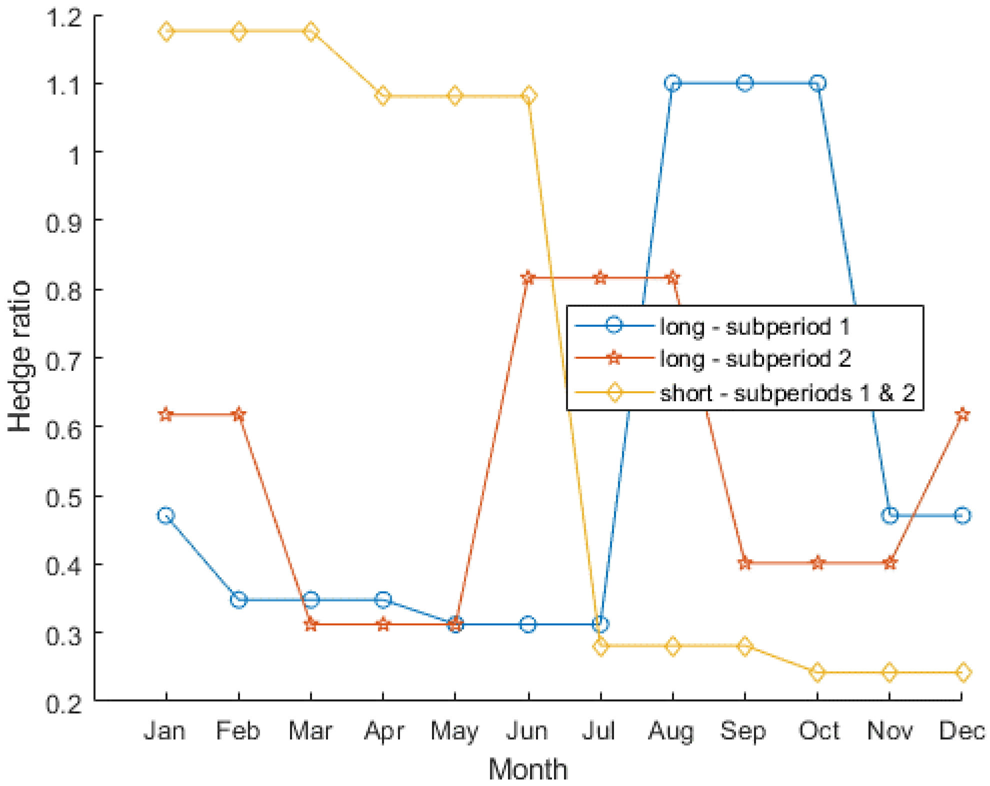

Figure 14. Optimized monthly hedge ratios for Stockholm

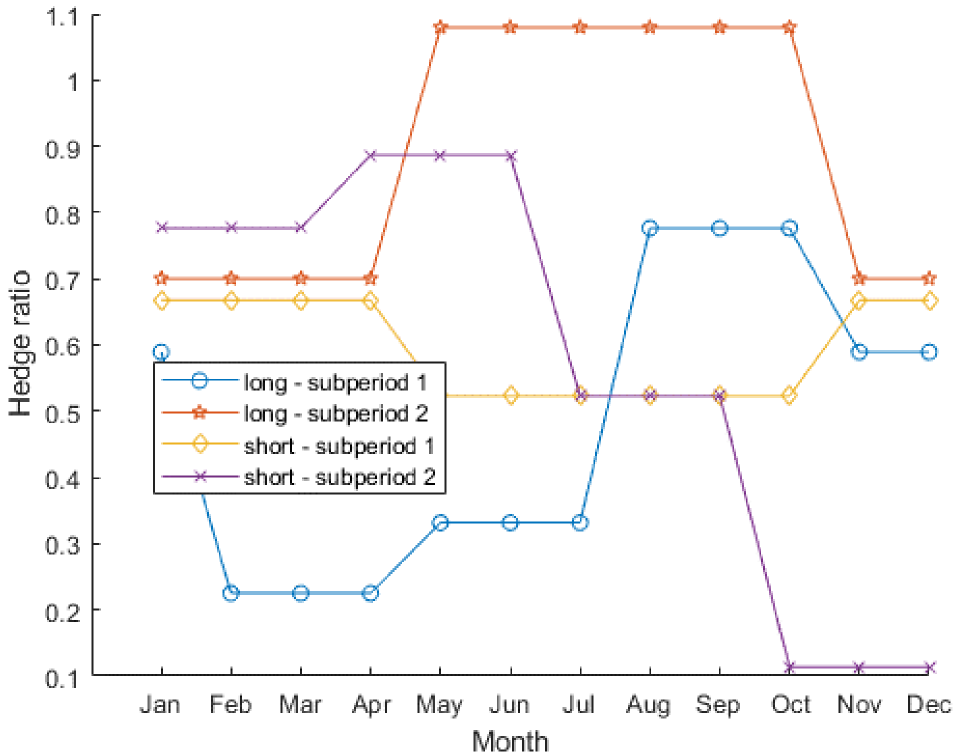

Figure 15. Optimized monthly hedge ratios for Oslo

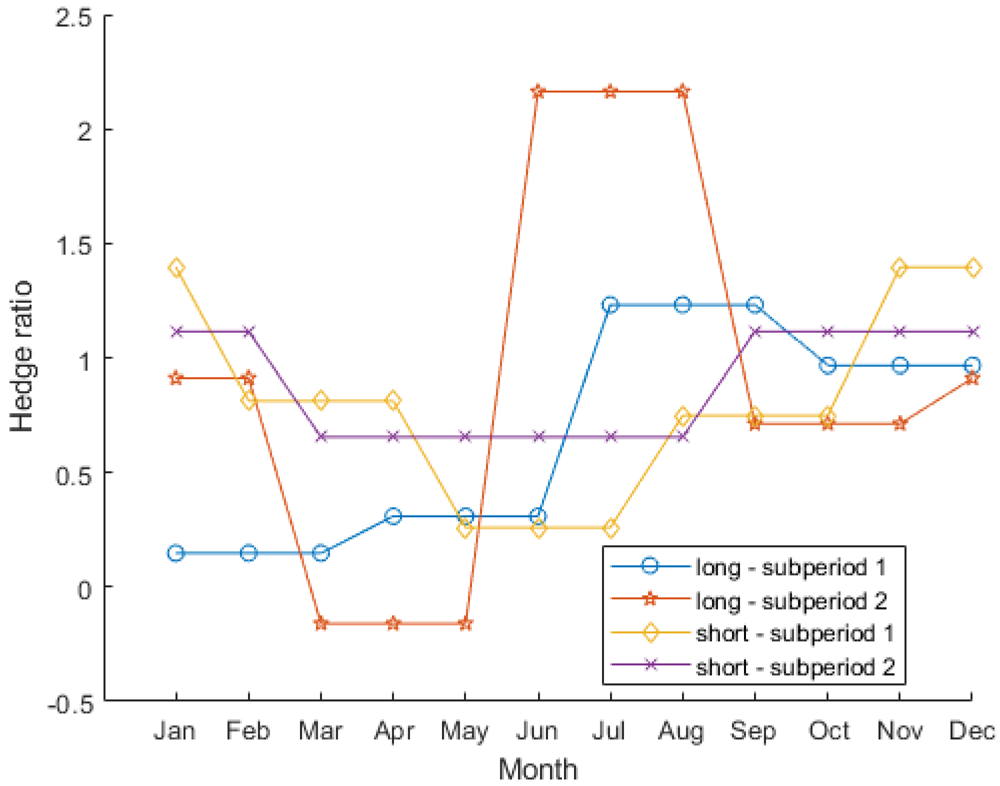

Figure 16. Optimized monthly hedge ratios for Copenhagen

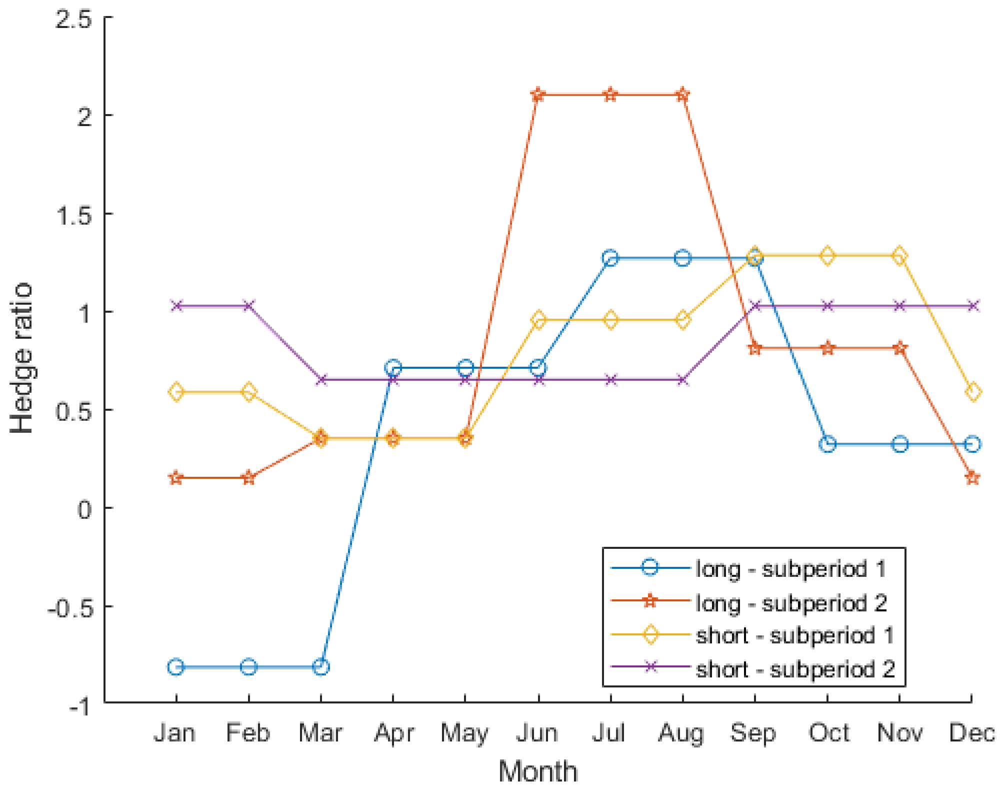

Figure 17. Optimized monthly hedge ratios for Aarhus

The tables 17 and 18 present the minimum and maximum hedge ratios for those static hedges that are optimal for a particular bidding area and hedger type (long or short) in the subperiods 1 and 2. These optimal static hedges are those that have been given in the tables 11 and 16.

From the table 17 we see that two minimum hedge ratios for long hedgers are negative and thus they lead to “Texas hedges”. The Texas hedge is an ironic term (as it is not really a hedge) that means a speculative position where the futures position has the same sign as the cash position (Power & Vedenov 2010, 302), in other words the hedger (who is now a speculator) has a long/short position both in the spot market and futures market. The obvious reason for the optimality of these Texas hedges is that there is low or negative correlation between the spot and futures prices and thus buying/selling both the commodity and its futures acts as diversification which increases the likelihood of achieving profit.

Table 17. Minimum hedge ratios

Optimal hedge (subperiod 1)				
Helsinki	Stockholm	Oslo	Copenhagen	Aarhus
Long				
0.4425	0.3122	0.2252	0.1480	-0.8146
Short				
0.2838	0.2418	0.5230	0.2595	0.3483
Optimal hedge (subperiod 2)				
Long				
0.2641	0.3122	0.7002	-0.1596	0.1481
Short				
0.2838	0.2418	0.1139	0.6558	0.6495

From the table 18 it can be observed that the long hedging strategies that are optimal for Copenhagen and Aarhus in the subperiod 2 lead to very high maximum hedge ratios (higher than 2). These hedging strategies may be difficult to implement in practice as one isn’t necessarily able to enter large enough hedging positions (in other words, sell or buy enough futures). A possible solution to this is to set a limit to the smallest and largest allowed hedge ratios, but this solution may weaken hedging performance.

Table 18. Maximum hedge ratios

Optimal hedge (subperiod 1)				
Helsinki	Stockholm	Oslo	Copenhagen	Aarhus
Long				
0.8857	1.1001	0.7764	1.2312	1.2680
Short				
1.0896	1.1763	0.6674	1.3960	1.2826
Optimal hedge (subperiod 2)				
Long				
1.4969	0.8164	1.0796	2.1631	2.0986
Short				
1.0896	1.1763	0.8869	1.1147	1.0227

5.2. Clarifying investigations

The analysis of this chapter has indicated that the Oslo electricity spot price has the best hedging performance as it has the highest recorded 1st LPM reductions in both subperiods (8.04 % and 11.30 %) for long hedgers and the highest recorded 1st LPM reductions in both subperiods (3.55 % and 27.49 %) for short hedgers. To study what makes Oslo so special bidding area the 1st partial moments (from now on abbreviated as PMs) have been calculated for the spot and futures returns and presented in the tables 19 (1st upper partial moments) and 20 (1st lower partial moments). Upper partial moments are calculated simply by multiplying the spot and futures returns by -1 (in other words, the returns are "turned upside down") and then calculating the LPMs of the multiplied returns when the target return is 0 (MathWorks 2022b). Thus, the 1st upper partial moments measure the magnitude of positive returns whereas the 1st lower partial moments measure the magnitude of negative returns. The upper partial moments of returns are important for long hedgers because they want to decrease positive returns that imply increase in the spot price. Correspondingly, the lower partial moments of returns are important for short hedgers because they want to decrease negative returns that imply decrease in the spot price. The PMs have been calculated separately for the two out-of-sample subperiods in order to see if the PM values vary substantially between these periods. From the tables we see that the PMs are always smaller for the futures returns of a bidding area than for its respective spot returns. This means that the futures market tends to underestimate the magnitude of spot returns for each bidding area. Therefore, the row 8 in both tables presents ratios that have been calculated by dividing the PM of spot returns with the corresponding PM of futures returns. This way one can observe the differences in the futures markets capability to predict the returns for their bidding areas. By examining the tables, we see that the spot/futures ratio is always smallest for Oslo, so from all bidding areas the Oslo market predicts returns most accurately.

If we examine the table rows that contain the PMs of spot and futures returns, we can see that the PMs of spot returns are always smallest for Oslo (out of all bidding areas) while the PMs of futures returns are always highest for Oslo, with the exception of the upper partial moment in the subperiod 2 which slightly less than the highest value. Therefore, of all the examined bidding areas the futures market for Oslo almost always predicts the greatest returns while Oslo’s realized spot returns are always the smallest of all the bidding areas. It was stated in the introduction that the bidding areas prices differ from the system price because of congestion that takes place in the transmission system. Therefore, the differences in the spot returns of bidding areas originate from the differences in congestion taking place as a result of electricity imports to and electricity exports from bidding areas. Large returns take place when there are large jumps in bidding area spot prices and these jumps take place when the congestion situation of a bidding area changes suddenly. Thus, it can be concluded that the Oslo bidding area has the smallest spot returns because it is less likely to experience sudden unexpected changes in congestion. The reason for the tendency of the Oslo EPAD to predict the highest spot returns for its own bidding area may be that congestion and resulting price jumps are generally more predictable in Oslo than in other markets. Other EPAD markets are not able to predict congestion in their bidding areas as well because their congestion takes place suddenly and unexpectedly.

Table 19. 1st upper partial moments of weekly returns

Subperiod 1					Subperiod 2				
H	**S**	**O**	**C**	**A**	**H**	**S**	**O**	**C**	**A**
Spot (%)									
9.48	8.51	6.30	10.91	12.05	9.61	8.10	4.47	9.62	10.94
Futures (%)									
2.23	3.07	3.66	2.34	2.49	2.81	3.18	3.16	2.86	2.97
Spot/futures ratio									
4.25	2.77	1.72	4.66	4.85	3.42	2.55	1.41	3.36	3.68

Table 20. 1st lower partial moments of weekly returns

Subperiod 1					Subperiod 2				
H	**S**	**O**	**C**	**A**	**H**	**S**	**O**	**C**	**A**
Spot (%)									
9.48	8.51	5.96	10.89	12.04	9.87	8.62	6.01	9.91	11.23
Futures (%)									
2.35	3.29	3.66	2.49	2.61	3.08	3.66	4.54	3.05	3.18
Spot/futures ratio									
4.03	2.59	1.63	4.37	4.61	3.21	2.36	1.32	3.25	3.53

The table 21 presents in euros the means and variances both for the differences between each bidding area's spot price and the system spot price (referred from now on as spot differences) and for the EPAD prices in the out-of-sample period. Daily prices have been used in calculation. Because the EPAD prices are the differences between the bidding areas' electricity futures prices and the system futures price, they can be negative. From the table we see that the Oslo spot difference and EPAD price have the means that are closest to zero and that they have the smallest variances. In other words, for Oslo the area spot price and EPAD price most closely track the system price out of all studied bidding areas. Because it was stated in the introductory chapter that a bidding area gets a spot price that is different from the system price when there is a bottleneck in the transmission system, it can be concluded that the Oslo area experiences the least amount of congestion in its electricity transmission. Thus, predicting the bidding area spot price with futures is easiest in the case of Oslo. From the table it can be observed that the means of spot differences and EPAD prices are very close to each other. However, the variances of spot differences are much larger than the variances of EPAD prices. This again illustrates how EPAD prices underestimate the magnitude of spot prices.

Table 21. Spot differences and EPAD prices (€)

Helsinki	Stockholm	Oslo	Copenhagen	Aarhus
Mean				
7.29 / 7.03	1.78 / 2.09	-0.86 / -0.78	3.84 / 4.48	1.76 / 2.01
Variance				
54.35 / 13.42	18.69 / 3.56	5.81 / 0.83	46.10 / 12.29	43.04 / 14.94

The introduction stated that a bidding area gets a spot price that is different from the system price when there is a bottleneck in the transmission system and that power will always go from the low-price area to the high-price area if there are constraints in transmission capacity between two bidding areas. The following conclusions can be made from these two rules: If the spot difference is positive, congestion will take place because of electricity imports to the bidding area in question. If the spot difference is negative, congestion will take place because of electricity exports from the bidding area in question. If the spot difference is zero, no congestion will take place. The EPAD prices provide predictions about these situations: If the EPAD price is positive, congestion is predicted to take place because of electricity imports to the bidding area in question. If the EPAD price is negative, congestion is predicted to take place because of electricity exports from the bidding area in question. If the EPAD price is zero, no congestion is predicted to take place. In this interpretation it is supposed that if import and export congestion take place simultaneously within a bidding area, the bidding area price is obtained by subtracting the potential price fall of export congestion from the potential price rise of import congestion. Import and export congestion could take place simultaneously if large electricity exports decrease the amount of power available for the consumers of a bidding area and this creates a deficit which must be compensated through imports. Thus, if import and export congestions are exactly equal, a bidding area price should be equal to the system price as import and export congestions cancel each other out. This is because the power that cannot be exported to another bidding area due to congestion is available for the consumers of the exporting bidding area and this amount of extra power is equal to the electricity which cannot be imported due to congestion. Thus, the expression "import/export congestion" actually refers to *net* import/export congestion in this thesis.

In the table 22 the percentages of the aforementioned three possible situations in the daily spot differences and EPAD prices have been provided for the out-of-sample period. From the table we can observe that for Helsinki, Stockholm, Copenhagen and Aarhus (referred from now on with the abbreviation HSCA) import congestion is lot more common than export congestion. Only for Oslo export congestion is more common than import congestion. It can be then suggested that a large portion of the electricity produced in the Oslo bidding area is exported to these four other bidding areas, especially because Oslo is situated very close to these other locations. It can also be noticed that EPAD prices underestimate export congestion in the case of the HSCA bidding areas for which import congestion was more common. In the case of Oslo, the situation is the opposite and the EPAD price underestimates import congestion. One can thus say that the Oslo futures market has an "export bias" and that the HSCA futures markets have an "import bias". From the table 22 it can be seen that days with no congestion constitute less than 1 % of the studied period. However, because daily prices are examined it must be remembered that one cannot make a conclusion that there is congestion in the transmission system 99 % of (continuous) time. Oslo has the largest number of days with no congestion. The futures markets always predict that congestion will take place.

Table 22. Bidding area congestion according to spot differences and EPAD prices (%)

Helsinki	Stockholm	Oslo	Copenhagen	Aarhus
Import congestion				
90.93 / 99.94	62.11 / 94.89	29.65 / 19.81	74.63 / 96.93	57.83 / 68.37
Export congestion				
9.07 / 0.06	37.83 / 5.11	70.22 / 80.19	25.37 / 3.07	42.17 / 31.63
No congestion				
0.00 / 0.00	0.06 / 0.00	0.13 / 0.00	0.00 / 0.00	0.00 / 0.00

6. Conclusions

As the results of the empirical research have now been presented and analysed, the research questions outlined in the introductory chapter can be answered. The answer to the first question is that there are performance differences between short and long hedgers but based on the examination of two out-of-sample subperiods it cannot be said that these differences are systematic in any way. When a single subperiod is examined, in the case of some (but not all) bidding areas long hedgers outperform short hedgers and vice versa. When two different subperiods are compared, in the case of some bidding areas the order of the two types of hedgers remains the same (i.e., the outperformance of long/short hedgers in the subperiod 1 also continues in the subperiod 2) and in the case of some other bidding areas the order of the hedgers changes (i.e. unlike in the subperiod 1, short/long hedgers outperform long/short hedgers in the subperiod 2).

The answer to the second question is that because of the superior performance of the seasonally optimized hedge ratios there is seasonality present in the Nord Pool spot and futures markets. For both long and short hedgers, there is especially strong evidence for the presence of four three months long periods. However, there is no unambiguous indication in which months these four periods start. Only in the case of short hedging for Helsinki and Stockholm the period division remains the same in both subperiods. For these two bidding areas there are four 3-month periods which start in January, April, July and October. In the case of Helsinki, Stockholm and Oslo a pattern in hedge ratios can be observed: For long hedgers, the hedge ratios of the second half of the year tend to be substantially higher than the hedge ratios of the first half of the year. For short hedgers the situation is the opposite and thus the hedge ratios of the first half of the year tend to be substantially higher than the hedge ratios of the second half of the year. This pattern in hedge ratios can be explained by the tendency of electricity prices to go down during the first half of the year and rise during the second half of the year.

The answer to the third question is that hedging strategies based on the minimization of the 1st lower partial moment constantly outperform hedging strategies that are based on the minimization of variance. There are some instances in which variance-minimizing hedging strategies perform better, but in most situations the strategies based on the minimization of the 1st LPM outperform those that minimize variance.

The answer to the fourth research question is that the strategies that are optimal in reducing the magnitude of losses don’t necessarily reduce the number of losses, but they can increase the number of losses instead. Thus, these two hedging performance measures are clearly separate and if one wants to minimize them both simultaneously, they must be utilized in optimization as two separate objectives. One could for instance minimize the magnitude of losses and at the same time give a restriction that the number of losses must remain the same as in the unhedged portfolio or decrease from the number of the unhedged portfolio.

Generally hedging performance is rather limited but the 1st LPM reductions are on the same or somewhat higher scale as the variance reductions in the table 1. In the case of long hedging, the highest weekly 1st LPM reductions are recorded for Oslo, and they are 8.04 % for the subperiod 1 and 11.30 %, for the subperiod 2. For long hedging in the other bidding areas, weekly 1st LPM reductions vary between -0.51 – 3.83 % for the subperiod 1 and 2.23 – 6.26 % for the subperiod 2. In the case of short hedging, the highest weekly 1st LPM reductions are again recorded for Oslo, and they are 3.55 % for the subperiod 1 and 27.49 % for the subperiod 2. For short hedging in the other bidding areas, weekly 1st LPM reductions vary between -0.55 – 2.67 % for the subperiod 1 and between -0.64 – 10.22 % for the subperiod 2. The likely reason for the highest hedging performance of the Oslo spot price is that the Oslo bidding area experiences the least amount of congestion and thus its spot price is easiest to predict.

Because hedging performance measured by the 1st LPM reduction is rather limited in percentage terms, large losses from buying/selling electricity still pose a substantial threat for the financial performance of a company despite the use of hedging. Therefore, it can be concluded that hedging may not work well when it is most needed as reducing large losses would be very important in cashflow management. Hedging the electricity spot price with futures increases long-term profitability (as the losses are reduced) but it doesn't seem to be capable to secure short-term solvency (as large losses still pose a threat). Thus, the main tool for an electricity retailer or an electricity producer to manage its solvency is not futures hedging but ensuring the availability of a sufficient amount of working capital. The increase of profitability resulting from futures hedging can of course help to reduce the required amount of working capital. However, the amount of working capital is also largely affected by a company's capability to manage its operational costs (that do not result from the purchase of electricity). Additionally, bidding areas best manage their spot price volatility by building transmission networks that are high-powered enough to make congestion a rare event.

Some suggestions for further research can be proposed. It would be interesting to study cross-hedging with EPADs, in other words, whether the EPAD futures of one bidding area can be used to successfully hedge the electricity spot price of another bidding area and to see whether it is always so that a bidding area's own EPAD obtains the best hedging performance. One could also study the performance of hedging bidding area spot prices with only system price futures (and without EPADs) and compare this performance to the results presented in this thesis in order to see whether the use of EPADs is necessary for achieving the best hedging performance for the spot prices of bidding areas. Also, a study that tried to take into account the transaction and clearing costs of implementing the hedging strategies studied in this thesis could be executed in the Nord Pool markets. It would also be interesting to examine whether the weekday (ranging from Monday to Friday) on which a week-long hedge is initiated affects the hedging performance of bidding area spot prices. One could also compare dynamic seasonal hedge ratios instead of static seasonal hedge ratios by utilizing a rolling window so that the seasonal hedge ratio for the next point of time is estimated always when the rolling window moves one step forward in time. The months, for which the data is used in optimization, would be selected according to which season the time point (for which the hedge ratio is estimated) is situated in. It would also be important to perform a sensitivity analysis for the performance of hedge ratios both in the in-sample and out-of-sample periods in order to see whether the optimal hedge ratio is likely to remain constant over time. Additionally, hedging strategies should be optimized by minimizing the magnitude of losses and the number of losses simultaneously. Because optimized hedge ratios can sometimes be excessively large (as the hedger isn’t able to buy or sell enough futures), the impact on hedging performance of setting a maximum limit for hedge ratios could also be tested. Lastly, the seasonal optimization method for hedge ratios that was presented in this thesis could be applied in other commodity futures markets where seasonal patterns are likely to take place.

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Appendix 1. MATLAB code used to pre-process the returns for the codes of the appendices 2 and 3

```
clear all

% If the comment for a variable has the capitalized expression “INPUT”
% with it, this variable should be given a value manually to generate
% desired results.

% Daily spot prices are read for different bidding areas. The rows
% represent days and columns bidding areas.
spot=xlsread('Nord_Pool_spot_data.xlsx');
% Daily futures prices are read for different bidding areas.
future=xlsread('Nord_Pool_future_data.xlsx');
% Daily futures system price is read.
future_system=xlsread('Nord_Pool_future_system_data.xlsx');
% Daily prices of one euro as Norwegian krones are read. The rows
% represent days, the first column exchange rates, the second column the
% month in question (1-12) and the third column the weekday in question
% (1-5).
K_to_E=xlsread('krone_to_euro.xlsx');
% Because the spot prices are in krone, they must be converted to euro.
for i=1:5
   spot(:,i)=spot(:,i)./K_to_E(:,1);
end

% The whole futures prices of bidding areas are the sum of the system futures
% price and the EPAD futures prices.
future=future+future_system;

% Only the values for Friday are selected to calculate the weekly returns.
spot=spot(K_to_E(:,3)==5,:);
future=future(K_to_E(:,3)==5,:);
```

```
K_to_E=K_to_E(K_to_E(:,3)==5,:);

% Matrix is initialized for logarithmic spot returns.
spot_ret=NaN(size(spot,1)-1,size(spot,2));
% For each bidding area...
for i=1:size(spot,2)
   % ...and day...
   for j=1:size(spot,1)-1
      % ...the spot returns are calculated.
      spot_ret(j,i)=log(spot(j+1,i))-log(spot(j,i));
   end
end

% Matrix is initialized for logarithmic futures returns.
future_ret=NaN(size(future,1)-1,size(future,2));
% For each bidding area...
for i=1:size(future,2)
   % ...and day...
   for j=1:size(future,1)-1
      % ...the futures returns are calculated.
      future_ret(j,i)=log(future(j+1,i))-log(future(j,i));
   end
end

% Matrices are initialized for the spot and futures returns that are
% allocated to their months.
spot_ret_mon=NaN(size(spot_ret,1),size(spot_ret,2),12);
future_ret_mon=NaN(size(future_ret,1),size(future_ret,2),12);
% Loop for the days when returns take place
for i=2:size(K_to_E,1)
   % Loop for months
   for j=1:12
      % If a return takes place in a particular month...
```

```
        if K_to_E(i,2)==j
            % ... it is allocated to the matrix layer that corresponds to
            % this month.
            spot_ret_mon(i-1,:,j)=spot_ret(i-1,:);
            future_ret_mon(i-1,:,j)=future_ret(i-1,:);
        end
    end
end

% Length of the spot (and futures) price time series
size_ts=size(spot,1);

% If the value "2" is given for the variable "subperiod" (INPUT) the
% results are obtained for the subperiod 2. Otherwise, the results are
% obtained for the subperiod 1.
subperiod=2;
% If the variable "subperiod" has the value 2...
if subperiod==2
    % ...the weeks of the subperiod 2 are utilized.
    weeks=ceil(0.75*size_ts):size_ts-1;
else
    % Otherwise, the weeks for the subperiod 1 are utilized.
    weeks=size_ts/2:ceil(0.75*size_ts)-1;
end
```

Appendix 2. MATLAB code used to produce the results in table 6

```
%% Correct predictions of a spot return sign
% Spot returns are used to determine their signs.
spot_sign=spot_ret;
% Futures returns are used to determine their signs.
future_sign=future_ret;
% If a spot return is positive, it is given the value 1.
spot_sign(spot_sign>0)=1;
% If a spot return is negative or zero, it is given the value -1.
spot_sign(spot_sign<=0)=-1;
% If a futures return is positive, it is given the value 0.5.
future_sign(future_sign>0)=0.5;
% If a futures return is negative or zero, it is given the value -0.5.
future_sign(future_sign<=0)=-0.5;
% Matrices of spot and futures returns are summarized. If a sum is 1.5,
% both a spot return and a futures return are positive. If a sum is 0.5, a
% spot return is positive and a futures return is negative. If a sum is
% -0.5, a spot return is negative and a futures return is positive. If a
% sum is -1.5, both a spot return and a futures return are negative.
accuracy=spot_sign+future_sign;
% Counts of those sums that are 1.5 are obtained for the in-sample period.
% The expected count of positive sign predictions that are correct by
% random chance is then subtracted (for the spot returns of each bidding
% area) from the obtained counts. The result after subtraction is then
% divided by the expected count of positive sign predictions that are
% incorrect by random chance. Finally, the result after division is
% multiplied by 100 to obtain percentages.
Excess_pos_in=100*(sum(accuracy(1:size_ts/2-1,:)==1.5)-(1/2)...
   *sum(spot_sign(1:size_ts/2-1,:)==1))./((1/2)*sum(spot_sign(1:size_ts/2-1,:)==1))
% Counts of those sums that are -1.5 are obtained for the in-sample period.
% The expected count of negative sign predictions that are correct by
% random chance is then subtracted (for the spot returns of each bidding
```

```
% area) from the obtained counts. The result after subtraction is then
% divided by the expected count of negative sign predictions that are
% incorrect by random chance. Finally, the result after division is
% multiplied by 100 to obtain percentages.
Excess_neg_in=100*(sum(accuracy(1:size_ts/2-1,:)==-1.5)-(1/2)...
   *sum(spot_sign(1:size_ts/2-1,:)==-1))./((1/2)*sum(spot_sign(1:size_ts/2-1,:)==-1))
% Counts of those sums that are 1.5 are obtained for the out-of-sample
% period. The expected count of positive sign predictions that are correct
% by random chance is then subtracted (for the spot returns of each bidding
% area) from the obtained counts. The result after subtraction is then
% divided by the expected count of positive sign predictions that are
% incorrect by random chance. Finally, the result after division is
% multiplied by 100 to obtain percentages.
Excess_pos_out=100*(sum(accuracy(size_ts/2:end,:)==1.5)-(1/2)...
   *sum(spot_sign(size_ts/2:end,:)==1))./((1/2)*sum(spot_sign(size_ts/2:end,:)==1))
% Counts of those sums that are -1.5 are obtained for the out-of-sample
% period. The expected count of negative sign predictions that are correct
% by random chance is then subtracted (for the spot returns of each bidding
% area) from the obtained counts. The result after subtraction is then
% divided by the expected count of negative sign predictions that are
% incorrect by random chance. Finally, the result after division is
% multiplied by 100 to obtain percentages.
Excess_neg_out=100*(sum(accuracy(size_ts/2:end,:)==-1.5)-(1/2)...
   *sum(spot_sign(size_ts/2:end,:)==-1))./((1/2)*sum(spot_sign(size_ts/2:end,:)==-1))
```

Appendix 3. MATLAB code used to produce the results tabulated in the tables 7, 8, 12 and 13

```
%% Naïve hedge
% If the variable “hedge_type” (INPUT) has the value 1, the results for
% long hedging are calculated. Otherwise the results are calculated for
% short hedging.
hedge_type=1;
% Matrix is initialized for the 1st LPM reductions.
LPM1_reduct_LPM=NaN(1,size(spot_ret,2));
% Matrix is initialized for the 0th LPM reductions.
LPM0_reduct_LPM=NaN(1,size(spot_ret,2));
% Loop for bidding areas
for i=1:size(spot_ret,2)
   % 1st LPM reductions are calculated.
   LPM1_reduct_LPM(i)=hedging(spot_ret(weeks,i),future_ret(weeks,i),1,1,...
      hedge_type,1);
   % 0th LPM reductions are calculated.
   LPM0_reduct_LPM(i)=hedging(spot_ret(weeks,i),future_ret(weeks,i),1,0,...
      hedge_type,1);
end
%% Optimized static hedge
% If the variable “hedge_type” (INPUT) has the value 1, the results for
% long hedging are calculated. Otherwise, the results are calculated for
% short hedging.
hedge_type=0;
% Length of a seasonal period (months) (INPUT)
period=3;

% Matrix is initialized for the optimized LPM hedge ratios.
HR_LPM=NaN(size(1:period:12,2),size(spot_ret,2),period);
% Matrix is initialized for the optimized MV hedge ratios.
HR_MV=NaN(size(1:period:12,2),size(spot_ret,2),period);
```

```
% Loop for changing the starting month of the first seasonal period
for i=0:period-1
   % Loop for the starting months of the seasonal periods
   for j=[1:period:12]+i
      % Loop for the bidding areas
      for k=1:size(spot_ret,2)
         % Months are modified to take values 1-12 (e.g. 13 becomes
         % 1).
         months=mod([j:j+period-1]+11,12)+1;
         % Negative of the LPM reduction is set to be minimized.
         optfun1=@(HR_LPM) -hedging(spot_ret_mon(1:size_ts/2-1,k,months),...
            future_ret_mon(1:size_ts/2-1,k,months),HR_LPM,1,hedge_type,1);
         % Negative of the MV reduction is set to be minimized.
         optfun2=@(HR_MV) -hedging(spot_ret_mon(1:size_ts/2-1,k,months),...
            future_ret_mon(1:size_ts/2-1,k,months),HR_MV,1,hedge_type,2);
         % Minimization is carried out with the Nelder-Mead
         % optimization algorithm and the resulting hedge ratio is
         % saved to its matrix.
         HR_LPM((j-1-i)/period+1,k,i+1)=fminsearch(optfun1,1);
         HR_MV((j-1-i)/period+1,k,i+1)=fminsearch(optfun2,1);
      end
   end
end

% Matrix is initialized for the weekly LPM hedge ratios of the out-of-sample
% period.
HR_LPM_week=NaN(length(weeks),size(spot_ret,2),period);
% Matrix is initialized for the weekly MV hedge ratios of the out-of-sample
% period.
HR_MV_week=NaN(length(weeks),size(spot_ret,2),period);
% Value of the first week of the out-of-sample period is saved to the first row.
n=1;
% Loop for going through the weeks of the out-of-sample period
```

```
for i=weeks+1
   % Loop for changing the starting month of the first seasonal period
   for j=0:period-1
      % Loop for the starting months of the seasonal periods
      for k=[1:period:12]+j
         % Loop for the bidding areas
         for l=1:size(spot_ret,2)
            % Months are modified to take values 1-12 (e.g. 15
            % becomes 3).
            months=mod([k:k+period-1]+11,12)+1;
            % If a seasonal period contains a particular
            % month...
            if ismember(K_to_E(i,2),months)
               % ...the hedge ratio of that period is allocated to
               % the week in question (which takes place in that
               % month).
               HR_LPM_week(n,l,j+1)=HR_LPM((k-1-j)/period+1,l,j+1);
               HR_MV_week(n,l,j+1)=HR_MV((k-1-j)/period+1,l,j+1);
            end
         end
      end
   end
   % Value of the next week is saved on the next row.
   n=n+1;
end

% Matrix is initialized for the 1st LPM reductions by LPM hedging.
LPM1_reduct_LPM=NaN(period,size(spot_ret,2));
% Matrix is initialized for the 1st LPM reductions by MV hedging.
LPM1_reduct_MV=NaN(period,size(spot_ret,2));
% Matrix is initialized for the 0th LPM reductions by LPM hedging.
LPM0_reduct_LPM=NaN(period,size(spot_ret,2));
% Matrix is initialized for the 0th LPM reductions by MV hedging.
```

```
LPM0_reduct_MV=NaN(period,size(spot_ret,2));
% Matrix is initialized for the minimum hedge ratios of LPM hedging.
min_HR_LPM=NaN(period,size(spot_ret,2));
% Matrix is initialized for the minimum hedge ratios of MV hedging.
min_HR_MV=NaN(period,size(spot_ret,2));
% Matrix is initialized for the maximum hedge ratios of LPM hedging.
max_HR_LPM=NaN(period,size(spot_ret,2));
% Matrix is initialized for the maximum hedge ratios of MV hedging.
max_HR_MV=NaN(period,size(spot_ret,2));
% Loop for the possible starting months of the first period
for i=1:period
   % Loop for the bidding areas
   for j=1:size(spot_ret,2)
      % 1st LPM reductions are calculated for LPM hedging.
      LPM1_reduct_LPM(i,j)=hedging(spot_ret(weeks,j),...
         future_ret(weeks,j),HR_LPM_week(:,j,i),1,hedge_type,1);
      % 0th LPM reductions are calculated for LPM hedging.
      LPM0_reduct_LPM(i,j)=hedging(spot_ret(weeks,j),...
         future_ret(weeks,j),HR_LPM_week(:,j,i),0,hedge_type,1);
      % 1st LPM reductions are calculated for MV hedging.
      LPM1_reduct_MV(i,j)=hedging(spot_ret(weeks,j),...
         future_ret(weeks,j),HR_MV_week(:,j,i),1,hedge_type,1);
      % 0th LPM reductions are calculated for MV hedging.
      LPM0_reduct_MV(i,j)=hedging(spot_ret(weeks,j),...
         future_ret(weeks,j),HR_MV_week(:,j,i),0,hedge_type,1);
      % Minimum hedge ratios are calculated for LPM hedging.
      min_HR_LPM(i,j)=hedging(spot_ret(weeks,j),...
         future_ret(weeks,j),HR_LPM_week(:,j,i),1,hedge_type,3);
      % Minimum hedge ratios are calculated for MV hedging.
      min_HR_MV(i,j)=hedging(spot_ret(weeks,j),...
         future_ret(weeks,j),HR_MV_week(:,j,i),1,hedge_type,3);
      % Maximum hedge ratios are calculated for LPM hedging.
      max_HR_LPM(i,j)=hedging(spot_ret(weeks,j),...
```

```
            future_ret(weeks,j),HR_LPM_week(:,j,i),1,hedge_type,4);
        % Maximum hedge ratios are calculated for MV hedging.
        max_HR_MV(i,j)=hedging(spot_ret(weeks,j),...
            future_ret(weeks,j),HR_MV_week(:,j,i),1,hedge_type,4);
    end
end

% Matrix is initialized for the values which are given for the most optimal
% starting month of the first seasonal period in the case of LPM hedging.
Selection_LPM=NaN(3,size(LPM1_reduct_LPM,2));
% Matrix is initialized for the values which are given for the most optimal
% starting month of the first seasonal period in the case of MV hedging.
Selection_MV=NaN(3,size(LPM1_reduct_MV,2));
% Loop for the possible starting months of the first seasonal periods
for i=1:size(LPM1_reduct_LPM,1)
    % Loop for the bidding areas
    for j=1:size(LPM1_reduct_LPM,2)
        % Starting month which has the highest 1st LPM reduction is selected
        % for LPM hedging.
        if LPM1_reduct_LPM(i,j)==max(LPM1_reduct_LPM(:,j))
            % For each bidding area three values are presented in their own
            % rows: starting month, 1st LPM reduction, 0th LPM reduction.
            Selection_LPM(1:3,j)=[i,LPM1_reduct_LPM(i,j),LPM0_reduct_LPM(i,j)];
        end
        % Starting month which has the highest 1st LPM reduction is selected
        % for MV hedging.
        if LPM1_reduct_MV(i,j)==max(LPM1_reduct_MV(:,j))
            % For each bidding area three values are presented in their own
            % rows: starting month, 1st LPM reduction, 0th LPM reduction.
            Selection_MV(1:3,j)=[i,LPM1_reduct_MV(i,j),LPM0_reduct_MV(i,j)];
        end
    end
end
```

```
% Function for calculating the metric values resulting from static hedging
function metric_value=hedging(NP_spot_ret,NP_future_ret,HR,LPM,hedge_type,metric)
% If long hedging is studied, the signs of the returns are reversed.
if hedge_type==1
   sign=-1;
% If short hedging is studied, the returns retain their original signs.
else
   sign=1;
end
% Spot returns of the different monthly layers are summarized into a single
% layer.
NP_spot_ret=nansum(NP_spot_ret,3);
% Futures returns of the different monthly layers are summarized into a
% single layer.
NP_future_ret=nansum(NP_future_ret,3);
% Returns of the hedge portfolio are calculated when a hedger takes
% offsetting positions in spot and futures markets.
hedge_portfolio_ret=sign*(NP_spot_ret-HR.*NP_future_ret);
% Spot returns are utilized for the spot portfolio.
spot_portfolio_ret=sign*NP_spot_ret;
% Metric value is obtained by calling the metrics function.
metric_value=metrics(hedge_portfolio_ret,spot_portfolio_ret,HR,LPM,metric);
end

% Function for different metrics
function metric_value=metrics(hedge_portfolio_ret,spot_portfolio_ret,HR,LPM,metric)
% If the variable “metric” has the value 1...
if metric==1
   % ...the LPM reduction is calculated.
   metric_value=100*(1-lpm(hedge_portfolio_ret(:,1),0,LPM)/...
      lpm(spot_portfolio_ret(:,1),0,LPM));
% If “metric” has the value 2...
elseif metric==2
```

```
    %...the variance reduction is calculated.
    metric_value=100*(1-var(hedge_portfolio_ret(:,1))/var(spot_portfolio_ret(:,1)));
% If "metric" has the value 3...
elseif metric==3
    % ...the minimum hedge ratio is calculated.
    metric_value=min(HR);
% If "metric" has the value 4...
elseif metric==4
    % ...the maximum hedge ratio is calculated.
    metric_value=max(HR);
end
end
```