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### Deltaker

**Navn:** Håvard Øvernes og Steinar Råmundal Halse

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**Navn på veileder \*:** Geir Bjønnes

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## Master Thesis

# - Hedging electricity price risk -

Authors:  
Steinar Halse  
Håvard Øvernes

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Geir Bjønnes

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The school takes no responsibility for the methods used, results found, or  
conclusions drawn.*

## **Abstract**

In this thesis we analyze how effective it is to hedge electricity spot prices with futures. Using data from 2004 to the end of 2022 with the Nord Pool system price as spot and the monthly and quarterly futures from Nasdaq as the hedging tool in our main analysis, we try five different hedging strategies: Naïve, OLS minimum variance, OLS minimum variance with basis, Rolling OLS minimum variance and GARCH. The hedging effectiveness is defined as the variance reduction compared to an unhedged spot position. We apply two definitions of the spot returns; (case A) the difference between the daily prices on the last day of each period, and (case B) the difference in average prices of each period.

Evaluating the hedging performance of monthly futures traded daily, weekly and monthly, as well as quarterly futures traded monthly and quarterly, we find the best results for monthly futures traded monthly where the results are statistically significantly better than zero in 8 out of total 10 scenarios (5 strategies x 2 cases). In case A we find that the hedging effectiveness is between 49% and 58% out-of-sample, and in case B between -23% and 21%.

On the other hand, the hedging effectiveness varies greatly from year to year, and when we apply the same methodology to UK and Germany from 2014 to 2022, we find significantly lower hedging performance in these markets. Overall, we find it questionable whether futures with the strategies analyzed in this thesis are economically effective tools to hedge electricity market spot exposure.

## **Acknowledgments**

We would like to thank our supervisor Geir Bjønnes for his guidance throughout the process and valuable feedback in the last weeks of our work with this thesis. We have also benefitted from Nord Pool, Nasdaq, Bergen Offshore Wind Center, energy consultant Torbjørn Haugen and professor Juan Ignacio Peña from Universidad Carlos III de Madrid for various data access, interview participation and insightful responses to our inquiries.

*“To hedge, or not to hedge,  
that is the question”*

Unknown

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## 1. Introduction and motivation

With spiking prices and unprecedented volatility in recent years, risk management has become increasingly important for market participants in the electricity market. In this thesis we investigate how effective futures can be as a tool to manage the spot price risk in this market.

As to our motivation for studying the electricity market in the first place, let us zoom out and look at the big picture. The electricity market is important not only to power our society so that we can live prosperous and meaningful lives, but it is also a crucial element in meeting the threats of climate change. In 2021, electricity generation was the source of 39 percentage of total greenhouse gas emissions worldwide (IEA, 2022). Increasing electricity demand from both economic growth and electrification of new sectors and industries means that decarbonizing the electricity system is fundamental in order to reach climate targets. According to IEA, keeping on track for a 1.5 degrees scenario will by 2030 require 4.2 trillion USD (4% of global GDP) in annual clean energy investments, compared to current annual investments of approximately 1.3 trillion (IEA, 2022). In Europe, the REPowerEU plan targets a tripling of wind and PV installed capacity from 412GW in 2022 to 1236GW in 2030 (BNEF, 2022).

The majority of renewable energy projects are currently based on long term Power Purchase Agreement (PPA) offtake contracts or some form of government subsidies like Contract for Difference (CfD), Feed-in-Tariffs (FIT) or Green certificates. However, as the technologies matures and installed capacity reaches certain milestones, support schemes are likely to be phased out and demand for PPA offtake is not limitless. Therefore, merchant projects relying on the market spot prices can play an increasingly important role in reaching the required scale of build out.

Meanwhile, the price risk these merchant projects face is significant, and with it the need for risk management. Therefore, we want to see how hedging with futures might be one of the tools that could be used to reduce some of the risk and as such potentially increase feasibility of renewable energy projects, while also being applicable to other market participants for their risk management.



Personally, our interest in the energy and finance markets - and in the interconnection of these, was central when choosing the thesis topic. As we write this in Norway, our main geographical area of interest is the Nordics, so we therefore focus our main part of the analysis on this market, while also testing the methodology on UK and Germany to check its applicability in other markets.

## 2. Background: about the electricity market

### 2.1 The physical market

The electricity market in the Nordics is divided into defined price areas as shown in Figure 1. Nord Pool is the “stock exchange” for trading electricity, and is again connected to other European markets. There is a connected algorithm called Eufemia for clearing day-ahead auctions in a total of 25 European countries, constructed so that the electricity always flow to areas with higher price (Nord Pool, 2022). This auction which happens 12:00 every day is cleared based on the merit order system- in each zone, the most expensive supplier to clear set the price for all. The clearing price for the whole Nordics is called the System Price.

Following this auction, the grid operators (Statnett in the case of Norway) adjust the clearing price for each zone based on transmission constraints. After the day-ahead auction, there is then an intra-day market to cover the gaps between the auction-clearing supply and the actual demand. This market clears until 45 minutes before physical delivery. Then finally there is a real time regulating power market to stabilize the grid frequency (Nord Pool, 2022). Physical electricity markets all over the world are set up in a similar way, always matching supply with demand.

Figure 1: Nord Pool price zones.



There are 15 different price zones and one “System Price” referring to clearing price of all areas before considering transmission constraints. Source: Nord Pool (2022)

## *2.2 The financial market*

In addition to the market for physical delivery of electricity described above, there are financial markets for trading electricity price derivatives. Nasdaq is the clearinghouse for Nordic electricity derivatives, and they offer various forms of futures and options. The System Price (as described above - the common price for the whole Nordics) is the underlying on which the Nordic Electricity System Price futures are based on. We will focus on futures and not options in this thesis.

In addition to the System Price, there are futures called Electricity Price Area Difference (EPAD) – for which the underlying is the difference between the System Price and the price in each price zone. Hence if we want to hedge the price of a specific price area, we can combine the System Price future with an EPAD future for that area. However, due to the relatively small size of each price zone, there is a limited number of market participants in the EPAD markets.

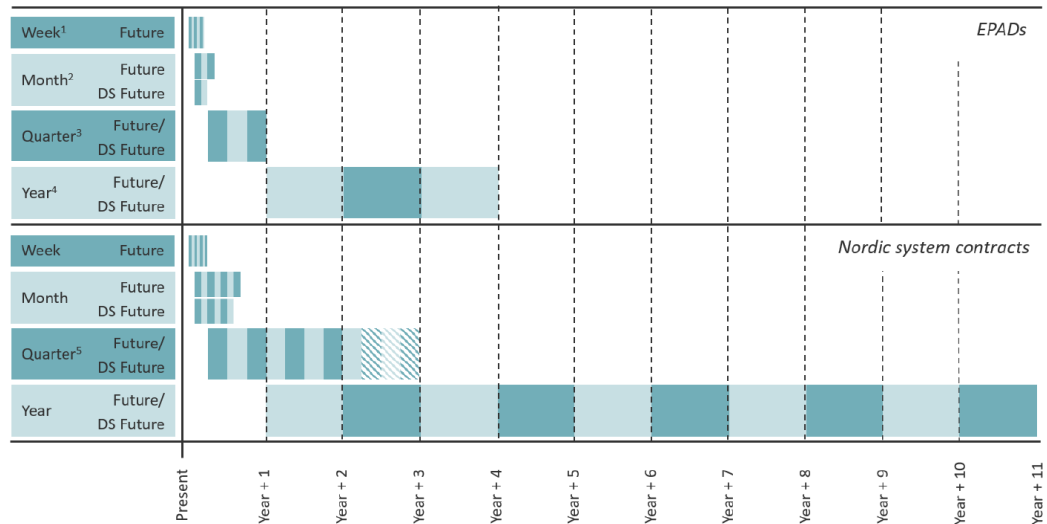
Furthermore, strict requirements for collateral posting have resulted in many of the already few market participants to enter bilateral agreements outside the clearing house – further worsening the lack of liquidity (Thema Consulting, 2021). Due to lack of historical data (EPADs are relatively new) and low trading volume we have chosen to not include EPADs in our analysis.

Regarding settlement of the futures, regular futures have daily mark-to-market settlements in the trading period, while Deferred Settlement futures (DS futures) are like forwards with the mark-to-market value accumulated until the end of the trading period (Nasdaq, 2023). When settling a contract in the delivery period, the contract volume (for example 1 megawatt (MW)) is multiplied with the difference between the future price and the spot price for each hour of the delivery period and determines how much the trading participants will receive or pay. These contracts traded on Nasdaq are pure financial instruments, with no actual delivery of physical electricity.

Figure 2 shows an overview of the different futures available on Nasdaq for the Nordic market and how many periods in advance you can trade weekly, monthly, quarterly and annual futures. While there are futures up to 10 years in the future, beyond 3 years the liquidity is very limited and if you can find a counterpart at all, the bid-ask-spread and cost of trading for large volumes is prohibitively high

(Thema Consulting, 2021). In this thesis we focus on near term monthly and quarterly futures, which are among the most traded. The price of Futures and DS Futures as quoted on Nasdaq are for all practical reasons within the scope of our thesis identical, and therefore we refer to them simply as Futures.

Figure 2: Trading horizon for different future contract types.



Overview of the available trading horizons on Nasdaq for the Nordic system price contracts and the Electricity Price Area Difference (EPADs) contracts, ranging from 1 week to 10 years. Futures have daily mark-to-market settlements, while DS Futures have deferred settlement to the end of the trading period. Source: (Thema Consulting, 2021).

### 2.3 Market characteristics' implications for market participants

The electricity market has certain characteristics making it different from other commodity markets. In general electricity is a non-storable commodity which must be produced the same second it is used (hydropower to a certain degree being an exception). If we look at for example gold and oil markets, the spot and future prices are closely linked because the physical commodity can be bought and stored until the future maturity date. The lack of such mechanism cause a weaker relationship between spot and future prices in the electricity market, especially for futures with distant maturity, and therefore makes it more difficult to hedge spot with futures (Martínez & Torró, 2018).

Other characteristics include seasonality and limited elasticity of both supply and demand, which together with the non-storability causes electricity prices to be extremely volatile (Zanotti et al., 2010). The volatility of electricity markets are further impacted by an increasing amount of intermittent renewable energy with

zero marginal cost (Peña, 2023). In Europe, this volatility has reached unprecedented levels in recent years as Russia's invasion of Ukraine led to natural gas shortages on top of an already very volatile market. For market participants this volatility makes risk management more important than ever.

Another complicating characteristic is that electricity prices are cleared hour-by-hour. While futures are settled based on the average price of the period (for example all hours of a month in case of a monthly future), a participant in the spot market must buy/sell the electricity at the price cleared for each particular hour. For intermittent renewables like wind and solar selling electricity on the spot market, this means that the revenues they realize are normally below the average price for a certain period. Because when one wind project is producing energy, other wind projects, all with zero marginal cost, are also likely producing at the same time, and therefore the clearing price goes down the hours they sell electricity. Reversely, flexible generation like hydro power can collect above average prices because they can choose whether to sell or not based on the price level.

If we look at the new renewable energy projects required to meet climate targets, an increasingly larger share of investments in renewable energy projects are through the project finance structure, especially in developed markets (Steffen, 2018). As opposed to corporate finance which means the project is financed on the balance sheet of a company, in project finance there is a standalone business entity where debt is collateralized by the project assets and future cash flow only. Therefore, the cornerstone of any project finance-based project is the offtake revenues. Historically bilateral Power Purchase Agreements (PPA) and/or government subsidies have secured long term cash flows for renewable energy projects, however going forward the exposure to market prices is expected to increase (McKinsey, 2022). Hence, there is a need to stabilize cash flow – for example through hedging with futures.

### 3. Literature review

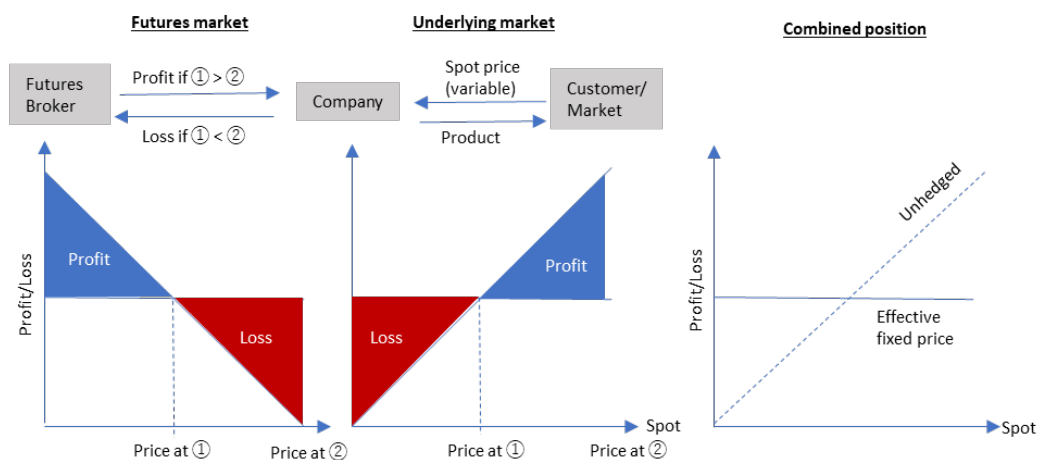
#### 3.1 Hedging in general

The literature about hedging in general goes a long way back. The classical work of Modigliani and Miller (1958) argues that because firm value only depends on the firm's assets and the cashflow generated from these, capital structure - including risk management, does not affect the firm value. Sharpe (1964) introduced the Capital Asset Pricing Model (CAPM) which implies that because investors effectively can diversify away company specific risk, instead of costly hedging which does not add value, companies should focus on maximizing their present value – assuming higher risk is rewarded with higher returns. Stultz (1996) however, defended the value of hedging and pointed out that there is a long list of assumptions for these theories to hold true in the real world, such as no taxes, bankruptcy cost, information asymmetry etc.

#### 3.2 Hedging with futures

The point of hedging is to reduce the exposure to price fluctuations in an underlying market. With futures, this can be done by taking a position in the futures market that is opposite to the position you have in the underlying market. This way any movements in the underlying price result in the payoff of the two positions cancelling out, as illustrated in Figure 3.

Figure 3: General concept of hedging with futures



By taking an opposite position in the futures market, price movements in the underlying market are cancelled out by the hedge payoff, achieving an effective fixed price in the combined position.

Source: concept from LME (2020), modified by Authors

The complications arise when the underlying we want to hedge is different from the underlying of the future being traded. This difference can for example be in the definition of the underlying (product specification) or time and place of delivery. This difference is called the basis, and basis risk hence refers to the risk we are taking by using a hedging instrument that is different from what we are trying to hedge.

If there is no basis risk, we can eliminate risk of the underlying position by entering the future with a hedge ratio of 1: meaning 1 unit of the future for 1 unit of the underlying, also called a naïve hedge. When there is basis risk, the exercise becomes finding the optimal hedge ratio. Minimizing the variation is most commonly recognized as the objective when looking for the optimal hedge ratio, not return maximization or minimizing reduction in return - because the return depends on which side of the trade you are on (Zanotti et al., 2010).

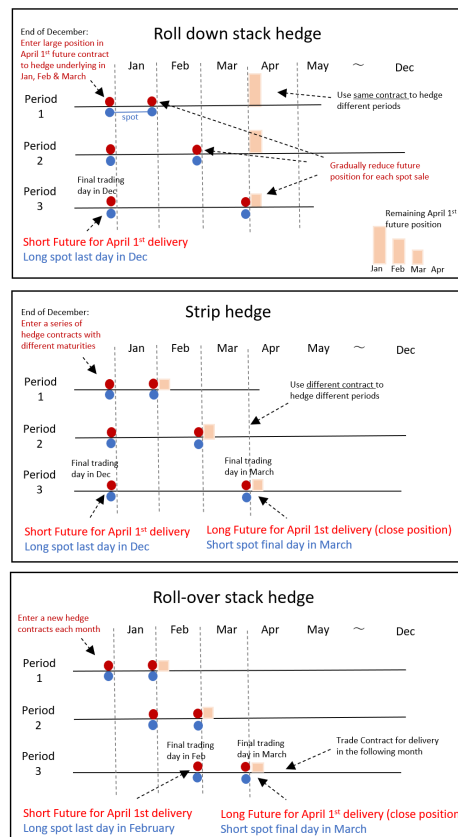
Ederington (1979) developed a framework using the spot and futures in an OLS regression and taking the resulting beta as the minimum variance hedge ratio (Equation 6). The same Ederington (1979) also introduced a method of evaluating hedge effectiveness (Equation 5), defining it as how much variance is reduced compared to the unhedged position in %.

Building on the OLS minimum variance framework, Ederington & Salas (2008) expands the model to include the difference between the spot and future as another independent variable in the regression (Equation 10). The rationale of the theory is that when spot prices are partially predictable, the spot price tends to diverge towards the future price. By including the difference between spot and futures price as an explanatory variable, the beta coefficient corresponding to the future price is more accurately picking up the unpredictable price change.

The OLS-model has been criticized for the assumption of unconditional distribution of spot and futures, which is often not the case - and assumptions of conditional distribution of spot and futures could be more appropriate (Park & Switzer, 2013). As such, models such as GARCH which considers conditional distribution and variation have also frequently been applied for finding the optimal hedging ratio with futures.

In addition to finding the optimal hedging ratio, how to roll over from one future contract to the next is another core element in setting up a hedging strategy. While not being an exhaustive list of all possible strategies, Gjerde (1987) defines a good representation of strategies with the 3 following approaches: Roll-down stack hedge, Strip hedge and Roll-over stack hedge - illustrated in Figure 4.

Figure 4: Hedge roll over strategies in the literature



Roll down stack hedge:  
Use the same futures contract to secure all sales of the underlying commodity until a specified time in the future. The futures position is gradually reduced for each spot sale.

Strip hedge:  
Buy/sell a series of futures over many maturities.

Roll-over stack hedge:  
Buy/sell futures contracts for a nearby delivery date. Prior to or on the delivery date you roll over to a new position.

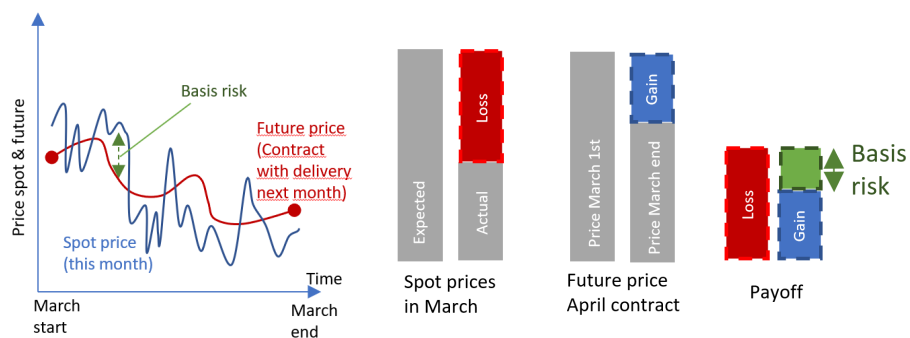
### 3.3 Hedging for electricity markets

While there is extensive literature on various kinds of commodities hedging, the literature is somewhat limited when it comes to hedging electricity specifically. The literature we found is centered around the Roll-over stack hedge concept, using close-to-maturity weekly or monthly futures with trading frequency on daily, weekly or monthly basis.

As illustrated in Figure 5, when using the roll-over stack hedge, the studies we reviewed hedge the spot return of one period with the price change of a future contract with delivery in another (near future) period. For example, a spot price

position in March is hedged at the end of February by taking the opposite position in the April front month future. Assuming there is correlation between March and April spot prices, the movements in March spot prices will impact the expected April spot prices and therefore the front month contract with delivery in April. The payoff of the March spot position is hence offset by the payoff of the opposite position in the April contract. Since the correlation between the spot and future is not perfect, there is basis risk and a need to find the optimal hedge ratio.

Figure 5: Concept applied in the literature of hedging with futures in electricity markets.



The studies on hedging electricity market spot prices with futures that we reviewed all applied the concept of hedging spot return of one period with the price change of a future contract with delivery in another (near future) period. In this example illustrated here, the March spot price position is hedged by shorting the April front month future. Assuming there is correlation between March and April prices, the reduction in March prices are offset by the payoff of the April contract short position. Since the correlation between the spot and future is not perfect, there is basis risk and a need to find the optimal hedge ratio.

We identified six studies which are all using the Roll-over stack hedge and comparable approaches for finding the optimal hedge ratio and measuring the hedge effectiveness. Table 1 presents an overview of these studies.



Table 1. Overview of studies on electricity market hedging with futures.

Study	Market and period	Underlying spot	Future	Trading frequency	Hedging strategies, results & remarks																																		
Bystrom (2003)	Nordpool  In-sample: 1996/1/2 – 1997/11/30  Out-of-sample: 1997/12/1 – 1999/10/21	One day spot price	Weekly	Daily	<p>Out-of-sample variance reduction for overlapping weekly portfolio:</p> <table border="1"> <thead> <tr> <th>Method</th> <th>Out-of-sample variance reduction</th> </tr> </thead> <tbody> <tr> <td>Naïve</td> <td>17.79%</td> </tr> <tr> <td>OLS</td> <td>16.44%</td> </tr> <tr> <td>Bivariate GARCH</td> <td>12.87%</td> </tr> <tr> <td>Orthogonal GARCH</td> <td>8.97%</td> </tr> <tr> <td>50-days moving average</td> <td>13.46%</td> </tr> </tbody> </table> <p>• Overall low hedge performance • Naïve give best result, followed by OLS • In addition to main analysis with overlapping weekly portfolio of spot and future positions, non-overlapping weekly portfolio (Monday to Monday, Tuesday to Tuesday etc.) was also analyzed for each method. Naïve hedge, Monday to Monday best performance with 29% variance reduction. • Longer maturity futures also evaluated by author, but as “hedging performance deteriorated”, he does not report results of that analysis.</p>	Method	Out-of-sample variance reduction	Naïve	17.79%	OLS	16.44%	Bivariate GARCH	12.87%	Orthogonal GARCH	8.97%	50-days moving average	13.46%																						
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Torro (2009)	Nordpool  In-sample: 1998/1/1 – 2003/10/5  Out-of-sample: 2003/10/6 – 2008/12/28	Weekly average spot price	Weekly	Weekly	<p>Out-of-sample variance reduction per hedging duration:</p> <table border="1"> <thead> <tr> <th>Method</th> <th>3 weeks</th> <th>2 weeks</th> <th>1 week</th> </tr> </thead> <tbody> <tr> <td>Naïve</td> <td>81.71%</td> <td>69.09%</td> <td>27.62%</td> </tr> <tr> <td>OLS</td> <td>82.60%</td> <td>75.83%</td> <td>58.93%</td> </tr> <tr> <td>OLS w/basis</td> <td>82.86%</td> <td>74.98%</td> <td>59.07%</td> </tr> <tr> <td>ADC-GARCH*</td> <td>74.48%</td> <td>70.26%</td> <td>57.69%</td> </tr> </tbody> </table> <p>*Asymmetric Dynamix Covariance Matrix (ADC-GARCH) • Very high hedge efficiency compared to other studies • Results are not conclusive in favour of any method. • Better performance using longer hedging duration with “exit” close to delivery. • Basis (Future-Spot) predictive power on spot price changes: 25%-50%</p>	Method	3 weeks	2 weeks	1 week	Naïve	81.71%	69.09%	27.62%	OLS	82.60%	75.83%	58.93%	OLS w/basis	82.86%	74.98%	59.07%	ADC-GARCH*	74.48%	70.26%	57.69%														
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Method	Nord Pool	Germany	France																																				
Naïve	-7.35%	3.37%	-1.94%																																				
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Martinez & Torro (2018)	Germany In: 2004/1-2012/4 Out: 2012/5-2015/12  Netherlands In: 2004/1-2008/12 Out: 2009/1-2016/4  UK In: 2004/11-2007/11 Out: 2007/11-2016/2	Weekly & Monthly average spot price	Monthly	Weekly & Monthly	<p>Out-of-sample variance reduction per country and hedging duration:</p> <table border="1"> <thead> <tr> <th rowspan="2">Method</th> <th colspan="2">UK</th> <th colspan="2">Netherlands</th> <th colspan="2">Germany</th> </tr> <tr> <th>1 week</th> <th>1 month</th> <th>1 week</th> <th>1 month</th> <th>1 month</th> <th>1 month</th> </tr> </thead> <tbody> <tr> <td>Naïve</td> <td>6.01%</td> <td>0.39%</td> <td>64.86%</td> <td>60.35%</td> <td>60.35%</td> <td>60.35%</td> </tr> <tr> <td>OLS</td> <td>6.06%</td> <td>0.28%</td> <td>62.30%</td> <td>51.00%</td> <td>51.00%</td> <td>51.00%</td> </tr> <tr> <td>OLS w/basis</td> <td>5.75%</td> <td>-3.72%</td> <td>69.06%</td> <td>55.65%</td> <td>55.65%</td> <td>55.65%</td> </tr> </tbody> </table> <p>• Excellent hedging results in monthly hedges, poor results in weekly • No hedging strategy clearly dominates the remaining strategies. • Electricity hedges must be made for long periods, otherwise the result can be negative. • This study also analyze natural gas hedge, and the combination of natural gas and electricity (spark spread). Results summarized here are for electricity only</p>	Method	UK		Netherlands		Germany		1 week	1 month	1 week	1 month	1 month	1 month	Naïve	6.01%	0.39%	64.86%	60.35%	60.35%	60.35%	OLS	6.06%	0.28%	62.30%	51.00%	51.00%	51.00%	OLS w/basis	5.75%	-3.72%	69.06%	55.65%	55.65%	55.65%
Method	UK		Netherlands		Germany																																		
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Hanly (2018)	Nordpool, UK, Germany.  In: 2004/9/15-2012/8 Out:2012/9-2014/10/1	One day spot price	Weekly & Monthly	Weekly & Monthly	<p>Out-of-sample variance reduction per country and futures used:</p> <table border="1"> <thead> <tr> <th rowspan="2">Method</th> <th colspan="2">UK</th> <th colspan="2">Nordpool</th> <th colspan="2">Germany</th> </tr> <tr> <th>Week</th> <th>Month</th> <th>Week</th> <th>Month</th> <th>Week</th> <th>Month</th> </tr> </thead> <tbody> <tr> <td>OLS</td> <td>5.33%</td> <td>14.78%</td> <td>-0.45%</td> <td>16.31%</td> <td>8.79%</td> <td>10.22%</td> </tr> <tr> <td>Constant Correlation GARCH</td> <td>6.66%</td> <td>8.85%</td> <td>-3.92%</td> <td>17.10%</td> <td>9.80%</td> <td>8.82%</td> </tr> </tbody> </table> <p>• Overall low hedge performance • Only obtain good results on a period by period basis • Hedge effectiveness depends on country, best results in Nord Pool market</p>	Method	UK		Nordpool		Germany		Week	Month	Week	Month	Week	Month	OLS	5.33%	14.78%	-0.45%	16.31%	8.79%	10.22%	Constant Correlation GARCH	6.66%	8.85%	-3.92%	17.10%	9.80%	8.82%							
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Peña (2023)	Spain 2007/7/7 - 2022/8/12	One day spot price	Monthly	Daily, weekly & monthly	<p>Out-of-sample variance reduction per hedging duration:</p> <table border="1"> <thead> <tr> <th rowspan="2">Method</th> <th colspan="3">Hedge duration and effectiveness</th> </tr> <tr> <th>1 Day</th> <th>1 Week</th> <th>1 Month</th> </tr> </thead> <tbody> <tr> <td>Naïve</td> <td>3%</td> <td>4%</td> <td>16%</td> </tr> <tr> <td>OLS</td> <td>3%</td> <td>3%</td> <td>-16%</td> </tr> <tr> <td>OLS w/basis</td> <td>3%</td> <td>5%</td> <td>-1%</td> </tr> <tr> <td>Rolling OLS</td> <td>6%</td> <td>9%</td> <td>-10%</td> </tr> <tr> <td>BEKK_T GARCH</td> <td>0%</td> <td>-6%</td> <td>-43%</td> </tr> </tbody> </table> <p>• Overall low hedge performance • Naïve hedge best results, BEKK-T GARCH worst • Hedging effectiveness varies over time</p>	Method	Hedge duration and effectiveness			1 Day	1 Week	1 Month	Naïve	3%	4%	16%	OLS	3%	3%	-16%	OLS w/basis	3%	5%	-1%	Rolling OLS	6%	9%	-10%	BEKK_T GARCH	0%	-6%	-43%							
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This table presents an overview of the studies we found that use comparable approach for finding the optimal hedge ratio, and which all use variance reduction as the definition of hedge effectiveness.

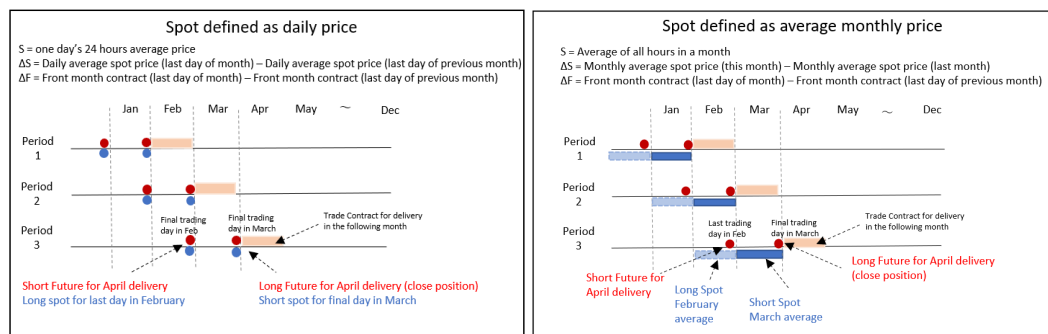
We find that when it comes to defining the underlying spot position being hedged, the studies use different approaches;

- Bystrom (2003), Zanotti (2010), Hanly (2018) and Peña (2023) defines spot as the daily price (average of 24 hours in a day).
- Torro (2009) and Martinez & Torro (2018) defines spot as the average price of the period being hedged; the average price of all hours in a week if weekly or all hours in a month if monthly.

The difference in definition of spot means that also the *change* in spot price is defined differently;

- Bystrom (2003), Zanotti (2010), Hanly (2018) and Peña (2023) define the change in spot as the difference between the daily price at the end of each period being hedged. For example, from Friday one week to Friday the next if weekly.
- Torro (2009) and Martinez & Torro (2018) define change in spot as the change in average price. For example, the change from March average spot price to April average spot price if monthly.

Figure 6: Different definitions of spot price in the literature



Bystrom (2003), Zanotti (2010), Hanly (2018) and Peña (2023) defines spot as the daily price on the last day of the period (average price of 24 hours in a day), while Torro (2009) and Martinez & Torro (2018) defines spot as the average price of the whole period being hedged; the average price of all hours in a week if weekly or all hours in a month if monthly.

The difference in spot definition has implications for what exposure is being covered. By using the (one day) daily price, we are only hedging our exposure for the (one day) daily price at the end of the period. Any price movements between these two dates becomes irrelevant because we calculate the difference in price as the difference between these two specific dates. To hedge the exposure for the dates in-between, we need to close one future position every day. Bystrom (2003) does this overlapping daily trading of weekly futures in his study, but Zanotti

(2010), Hanly (2018) and Peña (2023) does not include this element, and are as such in effect only hedging a one day position either a week or a month in the future. Torro (2009) and Martinez & Torro (2018) on the other hand are hedging an exposure for the whole period by using average prices as spot. We find it quite puzzling that only Bystrom (2003) address this aspect, and that this distinct difference among the studies in the literature it is not even mentioned by others.

Some common findings across the studies are;

- Relatively low hedging effectiveness compared to hedging with other commodities, which in general have risk reductions around 60-90% depending on the underlying commodity (Hanly et al., 2018).
- Simple hedges often do better than the more advanced techniques.
- Optimal hedge ratio and hedging effectiveness varies over time and between markets.

## **4. Methodology**

### ***4.1 Research question***

How effective is it to hedge electricity spot prices with futures?

### ***4.2 Our contribution***

This thesis builds on the previous studies on this topic, adding the following aspects:

- Long time series 2004-2022 allows for good statistical significance and tracking over complete business cycles.
- By including the most recent data, we can evaluate hedging performance in the extraordinary market conditions of 2021 and 2022.
- We compare results applying both of the two different spot definitions used in the literature (last day of period and average).
- As far as we know, we are the first to apply a year-by-year approach to finding hedge ratio and measuring hedging efficiency in a study on the Nordic market, based on Peña's (2023) study with this methodology on the Spanish market.
- While other studies are using weekly and/or monthly futures, we also evaluate the effectiveness of quarterly futures in addition to monthly futures (we do not cover weekly futures)

### ***4.3 Scope***

Our scope and limitations are:

- We follow the established literature and apply the roll-over stack hedge concept; using close-to-maturity monthly and quarterly futures we hedge the unhedged spot return of one period with the price change of a future contract with delivery in another (near future) period. Hence, we do not evaluate other roll-over strategies, use of annual contracts or performance of (not closing) holding the contract to maturity and into the delivery period.
- We use the Nordic System price as spot, and do not consider area price differences.

- We use daily, weekly, monthly and quarterly average electricity prices, and do not consider if the market participant's actual spot revenue/cost is above or below this average due to their production/demand hourly profile.
- We do not consider collateral requirements, interest rates or any other direct or indirect costs of hedging or not hedging.
- We do not consider risks like execution risks, model risk and liquidity risks in our calculations.

#### ***4.4 Hypothesis***

Variance reduction from hedging compared to an unhedged spot market position is statistically significantly different from zero.

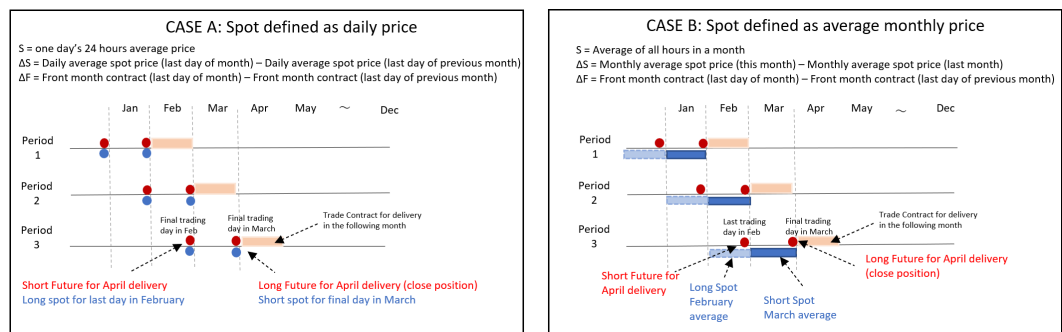
## 4.5 Hedging

In this part we will describe the theory and methodology of different versions of the roll-over stack-hedge. We will calculate the optimal hedge ratio and hedging effectiveness in-sample and out-of-sample using five different hedging strategies: the naïve hedge, the ordinary least square (OLS) minimum variance (“MV”), the OLS minimum variance with basis (“EDS”), the rolling minimum variance (“RMV”) and finally the generalized autoregressive conditional heteroskedasticity with constant conditional correlation (“GARCH”).

### 4.5.1 Unhedged position

To evaluate if the different hedging strategies have been effective, we need to compare the variance of the payoff using the strategies with the variance of the unhedged position. As explained in the literature review, the previous studies on hedging with futures in electricity markets have two different ways of defining the underlying spot; as the price at the end of a period (referred to as case A) or as the average price of a period (case B). We report the results of our analysis using each of these approaches from established literature.

Figure 7: Illustration of Case A and Case B



Case A defines spot as the daily price (average of 24 hours in a day) on the last day of each month, Case B defines spot as the average price of the period being hedged; all hours in a month. For Futures, in both cases at the end of each month we roll over by closing the “c1”(next month) contract and enter the “c2”(next-to-next month) contract.

While our primary emphasis will be on monthly returns, in our analysis we will incorporate daily, weekly, monthly and quarterly returns symbolized as  $k = d, w, m, q$ . The spot return is calculated as:

$$\Delta_k S(t_i) = S(t_i) - S(t_{i-k}) \quad (1)$$

Where in case A,  $S(t_i)$  is the electricity spot price on the last day of a period, and in case B it is the average electricity spot price of the period (for example month). The spot price change  $S(t_i) - S(t_{i-k})$  is hence either the difference between the prices at the end of each period or the difference between the average price of each period.

For averages we use the average spot price of all hours during the period (including non-trading days). For simplicity we will use the denotation  $\Delta_k S(t_i)$  as spot return for both case A and case B. The payoff of the unhedged position/spot return is:

$$PS(t_i, k) = \Delta_k S(t_i) \quad (2)$$

And the variance of the unhedged position is:

$$\sigma_{unhedged P}^2 = VAR(PS(t_i, k))$$

#### 4.5.2 Hedged position

The return of the futures is defined as:

$$\Delta_k F(t_i) = F(t_i) - F(t_{i-k}) \quad (3)$$

Where at the end of each month we roll over by closing the “c1”(next month) contract and enter the “c2”(next-to-next month) contract, and  $F(t_i) - F(t_{i-k})$  is hence the price change from we entered until we closed the position. The payoff of the hedged position is calculated by taking the return of the unhedged position minus the return of the hedged position:

$$PH(t_i, k) = \Delta_k S(t_i) - H(t_{i-k}) * \Delta_k F(t_i) \quad (4)$$

where  $H(t_{i-k}) * \Delta_k F(t_i)$  is return of the hedged position and  $H(t_{i-k})$  is the hedge ratio, which we calculate with the five different strategies which we will describe in details in following sections. The variance of the payoff of the hedged position is:

$$\sigma_{hedged P}^2 = VAR(PH(t_i, k))$$

#### 4.4.3 Hedging efficiency

To find the hedging efficiency we follow the Ederington (1979) approach and compare the variance of the spot position against the variance of the hedged position, and then calculate the % variance reduction as the hedge efficiency:

$$EHP_{k,z} = 1 - \frac{VAR(PH(t_{i,k}))}{VAR(PS(t_{i,k}))} \quad (5)$$

Where  $z$  is the different strategies.

The closer  $EHP_{k,z}$  is to 0 the lower the efficiency of the hedged position, and the closer  $EHP_{k,z}$  is to 1 the higher the efficiency (Peña, 2023).

#### 4.4.4 In- and out-of-sample

To see if any of the strategies would work in the real world, we will have to test them with an out-of-sample evaluation. Together with a description of the strategies, in the following sections we will describe how we find and apply the hedge ratios for each strategy in- and out-of-sample.



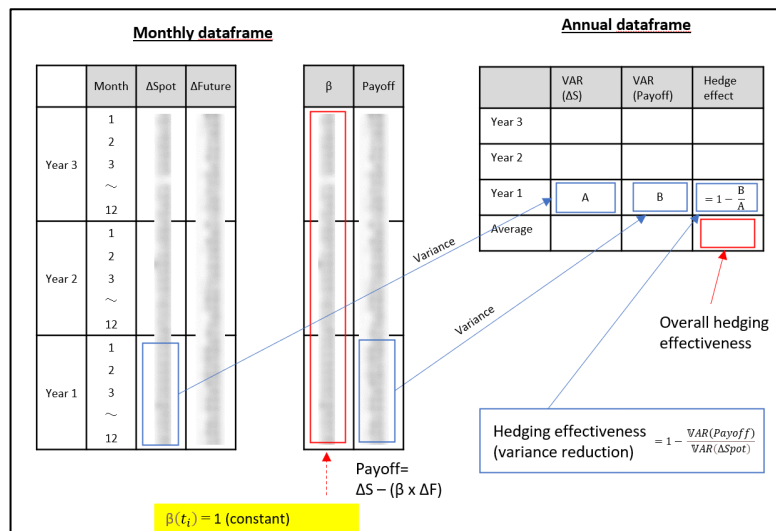
#### 4.4.5 The Naïve hedge

With the Naïve hedge we hedge with the same quantity as you have in the spot market. The hedge ratio  $h_t$  is set to a ratio of 1:1. There are many good reasons to use the naive hedge, it will minimize the transaction costs by having a constant hedge ratio and reduce time used estimating hedging ratios and the risk of making mistakes on complex models (Wang et al., 2015). As we identified in the literature review on other studies of hedging in the electricity markets, the simple naïve hedge often outperforms the other more complex strategies.

To calculate the payoff of the hedged position for each period (for example per month), we use Equation (4) with a constant beta of 1. When we have time series of both spot returns and hedge payoff, we calculate the variance of each per year and store it in an annual data frame. Then we apply Equation (5) to calculate the difference in variance as a measure of hedge effectiveness. To find the overall hedging effectiveness of the strategy, we take the average hedge effectiveness per year in the analysis.

Since the hedge ratio is constant at 1, the in-sample results will be the same as the out-of-sample results.

Figure 8: The Naïve hedge concept



Illustrative picture: We calculate the hedge payoff of applying the constant 1 to 1 hedge ratio. Then we compute the variance of the unhedged spot returns and hedged payoff per year and add it to the annual data frame, where we compare the variances to find the hedging efficiency. .

#### 4.4.6 OLS Minimum Variance (MV)

For the simple ordinary least square regressions we assume that there is a relationship between the two variables x (futures) and y (spot) and an increase in futures prices will make an increase in spot prices (Brooks, 2019). The ordinary least square hedge ratio is calculated by running the OLS-regression, where changes in spot prices are regressed on changes in future prices.

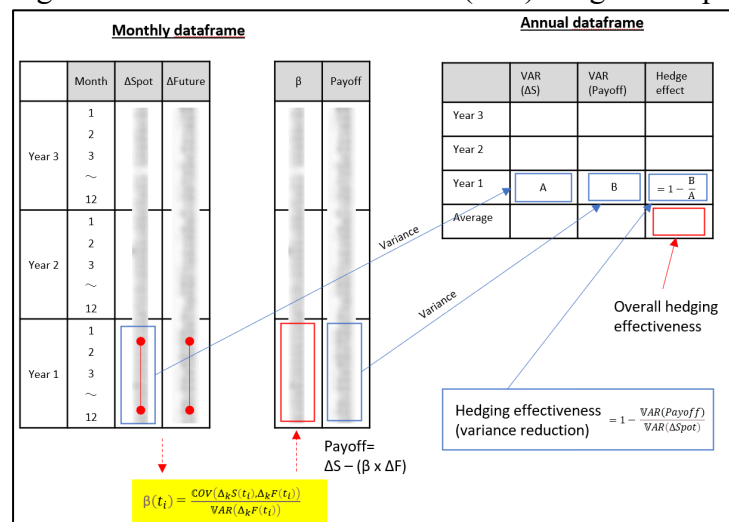
$$\Delta_k S(t_i) = \alpha + H_{k,MV}^*(t_{i-k}) * \Delta_k F(t_i) + \epsilon_t \quad (6)$$

Where  $\Delta_k S(t_i)$  and  $\Delta_k F(t_i)$  is the spot and futures return,  $H_{k,MV}^*(t_{i-k})$  is the slope of the regressions and the optimal hedge ratio and  $\epsilon_t$  is the error term. We could also find the hedge ratio by calculating the beta directly with the unconditional minimum variance formula:

$$H_{k,MV}^*(t_{i-k}) = \frac{COV(\Delta_k S(t_i), \Delta_k F(t_i))}{VAR(\Delta_k F(t_i))} \quad (7)$$

Using the same year-by-year approach as done by Peña (2023) in his study on the Spanish electricity market, we apply the regression in Equation (6) or calculation in Equation (7) using spot and future data for one year at the time, and find one hedge ratio for each year. The in-sample hedge ratio is hence the ratio based on the data for that year while the out-of-sample hedge ratio is using the beta from the previous year. When we have the betas, we can calculate the hedge payoff for each period (for example month in case of monthly trading frequency), compare the variance year by year as with the Naïve hedge.

Figure 9: OLS Minimum Variance (MV) hedge concept



Illustrative picture: Based on observations in each year (daily trading frequency: n=250, weekly: n=52, monthly: n=12) we run the OLS minimum variance regression to find the  $\beta$ . We use the  $\beta$  from each year as the in-sample hedge ratio for that year, and as the out-of-sample hedge ratio for the next year. For each trade, we then calculate the hedge payoff of applying the hedge ratio. We compute the variance of the unhedged spot returns and hedged payoff per year and add it to the annual data frame, where we compare the variances to find the hedging efficiency.

#### 4.4.7 OLS Minimum Variance with Basis (EDS)

The third strategy is from Ederington and Salas (2008), which builds on the OLS minimum variance hedge by adding a new explanatory term to that regression. The term they add is the difference between the current future and spot price (the basis) as a proxy for the expected spot price change in the next period.

$$E(\Delta_k S(t_i)) = \lambda (F(t_{i-1}) - S(t_{i-1})) \quad (8)$$

The rationale as cited by Martinez and Torro (2018, p732) is that “if futures prices are unbiased predictors of future spot prices, the basis will be a measure of the expected change in the spot price until maturity (Fama & French, 1987)“. By adding this term, Ederington and Salas (2008) argue that we can reduce the bias and increase the regression efficiency. We can use the following equation to find the hedge ratio;

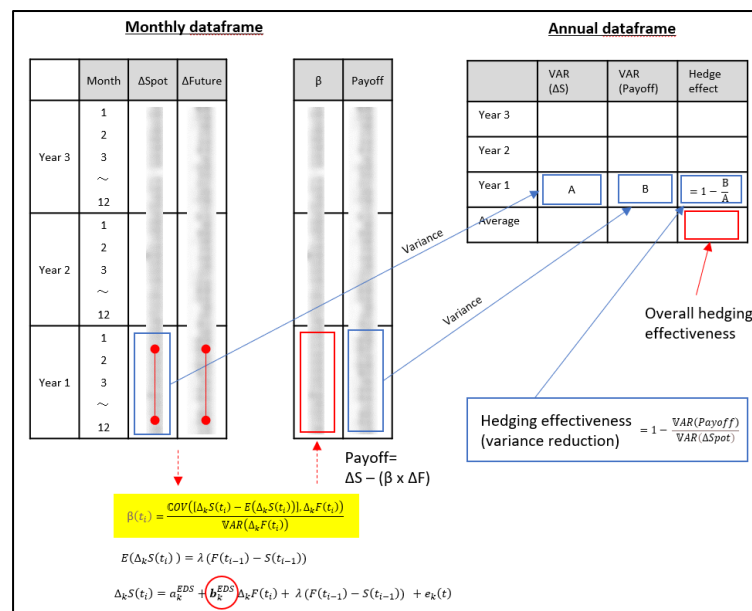
$$H_{k,EDS}^*(t_{i-k}) = \frac{\text{COV}([\Delta_k S(t_i) - E(\Delta_k S(t_i))], \Delta_k F(t_i))}{\text{VAR}(\Delta_k F(t_i))} \quad (9)$$

Which is equivalent to the beta in the following regression;

$$\Delta_k S(t_i) = a_k^{EDS} + b_k^{EDS} \Delta_k F(t_i) + \lambda (F(t_{i-1}) - S(t_{i-1})) + e_k(t) \quad (10)$$

When we have the beta for each year, we follow the same procedure as the OLS minimum variance strategy to calculate the hedging effectiveness.

Figure 10: OLS Minimum Variance with Basis (EDS) hedge concept



Illustrative picture: Based on observations in each year (daily trading frequency: n=250, weekly: n=52, monthly: n=12) we run the Ederington and Salas (2008) regression to find the β EDS. We use the β from each year as the in-sample hedge ratio for that year, and as the out-of-sample hedge ratio for the next year. For each trade, we then calculate the hedge payoff of applying the hedge ratio. We compute the variance of the unhedged spot returns and hedged payoff per year and add it to the annual data frame, where we compare the variances to find the hedging efficiency.

#### 4.4.8 Rolling Minimum Variance (RMV)

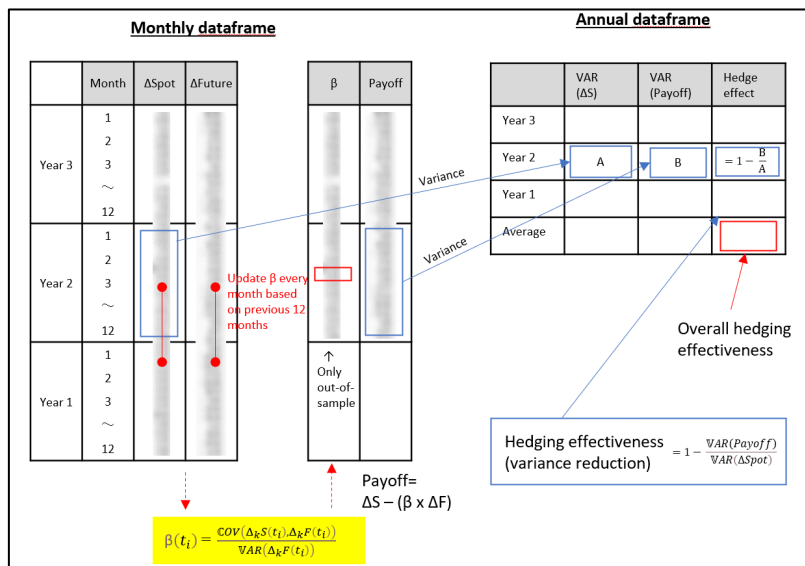
For the rolling minimum variance hedging strategy, we update the hedge ratio continuously for every period (for example per month if monthly trading frequency). The rolling minimum variance hedge ratio allows for time varying variances and covariances (Peña, 2023). We compute the optimal hedge ratio for time  $t_i$  using OLS/minimum variance up to  $t_{i-k}$ .

$$H_{k,RMV}^*(t_{i-k}) = \frac{COV(\Delta_k S(t_i), \Delta_k F(t_i))}{VAR(\Delta_k F(t_i))} \quad (11)$$

The rolling window is moved forward by adding one observation and removing the last observation, where the sample period is fixed at one year, and the hedge ratio is updated for every period (daily, weekly and monthly). After we find the continuous hedge ratios, we can calculate the payoff, the variance of the payoff, and the hedge effectiveness using same approach as the previously mentioned strategies.

Because we always use the observations from the preceding one year, this strategy will only have out-of-sample hedging ratio and results.

Figure 11: Rolling Minimum Variance (RMV) hedge concept



Illustrative picture: Based on a rolling window of observations (daily trading frequency: n=250, weekly: n=52, monthly: n=12) we run the OLS minimum variance regression to find the  $\beta$  for each trade. We then calculate the hedge payoff of each trade by applying the unique hedge ratio. We compute the variance of the unhedged spot returns and hedged payoff per year and add it to the annual data frame, where we compare the variances to find the hedging efficiency.

#### 4.4.9 GARCH

The Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model is built on the assumption that there is autocorrelation and heteroskedasticity in the error term, and that there is volatility clustering in the data. The GARCH model tries to predict future volatility. To capture the varying variance, the conditional variance can be calculated as function of past errors and its own lags (Byström, 2003). We calculate the conditional variance for spot and futures returns and find the conditional covariance between them.

We estimate the GARCH hedge ratio by using the same principles as the RMV method, by continuously updating the conditional covariance, the rolling hedge ratio. The sample period is fixed at 3 years (36 months) to get enough observations. For every new period we add one observation to the hedge ratio and removes the last one. This ensures that we have enough observations but also that the hedge ratio is based on the most recent data and that the GARCH model may be able to capture some of the conditional variation. As in (Bystrom, 2003), the GARCH model we will be using will be a bivariate model with constant conditional correlation, which is based on Bollerslev (1990) model.

The mean equation we will be using is an AR (1): an autoregressive model with 1 lag. The conditional variance equation we will be using is GARCH (1,1).

The GARCH model for spot and futures returns is calculated as follows:

$$\Delta_k S(t_i) = \alpha_{S,1} + \alpha_{S,2} \Delta_k S(t_{i-1}) + \epsilon_{S,t} \quad (12)$$

$$\Delta_k F(t_i) = \alpha_{F,1} + \alpha_{F,2} \Delta_k F(t_{i-1}) + \epsilon_{F,t} \quad (13)$$

The conditional variance for spot and futures is:

$$\sigma_{S,t}^2 = \phi_{S,1} + \phi_{S,2} \epsilon_{S,t-1}^2 + \phi_{S,3} \sigma_{S,t-1}^2 \quad (14)$$

$$\sigma_{F,t}^2 = \phi_{F,1} + \phi_{F,2} \epsilon_{F,t-1}^2 + \phi_{F,3} \sigma_{F,t-1}^2 \quad (15)$$

Where  $\sigma_{S,t}^2$  and  $\sigma_{F,t}^2$  is the conditional variance of  $\epsilon_{S,t}$  and  $\epsilon_{F,t}$

And the conditional covariance between  $\varepsilon_{S,t}$  and  $\varepsilon_{F,t}$  is:

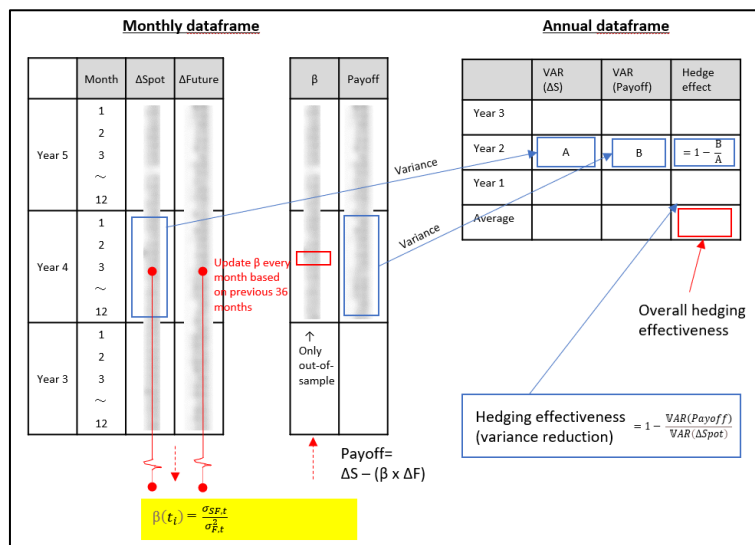
$$\sigma_{SF,t} = \rho\sigma_{S,t}\sigma_{F,t} \quad (16)$$

The hedge ratio is:

$$H_{k,GARCH}^*(t_{i-k}) = \frac{\sigma_{SF,t}}{\sigma_{F,t}^2} \quad (17)$$

After we find the continuous hedge ratios, we can calculate the payoff of the hedged position and the variance of the hedged position. Then we have everything we need to calculate the hedge efficiency. Since this is also a continuous hedging method like RMV, this will also only be an out-of-sample hedging-method.

Figure 12: GARCH hedge concept



Illustrative picture: Based on a 3 year rolling window of observations we run the GARCH regressions to find the  $\beta$  for each trade. We then calculate the hedge payoff of each trade by applying the unique hedge ratio. We compute the variance of the unhedged spot returns and hedged payoff per year and add it to the annual data frame, where we compare the variances to find the hedging efficiency.

## 5 Data

### 5.1 Data source and set up

From Refinitiv Eikon we use the data summarized in Table 2. We use monthly and quarterly futures with 2 different maturities because at the end of each month/quarter we roll over by closing the “c1”(next period) contract on the last day it is traded, and enter the “c2”(next to next period) contract. This way we always close the same contract as we entered in previous period, and use the price difference of the future to hedge our spot position.

Table 2: Data used in analysis with monthly futures.

Instrument	Period	Retrieval code	Full instrument name in Refinitiv Eikon
Nord Pool spot	2004/1/1 – 2022/12/31	FXSYSAL=NPX	Nordpool ASA Elspot Base Fixing System Price - Average - EUR
Nord Pool monthly futures	2004/1/1 – 2022/12/31	ENOMc1 & ENOMc2	Nasdaq Commodities Nordic Electricity Baseload DS Monthly Energy Future Continuation 1 & 2
Germany spot	2014/1/1 – 2022/12/31	BBLDE24	Epex Spot Germany Baseload Hour 01 to 24
Germany monthly futures	2014/1/1 – 2022/12/31	TRDEBMc1 & TRDEBMc2	TRPC Electricity Germany Baseload Monthly Continuation 1 & 2
UK spot	2014/1/1 – 2022/12/31	EHLGBAV	N2EX Hourly Average
UK monthly futures	2014/1/1 – 2022/12/31	UBLIMc1 & UBLIMc2	ICE Europe UK Base Electricity Monthly Energy Future

Data from Refinitiv Eikon used in analysis. We can replace the Mc1 at the end of the future retrieval code with Qc1 to get quarterly instead of monthly futures. Historical GBP/EUR exchange rates retrieved from Investing.com

Regarding the spot, we attain the daily cleared spot price, which is an average of the price for each of the 24 hours in the *next* day - making the spot price in itself one kind of a future. For the spot we therefore adjust the date retrieved from Refinitiv Eikon one day forward, so that the spot price corresponds to the day of delivery instead of the day of the auction.

While many studies use log returns, studies like Martínez & Torr6 (2018) and Pe6a (2023) use Euro return in their regressions. We chose to use Euro returns because we agree with Alexander et al. (2013) as cited by Mart6nez & Torr6 (2018, p 733) and the reasoning that “...for assets with prices that can jump, log returns can be highly inaccurate proxies for percentage returns even when measured at the daily frequency. Additionally, since the hedged portfolio can have zero value, its percentage return may even be undefined. Thus, our hedging portfolio is based on profit and loss rather than on log or percentage returns”. We

checked that the Euro returns did not have a unit root, which the price itself did have according to the ADF and KPSS test – as shown in Table 3 below.

### 5.2 Descriptive statistics

To get a better overview of the data, we have done certain statistical tests, Bera and Jarque (BJ) for normality, Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin KPSS for stationarity, ARCH Engle test for heteroskedasticity and arch effects and Ljung Box test for autocorrelation.

Table 3: Descriptive statistics

	Monthly Contracts									Quarterly Contracts					
	Traded Daily		Traded Weekly			Traded Monthly				Traded Quarterly					
	Spot Δ	Futures Δ	Spot Δ	Futures Δ	Spot Δ	Average	Spot Δ	Futures Δ	Spot Δ	Average	Spot Δ	Futures Δ	Spot Δ	Average	
Total Observations	4770		991			227				227			75		
Mean	0,01	0,00	0,00	-0,09	0,02	-0,10	0,01	0,03	0,01	0,15	0,86	1,06	-0,86	1,43	
Standard Deviation	13,96	4,07	22,88	9,77	14,89	36,18	25,31	19,83	35,94	18,78	17,85	20,94	24,07	13,01	
Kurtosis	53,10	129,77	33,53	59,47	47,25	47,35	38,88	29,83	49,89	49,44	34,65	10,72	29,66	4,01	
Skewness	-0,53	-0,11	-1,48	-1,20	-1,83	-1,75	1,83	-0,61	-1,78	-4,46	0,84	0,14	-3,94	0,77	
Bera Jarque p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,14	0,00	
ADF															
Critical Value (99%)	-3,43	-3,43	-3,43	-3,43	-3,43	-3,46	-3,46	-3,46	-3,46	-3,46	-3,46				
Price t-stat	-7,84	-4,11	-2,99	-7,00	-2,83	-6,62	-5,58	-6,08	-2,15	-2,34	-0,67	-4,24	-3,05	-3,65	
First difference t-stat	-20,35	-24,53	-18,90	-9,79	-17,54	-5,27	-4,00	-4,43	-5,33	-5,17	-8,30	-5,77	-3,73	-5,40	
KPSS-test-stat															
Critical Value (99%)	0,74	0,74	0,74	0,74	0,74	0,74	0,74	0,74	0,74	0,74	0,74	0,74	0,74	0,74	
Price t-stat	4,54	0,22	0,94	0,85	0,94	0,37	0,27	0,35	0,13	0,17	0,40	0,27	0,20	0,25	
First difference t-stat	0,01	0,01	0,15	0,05	0,17	0,04	0,03	0,04	0,03	0,04	0,04	0,17	0,10	0,26	
Correlation	0,03		0,29			0,90				0,33			0,86		
Tests on residuals from regressions p-values			0,32			0,33				0,21			0,70		
Bera Jarque	0,00		0,00			0,00				0,00			0,00		
Ljung Box Q(6)	0,00		0,00			0,00				0,00			0,01		
Ljung Box Q(18)	0,00		0,00			0,00				0,00			0,10		
ARCH Q*2(6)	0,00		0,00			0,00				0,00			0,56		
ARCH Q*2(18)	0,00		0,00			0,00				0,00			0,26		
			0,00			0,00				0,00			0,81		
													0,84		

Descriptive statistics for spot/spot average and futures returns (Except for price in the ADF test and KPSS test) Monthly contracts traded daily, weekly and monthly. Quarterly contracts traded monthly and quarterly.

Notes: Figures denote standard deviation, skewness, kurtosis is the excess kurtosis, Bera and Jarque test for non normality. ADF is the Augmented Dickey fuller test for stationarity, t-stat with a 99% critical value. KPSS is the Kwiatkowski–Phillips–Schmidt–Shin test stat for stationarity with 99% critical value. Bera Jarque tests on the residuals for non-normality, noted with p-values. Ljung box test on the residuals for autocorrelation with (6) and (18) lags noted with p-values ARCH Engle tests on the residuals for ARCH effects, heteroskedasticity with (6) and (18) lags, noted with p-values.

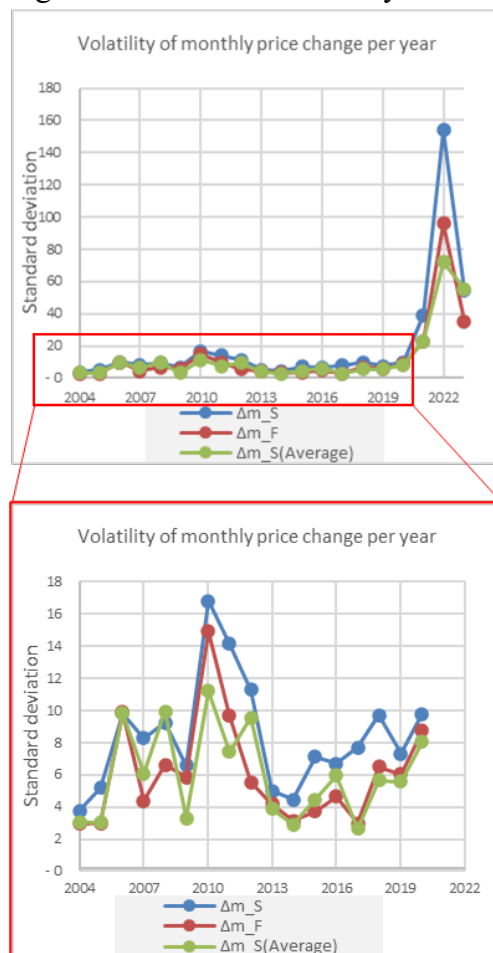
The Bera and Jarque tests yield p-values of zero, suggesting that neither daily, weekly, monthly returns, nor the residuals of the regressions, in all instances follow a normal distribution. Even if the assumption for normality does not hold, the parameters will be consistent (Brooks, 2019). Further tests for autocorrelation and ARCH tests for heteroskedasticity show p-values of zero for most of the cases, which indicates that there is autocorrelation and heteroskedasticity in the residuals with 6 and 18 lags for daily, weekly and monthly returns of monthly contracts. This autocorrelation and heteroskedasticity fade in the quarterly contracts traded monthly and are absent in the quarterly traded contracts. There is



autocorrelation, heteroskedasticity and non-normality in the data, which is not uncommon in financial data, however the standard error estimates in these cases might be inappropriate (Brooks, 2019).

According to Brooks (2019, p 392); «It is unlikely in the context of financial time series that the variance of the errors will be constant over time, and it makes sense to consider a model that does not assume that the variance is constant, and which describes how the variance of the errors evolves». We do observe volatility clustering in the data, and as shown in figure 13, how volatility changes from year to year and how it has exploded after 2020.

Figure 13: Historical volatility in future and spot prices Nord Pool



We notice how volatility in both spot and futures have gone off the charts since 2020. We therefore have to zoom in on the previous periods and exclude the last years to see the volatility. Blue: difference in daily spot price last day of month. Red: Difference in front month futures price at end of each month. Green: difference in average spot price per month

With all the necessary factors required for a GARCH model, we decided to implement it in our analysis. Given the low correlation between daily returns for spot and monthly futures, we don't expect good results from GARCH in this case, however for weekly returns the correlation between the futures and spot are a bit

higher. For monthly returns for spot and monthly futures where the correlation is high, we do expect the GARCH model to perform well. For quarterly contracts, we don't find the necessary factors to justify implementing it.

## 6 Results

### 6.1 Main results

Recalling from the explanation in the methodology, we have case A and case B representing definitions of spot as either the end of the period daily price or average price of the period. Table 4 shows the overall in- and out-of-sample optimal hedge ratios and hedge effectiveness using monthly and quarterly futures for each trading frequency and each strategy.

Table 4: Overall hedge ratios and hedge effectiveness

Hedge ratio	Trading	Case	IN SAMPLE			OUT OF SAMPLE					
			Naive	MV	EDS	Naive	MV	EDS	RMV	GARCH	
Hedge ratio	Monthly futures	DAILY		1	0.22	0.22	1	0.21	0.21	0.27	0.02
		Weekly	A	1	0.66	0.65	1	0.66	0.64	0.68	0.63
			B	1	0.47	0.47	1	0.46	0.47	0.50	0.48
		Monthly	A	1	1.11	1.20	1	1.09	1.19	1.10	1.02
			B	1	0.44	0.54	1	0.45	0.54	0.48	0.48
		Quarterly futures	Monthly	A	1	1.37	1.23	1	1.35	1.21	1.33
	B			1	0.51	0.44	1	0.53	0.45	0.52	
	Quarterly		A	1	0.22	0.60	1	0.13	0.54	0.63	
			B	1	0.26	0.19	1	0.23	0.14	0.52	

Hedge effectiveness	Trading	Case	IN SAMPLE			OUT OF SAMPLE					
			Naive	MV	EDS	Naive	MV	EDS	RMV	GARCH	
Hedge effectiveness	Monthly futures	DAILY		-27 %	1 %	1 %	-27 %	-3 %	-2 %	-5 %	0 %
		Weekly	A	7 %	15 %	14 %	7 %	11 %	12 %	8 %	9 %
			B	-8 %	14 %	13 %	-8 %	6 %	9 %	5 %	8 %
		Monthly	A	56 %	60 %	56 %	56 %	50 %	49 %	49 %	58 %
			B	-23 %	24 %	14 %	-23 %	17 %	17 %	10 %	19 %
		Quarterly futures	Monthly	A	36 %	48 %	45 %	36 %	13 %	30 %	35 %
	B			-23 %	19 %	15 %	-23 %	-2 %	9 %	-1 %	
	Quarterly		A	2 %	21 %	11 %	2 %	-78 %	-43 %	-4 %	
			B	-18 %	27 %	25 %	-18 %	-88 %	-129 %	-8 %	

Nord Pool 2004-2022. Data source used for analysis: Refinitiv Eikon

Case A:  $\Delta\text{spot} = \text{spot last day this month} - \text{spot last day previous month}$

Case B:  $\Delta\text{spot} = \text{this month average spot} - \text{previous month average spot}$

Naïve: Constant hedging ratio 1 (same in- and out-of-sample)      MV: OLS minimum variance

EDS: OLS minimum variance with basis (Ederington-Salas)

RMV: Non-Parametric 1 year rolling OLS minimum variance (only out-of-sample)

GARCH: Generalized AutoRegressive Conditional Heteroskedasticity (analyzed monthly futures only)

Hedge effectiveness defined as % reduction in variance of the hedged position compared to the unhedged position

From these results, we identify monthly futures traded monthly as the best performing strategy with out-of-sample hedge effectiveness between 49% and 58% in case A and between -23% and 19% in case B. For the monthly future traded monthly, the hedge effectiveness is statistically significantly better than 0 at the 95% confidence level in all cases and strategies except for case B with the Naïve hedge (the only negative hedging effectiveness result) and with the Rolling OLS minimum variance (RMV). More detailed results of the analysis on monthly futures traded monthly, are summarized in Table 5.

Table 5(A): Hedge ratio and effectiveness for monthly futures traded monthly.

	CASE A: Hedge ratio per year								
	In-sample			Out-of-sample					
	Naïve	MV	EDS	Naïve	MV	EDS	RMV	GARCH	
2022	1	1.5	1.4	1.0	1.5	1.1	1.1	1.1	
2021	1	1.5	1.1	1.0	1.0	0.9	1.2	1.1	
2020	1	1.0	0.9	1.0	1.0	1.1	0.9	1.0	
2019	1	1.0	1.1	1.0	1.2	1.2	1.1	1.0	
2018	1	1.2	1.2	1.0	0.7	1.9	1.6	1.0	
2017	1	0.7	1.9	1.0	0.9	0.9	0.7	0.9	
2016	1	0.9	0.9	1.0	1.6	1.2	1.2	0.9	
2015	1	1.6	1.2	1.0	0.5	0.8	1.1	1.2	
2014	1	0.5	0.8	1.0	1.1	1.1	0.8	1.3	
2013	1	1.1	1.1	1.0	1.8	1.5	1.5	1.0	
2012	1	1.8	1.5	1.0	1.1	1.3	1.6	1.0	
2011	1	1.1	1.3	1.0	0.9	1.3	0.8	0.9	
2010	1	0.9	1.3	1.0	0.9	1.1	1.0	1.0	
2009	1	0.9	1.1	1.0	1.2	1.2	1.1	1.0	
2008	1	1.2	1.2	1.0	1.5	1.4	1.1	0.9	
2007	1	1.5	1.4	1.0	0.9	0.8	1.0	1.0	
2006	1	0.9	0.8	1.0	0.7	1.7	0.8		
2005	1	0.7	1.7	1.0	1.1	1.0	1.0		
2004	1	1.1	1.0						

Average	<b>1.00</b>	<b>1.11</b>	<b>1.20</b>	<b>1.00</b>	<b>1.09</b>	<b>1.19</b>	<b>1.10</b>	<b>1.02</b>
stdev		0.34	0.28		0.34	0.28	0.27	0.10
n		19	19		18	18	18	16
st.error		0.08	0.06		0.08	0.07	0.06	0.02
t-stat		1.44	3.11		1.14	2.81	1.59	0.75
p-value		0.08	0.00		0.13	0.00	0.06	0.23

\*P-value is for the hypothesis that beta = 1

	CASE A: Hedge effectiveness per year								
	In-sample			Out-of-sample					
	Naïve	MV	EDS	Naïve	MV	EDS	RMV	GARCH	
2022	78 %	88 %	88 %	78 %	88 %	82 %	84 %	87 %	
2021	68 %	76 %	71 %	68 %	68 %	64 %	74 %	73 %	
2020	82 %	82 %	81 %	82 %	82 %	81 %	73 %	83 %	
2019	68 %	68 %	67 %	68 %	64 %	66 %	63 %	68 %	
2018	65 %	68 %	68 %	65 %	54 %	50 %	52 %	66 %	
2017	5 %	6 %	-14 %	5 %	6 %	6 %	0 %	6 %	
2016	38 %	39 %	39 %	38 %	15 %	35 %	8 %	40 %	
2015	58 %	67 %	63 %	58 %	36 %	49 %	60 %	61 %	
2014	2 %	13 %	10 %	2 %	-4 %	-4 %	-5 %	-14 %	
2013	85 %	86 %	86 %	85 %	55 %	77 %	70 %	86 %	
2012	60 %	74 %	72 %	60 %	65 %	68 %	73 %	59 %	
2011	59 %	60 %	59 %	59 %	58 %	59 %	54 %	59 %	
2010	69 %	69 %	60 %	69 %	68 %	68 %	57 %	75 %	
2009	56 %	58 %	55 %	56 %	49 %	49 %	47 %	58 %	
2008	69 %	71 %	71 %	69 %	67 %	70 %	60 %	69 %	
2007	52 %	57 %	57 %	52 %	48 %	47 %	47 %	53 %	
2006	76 %	78 %	78 %	76 %	74 %	13 %	72 %		
2005	11 %	15 %	-16 %	11 %	10 %	11 %	2 %		
2004	61 %	61 %	61 %						

Average	<b>56 %</b>	<b>60 %</b>	<b>56 %</b>	<b>56 %</b>	<b>50 %</b>	<b>49 %</b>	<b>49 %</b>	<b>58 %</b>
stdev	0.25	0.24	0.30	0.25	0.27	0.27	0.28	0.28
n	19	19	19	19	18	18	18	16
st.error	0.06	0.06	0.07	0.06	0.06	0.06	0.07	0.07
t-stat	9.85	10.67	7.99	9.85	7.86	7.78	7.41	8.43
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

\*P-value is for the hypothesis that hedge effectiveness = 0

Table 5(B): Hedge ratio and effectiveness for monthly futures traded monthly

	CASE B: Hedge ratio per year								
	In-sample			Out-of-sample					
	Naïve	MV	EDS	Naïve	MV	EDS	RMV	GARCH	
2022	1.0	0.2	0.5	1.0	0.4	0.4	0.7	0.8	
2021	1.0	0.4	0.4	1.0	0.5	0.4	0.6	0.6	
2020	1.0	0.5	0.4	1.0	0.7	0.7	0.6	0.4	
2019	1.0	0.7	0.7	1.0	0.3	0.6	0.5	0.3	
2018	1.0	0.3	0.6	1.0	0.1	0.8	0.2	0.2	
2017	1.0	0.1	0.8	1.0	0.1	0.4	0.0	0.4	
2016	1.0	0.1	0.4	1.0	0.3	0.5	0.3	0.4	
2015	1.0	0.3	0.5	1.0	0.4	0.3	0.4	0.6	
2014	1.0	0.4	0.3	1.0	0.6	0.6	0.5	0.5	
2013	1.0	0.6	0.6	1.0	0.8	0.5	0.8	0.6	
2012	1.0	0.8	0.5	1.0	0.3	0.7	0.5	0.6	
2011	1.0	0.3	0.7	1.0	0.6	0.6	0.6	0.6	
2010	1.0	0.6	0.6	1.0	0.3	0.5	0.5	0.5	
2009	1.0	0.3	0.5	1.0	0.3	0.3	0.3	0.3	
2008	1.0	0.3	0.3	1.0	1.0	0.9	0.4	0.3	
2007	1.0	1.0	0.9	1.0	0.7	0.4	0.7	0.6	
2006	1.0	0.7	0.4	1.0	0.5	0.6	0.6		
2005	1.0	0.5	0.6	1.0	0.5	0.6	0.6		
2004	1.0	0.5	0.6						

Average	<b>1.00</b>	<b>0.44</b>	<b>0.54</b>	<b>1.00</b>	<b>0.45</b>	<b>0.54</b>	<b>0.48</b>	<b>0.48</b>
stdev		0.24	0.16		0.24	0.17	0.19	0.14
n		19	19		18	18	18	16
st.error		0.06	0.04		0.06	0.04	0.05	0.04
t-stat	-	10.16	- 12.40	-	9.62	- 11.69	- 11.46	- 14.51
p-value		1.00	1.00		1.00	1.00	1.00	1.00

\*P-value is for the hypothesis that beta = 1

	CASE B: Hedge effectiveness per year									
	In-sample			Out-of-sample						
	Naïve	MV	EDS	Naïve	MV	EDS	RMV	GARCH		
2022	-96 %	9 %	-4 %	-96 %	4 %	3 %	-40 %	11 %		
2021	-18 %	16 %	16 %	-18 %	15 %	16 %	-6 %	17 %		
2020	7 %	33 %	30 %	7 %	31 %	30 %	29 %	35 %		
2019	38 %	51 %	51 %	38 %	37 %	51 %	46 %	39 %		
2018	-51 %	13 %	3 %	-51 %	4 %	-14 %	-26 %	12 %		
2017	-118 %	0 %	-64 %	-118 %	0 %	-14 %	-14 %	-16 %		
2016	-52 %	0 %	-6 %	-52 %	-4 %	-11 %	-10 %	-5 %		
2015	-25 %	7 %	5 %	-25 %	7 %	7 %	4 %	3 %		
2014	-31 %	16 %	16 %	-31 %	12 %	12 %	6 %	8 %		
2013	14 %	37 %	37 %	14 %	29 %	36 %	7 %	36 %		
2012	21 %	22 %	18 %	21 %	13 %	21 %	16 %	21 %		
2011	-73 %	14 %	-16 %	-73 %	-5 %	-7 %	-4 %	-1 %		
2010	42 %	68 %	68 %	42 %	48 %	67 %	61 %	65 %		
2009	-147 %	26 %	4 %	-147 %	26 %	26 %	27 %	27 %		
2008	-20 %	3 %	3 %	-20 %	-19 %	-15 %	-16 %	3 %		
2007	48 %	48 %	48 %	48 %	43 %	29 %	41 %	40 %		
2006	35 %	46 %	37 %	35 %	42 %	46 %	36 %			
2005	-6 %	21 %	19 %	-6 %	21 %	20 %	19 %			
2004	-7 %	18 %	7 %	-7 %						

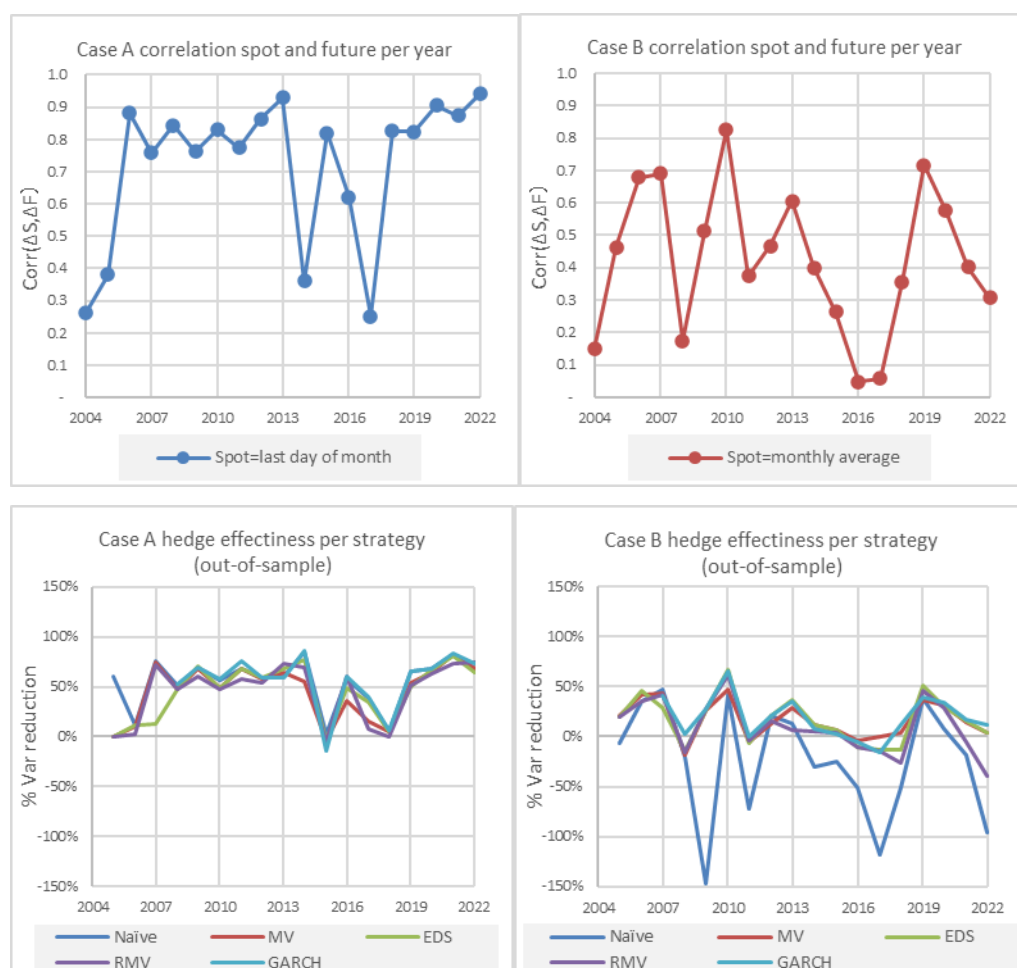
Average	<b>-23 %</b>	<b>24 %</b>	<b>14 %</b>	<b>-23 %</b>	<b>17 %</b>	<b>17 %</b>	<b>10 %</b>	<b>19 %</b>		
stdev	0.55	0.19	0.29	0.55	0.19	0.24	0.27	0.21		
n	19	19	19	19	18	18	18	16		
st.error	0.13	0.04	0.07	0.13	0.04	0.06	0.06	0.05		
t-stat	-	1.83	5.43	2.16	-	1.83	3.79	2.98	1.55	3.55
p-value		0.97	0.00	0.02	0.97	0.00	0.00	0.06	0.00	

\*P-value is for the hypothesis that hedge effectiveness = 0

## 6.2 Observations and discussion

We find that the hedge ratios and hedge effectiveness fluctuate from year to year together with the correlation between spot and futures. In both case A and B, the year-to-year movements of the correlation and hedge effectiveness appear to follow each other very closely. We also notice reasonably good hedging performance for most strategies in 2021 and 2022 when there was extreme volatility in spot prices.

Figure 14: Spot and futures correlation and hedge effectiveness per year



We can observe that hedge effectiveness is higher when correlation between spot and futures is high and vice versa

Nord Pool 2004-2022. Data source used for analysis: Refinitiv Eikon

Case A:  $\Delta\text{spot} = \text{spot last day this month} - \text{spot last day previous month}$

Case B:  $\Delta\text{spot} = \text{this month average spot} - \text{previous month average spot}$

Naïve: Constant hedging ratio 1 (same in- and out-of-sample)      MV: OLS minimum variance

EDS: OLS minimum variance with basis (Ederington-Salas)

RMV: Non-Parametric 1 year rolling OLS minimum variance (only out-of-sample)

GARCH: Generalized AutoRegressive Conditional Heteroskedasticity (analyzed monthly futures only)

Hedge effectiveness defined as % reduction in variance of the hedged position compared to the unhedged position

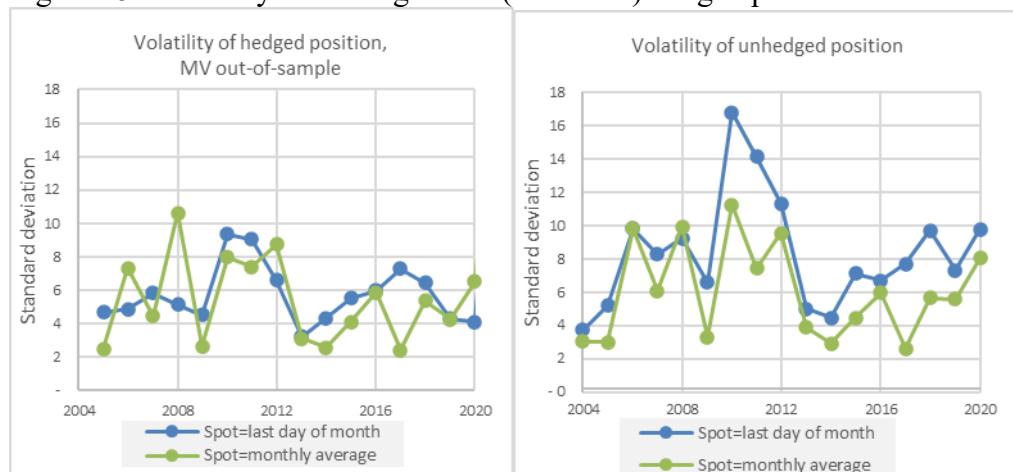
Further, we observe that GARCH is the best performing strategy in both cases, which is not that surprising considering we found autoregressive conditional heteroscedasticity (ARCH) effects in the data.

In case B, the Naïve hedge does extremely poorly around the years where the correlation between spot and futures are low, in some cases below  $-100\%$ , meaning that hedging actually more than doubles the variation compared to not hedging. This poor result for a constant 1 hedge ratio reflects that the optimal hedge ratios in this case is around 0.5 for all the other strategies.

When it comes to the difference in hedging effectiveness between case A and case B, it is important to recall how we measure effectiveness. When the spot is defined as the monthly average price, the unhedged position has lower volatility than if we define spot as the last day of the period price. Therefore, even though the volatility of the hedged position actually is quite similar in case A and case B, case B achieves lower hedge effectiveness because of the lower denominator.

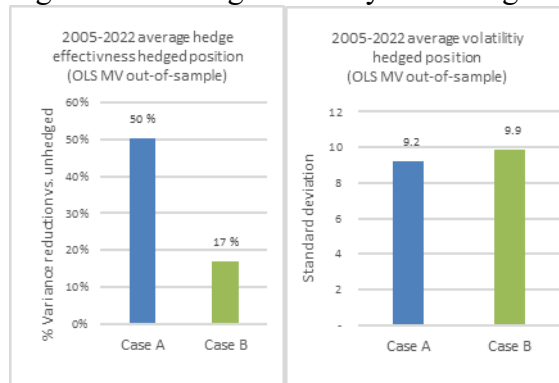
$$EHP_{k,Z} = 1 - \frac{\text{VAR}(\text{PH}(t_{i,k}))}{\text{VAR}(\text{PS}(t_{i,k}))}$$

Figure 15: Volatility of unhedged and (OLS MV) hedged positions.



While volatility is reduced in both case A and case B, the unhedged volatility in case A is higher than for case B and therefore Case A achieves a higher hedging effectiveness as measured by the var reduction definition. 2021 and 2022 are excluded in this graph as they are off the chart in order to see the variation between 2004 and 2020.

Figure 16: Average volatility of unhedged and (OLS MV) hedged positions.



While hedge effectiveness is much lower in case B than in case A, the volatility of the hedged positions in both cases are almost the same. This reflects the large impact of a different definition of the unhedged spot position used to calculate the hedge effectiveness.

While we have proven the statistical significance of the results, the economic significance is more up for subjective interpretation. Considering that case A, when applied to electricity markets, only hedges exposure of one single day at the end of the period, we find it more appropriate to look at the performance of case B, which covers exposure for the entire period, for evaluating usefulness in the real world.

For case B, the best hedge effectiveness we achieve is 19% variance reduction with the GARCH strategy, narrowly beating the OLS minimum variance strategy at 17%. While being low compared to hedging effectiveness in other commodity markets – which generally see risk reduction around 60-90% (Hanly et al., 2018), the variance reduction could in theory have some value in terms of smoothing cash flow of a market participant. However, when we consider the change in hedging effectiveness from year to year, as well as all the simplifying assumptions taken in our analysis, we consider the variance reduction of below 20% as not high enough to define it as an economically significant result, and we would not recommend a market participant to apply the strategies investigated here in the real world.



### 6.3 Application to other markets

To further evaluate the robustness of the various hedging strategies, we apply the same methodology to Germany and UK electricity markets with monthly futures traded monthly for the period 2014-2022, and compare this to results we get in Nord Pool for the same period. From the results in Table 6, we notice that the out-of-sample hedging performance is very poor in these markets, with results being mostly around 0% effectiveness or negative. These results are in line with (Hanly et al., 2018) which also compare these 3 markets and find best results for Nord Pool. Suggesting better hedging performance in less volatile markets, they comment that “Nord Pool is the least volatile market and that this probably reflects the production structure and generation fuel mix in each market. For example Norway has very large hydro generation capacity that is relatively flexible whereas the German market has relied on both nuclear and coal-fired generation that is less flexible (...) in addition to massive recent installation of renewables such as wind and solar (...)” (Hanly et al., 2018, p34).

Table 6: Results for Germany, UK and Nord Pool 2014-2022  
Germany 2014/1/1 - 2022/12/31:

	Case	IN SAMPLE			OUT OF SAMPLE			
		Naive	MV_in	EDS_in	Naive	MV_out	EDS_out	RMV
Hedge ratio	A	1	1.51	1.19	1	1.53	1.17	1.30
	B	1	0.87	0.74	1	0.90	0.76	0.82
Hedge effectiveness	A	23 %	35 %	31 %	23 %	-8 %	10 %	11 %
	B	-18 %	31 %	24 %	-18 %	-62 %	-1 %	4 %

UK 2014/1/1 - 2022/12/31:

	Case	IN SAMPLE			OUT OF SAMPLE			
		Naive	MV_in	EDS_in	Naive	MV_out	EDS_out	RMV
Hedge ratio	A	1	0.69	0.66	1	0.70	0.57	0.73
	B	1	0.55	0.59	1	0.57	0.56	0.48
Hedge effectiveness	A	-76 %	25 %	16 %	-76 %	-35 %	-40 %	-7 %
	B	-107 %	23 %	9 %	-107 %	-26 %	-14 %	2 %

Nord Pool 2014/1/1 - 2022/12/31:

	Case	IN SAMPLE			OUT OF SAMPLE			
		Naive	MV_in	EDS_in	Naive	MV_out	EDS_out	RMV
Hedge ratio	A	1	1.18	1.18	1	1.14	1.15	1.15
	B	1	0.34	0.51	1	0.35	0.52	0.40
Hedge effectiveness	A	62 %	66 %	61 %	62 %	55 %	55 %	52 %
	B	-37 %	16 %	6 %	-37 %	12 %	8 %	-2 %

#### 6.4 The basis as a predictor of future spot prices

The EDS hedging strategy is based on the premise that the current difference between future and spot price is a predictor of future spot price change. As a side note to our main analysis, we investigated if this theory holds in the Nord Pool electricity market with the data we have. We do this by running the following regression on monthly data for spot and futures;

$$\Delta_k S(t_i) = \alpha + \beta (F(t_{i-1}) - S(t_{i-1})) \quad (18)$$

The results we get from 226 monthly observations are summarized in Table 7. We find that the predictive power of the basis is not statistically significantly different from zero in either case A or case B. This result is coherent with the fact that we did not get significantly better results with the EDS strategy compared to the standard OLS minimum variance strategy. A plausible reason for the poor predictive power of the basis is in the nature of the electricity market – the electricity future is for a contract with electricity delivery in a different period than the current spot price. Because electricity cannot be stored, we do not have the cash-and-carry arbitrage mechanism present in other commodity and financial markets, and therefore we obtain lower predictive power of the basis compared to other studies on other markets.

Table 7: The basis as a predictor of future spot prices

Case	Average basis	Adjusted r squared	beta	St. error	t-stat	p- value
A	-2.36	7.25%	0.75	1.79	0.42	0.68
B	1.77	0.02%	0.07	0.73	0.09	0.93

## 7 Conclusion

Evaluating the hedging performance of monthly futures traded daily, weekly and monthly, as well as quarterly futures traded monthly and quarterly, we find the best results for monthly futures traded monthly where the results are statistically significantly better than zero in 8 out of total 10 scenarios (5 strategies x 2 cases). In case A we find that the hedging effectiveness is between 49% and 58% out-of-sample, and in case B between -23% and 21%. Even though the hedging effectiveness is higher when we define spot as the last day of the month (as is most common in the literature), we hence also reduce variance when defining spot as the average of the month – a definition we consider is more applicable in the real world for market participants.

On the other hand, the hedging effectiveness varies greatly between different time periods and markets. In addition to Nord Pool we apply the same methodology on UK and Germany from 2014 to 2022, but find lower hedging performance in these markets. Considering the relatively low variance reduction when defining spot as a monthly average, numerous simplifying assumptions and poor performance in other markets – we find it questionable whether futures with the strategies analyzed in this thesis are economically effective tools to hedge electricity market spot exposure.

While we followed the established literature and a rather theoretical and academic approach, other hedging methods could be more appropriate and applicable in the real world. For example, using contracts of various duration - and instead of closing them before maturity - holding them to maturity with different roll over strategies. Furthermore, measuring the hedging effectiveness on cash flow for a specific market participant instead of a hypothetical average would be an interesting future research topic. For example, a study on hedging opportunities for offshore wind considering the lower realized prices due to negative correlation between production and prices. Bergen Offshore Wind Center were kind enough to share detailed wind data with us as we had ambitions to incorporate that element, but unfortunately we ran out of time and will have to leave that topic for future research.

# Appendix

## Appendix 1. Variance and reduction per case(monthly futures traded monthly)

CASE A: VARIANCE										CASE A: VARIANCE REDUCTION VS SPOT									
SPOT	In-sample			Out-of-sample						SPOT	In-sample			Out-of-sample					
	Naive	MV	EDS	Naive	MV	EDS	RMV	GARCH	Naive		MV	EDS	RMV	GARCH					
2022	23 685	5 133	2 741	2 780	5 133	2 741	4 222	3 859	3 184										
2021	1 523	491	358	440	491	482	547	399	416	78 %	88 %	88 %	78 %	88 %	82 %	84 %	87 %		
2020	92	17	17	18	17	17	18	25	15	68 %	76 %	71 %	68 %	68 %	64 %	74 %	73 %		
2019	51	16	16	17	16	18	17	19	16	82 %	82 %	81 %	82 %	82 %	81 %	73 %	83 %		
2018	90	31	29	29	31	42	45	44	31	68 %	68 %	67 %	68 %	64 %	66 %	63 %	68 %		
2017	56	53	53	64	53	53	53	56	53	65 %	68 %	68 %	65 %	54 %	50 %	52 %	66 %		
2016	42	26	26	26	26	36	28	39	25	5 %	6 %	-14 %	5 %	6 %	6 %	0 %	6 %		
2015	48	20	16	18	20	31	25	19	19	38 %	39 %	39 %	38 %	15 %	35 %	8 %	40 %		
2014	18	18	16	16	18	19	19	19	21	58 %	67 %	63 %	58 %	36 %	49 %	60 %	61 %		
2013	23	3	3	3	3	10	5	7	3	2 %	13 %	10 %	2 %	-4 %	-4 %	-5 %	-14 %		
2012	123	49	32	34	49	44	40	34	50	85 %	86 %	86 %	85 %	55 %	77 %	70 %	86 %		
2011	195	80	78	79	80	82	79	89	81	60 %	74 %	72 %	60 %	65 %	68 %	73 %	59 %		
2010	276	87	86	109	87	87	89	118	68	59 %	60 %	59 %	59 %	58 %	59 %	54 %	59 %		
2009	41	18	17	18	18	21	21	21	17	69 %	69 %	60 %	69 %	68 %	68 %	57 %	75 %		
2008	82	25	23	23	25	27	25	33	25	56 %	58 %	55 %	56 %	49 %	49 %	47 %	58 %		
2007	65	32	28	28	32	34	34	35	31	69 %	71 %	71 %	69 %	67 %	70 %	60 %	69 %		
2006	92	22	20	21	22	24	80	26		52 %	57 %	57 %	52 %	48 %	47 %	47 %	53 %		
2005	25	22	21	29	22	22	22	24		76 %	78 %	78 %	76 %	74 %	13 %	72 %			
2004	13	5	5	5						11 %	15 %	-16 %	11 %	10 %	11 %	2 %			
Average	1 397	324	189	198	341	210	298	270	253	56 %	60 %	56 %	56 %	50 %	49 %	49 %	58 %		

CASE B: VARIANCE										CASE B: VARIANCE REDUCTION VS SPOT									
SPOT	In-sample			Out-of-sample						SPOT	In-sample			Out-of-sample					
	Naive	MV	EDS	Naive	MV	EDS	RMV	GARCH	Naive		MV	EDS	RMV	GARCH					
2022	5 149	10 110	4 664	5 344	10 110	4 949	4 972	7 203	4 571										
2021	522	618	437	437	618	445	438	551	432	-96 %	9 %	-4 %	-96 %	4 %	3 %	-40 %	11 %		
2020	62	57	41	43	57	42	43	44	40	-18 %	16 %	16 %	-18 %	15 %	16 %	-6 %	17 %		
2019	29	18	14	14	18	18	14	15	18	7 %	33 %	30 %	7 %	31 %	30 %	29 %	35 %		
2018	30	45	26	29	45	29	34	37	26	38 %	51 %	51 %	38 %	37 %	51 %	46 %	39 %		
2017	6	13	6	10	13	6	7	7	7	-51 %	13 %	3 %	-51 %	4 %	-14 %	-26 %	12 %		
2016	33	51	33	35	51	35	37	37	35	-118 %	0 %	-64 %	-118 %	0 %	-14 %	-14 %	-16 %		
2015	18	23	17	17	23	17	17	17	18	-52 %	0 %	-6 %	-52 %	-4 %	-11 %	-10 %	-5 %		
2014	7	10	6	6	10	7	7	7	7	-25 %	7 %	5 %	-25 %	7 %	7 %	4 %	3 %		
2013	13	12	9	9	12	10	9	13	9	-31 %	16 %	16 %	-31 %	12 %	12 %	6 %	8 %		
2012	88	69	68	71	69	76	69	74	69	14 %	37 %	37 %	14 %	29 %	36 %	7 %	36 %		
2011	52	91	45	61	91	55	56	55	53	21 %	22 %	18 %	21 %	13 %	21 %	16 %	21 %		
2010	122	70	39	39	70	64	40	47	42	-73 %	14 %	-16 %	-73 %	-5 %	-7 %	-4 %	-1 %		
2009	10	24	7	9	24	7	7	7	7	42 %	68 %	68 %	42 %	48 %	67 %	61 %	65 %		
2008	95	114	92	92	114	113	109	110	92	-147 %	26 %	4 %	-147 %	26 %	26 %	27 %	27 %		
2007	35	18	18	18	18	20	25	20	21	-20 %	3 %	3 %	-20 %	-19 %	-15 %	-16 %	3 %		
2006	92	60	50	59	60	54	50	59		48 %	48 %	48 %	48 %	43 %	29 %	41 %	40 %		
2005	8	8	6	6	8	6	6	6		35 %	46 %	37 %	35 %	42 %	46 %	36 %			
2004	8	8	7	7	8					-6 %	21 %	19 %	-6 %	21 %	20 %	19 %			
Average	336	601	294	332	601	331	330	462	340	-23 %	24 %	14 %	-23 %	17 %	17 %	10 %	19 %		

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