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Are the Nordic and German front month electricity futures prices cointegrated, and, if so, is it possible to develop a trading strategy based on this finding?

Master's thesis in Economics and Business Administration
Supervisor: Stein Frydenberg
May 2019

Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
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Kunnskap for en bedre verden

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Abstract

The fall of 2018 Einar Aas made a bet that the spread between Nordic and German electricity futures prices would converge, by going long in Nordic electricity prices and short in German electricity prices. The exact opposite happened, and he lost a huge amount of money. In this master thesis we investigate whether Nordic electricity futures and German electricity futures are cointegrated, and if it is possible to make a trading strategy based on this. We use The Engle-Granger Method and The Johansen and Juselius Method to test for cointegration. We find that there is cointegration between electricity futures in Nordic and Germany. We use this finding to create two separate trading strategies. One based on theory from Emery and Liu (2002), and one based on theory from Girma and Paulson (1999). The results from the trading strategies varied. Because of few statistically significant profits it seems like the market is efficient and that is not possible to gain any statistical arbitrage based on our strategies.

Sammendrag

Høsten 2018 veddet Einar Aas på at spreaden mellom nordiske og tyske futures på elektrisitetspriser skulle konvergere. Dette gjorde han ved å gå i en long-posisjon i nordiske strømpriser og en short-posisjon i tyske strømpriser. Det eksakt motsatte skjedde og han tapte enorme summer med penger. I denne masteroppgaven vil vi undersøke om det kan påvises kointegrasjon mellom futureskontrakter på nordiske og tyske strømpriser, og om det er mulig å utvikle en tradingstrategi basert på dette. Vi bruker Engle-Granger-metoden og Johansen og Juselius-metoden for å teste for kointegrasjon. Vi finner at det eksisterer kointegrasjon mellom futureskontraktene på nordiske og tyske strømpriser. Vi bruker dette funnet til å utvikle to separate tradingstrategier. Den ene strategien er basert på teori fra Emery and Liu (2002), mens den andre strategien er basert på teori fra Girma and Paulson (1999). Resultatene fra de to tradingstrategiene varierte noe og viser seg å være ustabile. På grunn av få statistisk signifikante profitter kan det virke som at markedet er effisient og det er ikke mulig med statistisk arbitrasje basert på våre strategier.

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We are responsible for all the content presented in this thesis and all potential errors are our own.

Trondheim May, 22 2019

Erik Liahjell Saue

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1 Introduction

The Energy Act established in 1991 opened for a liberalization of the power market in Norway, and the power exchange Nord Pool AS was established. The idea was that supply and demand should decide the electricity prices. In addition, the Nordic powerlines have been integrated with multiple other European countries, directly and indirectly, and new powerlines are on its way. Electricity is a commodity that cannot be stored in big quantities in an expedient way, and it must be consumed as soon as it is produced. This results in volatile prices, which opens for trading opportunities in the futures market.

One separates between the physical and financial power market. In the Nordic countries, Nord Pool ASA is a central exchange for physical power trading, while you can trade power financially settled through Nasdaq Commodities. A central exchange for financial power trading in the German market is the EEX. Unlike the physical market, you do not take power delivery in the financial market. The trades are cash settled. This opens for hedging opportunities for suppliers and demanders in the power market. In addition, traders can act in the financial market in hope of making money.

Einar Aas is a famous Norwegian power trader known for making money on power trading in the futures market, apparently by riding the term curve and being able to predict when the future curve shifted from contango to backwardation. Derivatives is a zero-sum game and what other wins, must other pay for. In early fall of 2018, Einar Aas all of a sudden lost at least NOK 1.3 billion on trading electricity (Bøe *et al.*, 2018). We became interested in the strategy that Einar Aas used in this trade. The trade he made was a so-called “spread-trade” between German and Nordic futures prices. His position would be profitable if the spread, i.e. the difference, between the prices converged. We have consequently investigated whether these prices are cointegrated. Do they have a long-term dependency?

A second motivation for this paper is to develop a spread-trading strategy that could be profitable in the long-run. The idea is to develop a strategy that let us know which position we should take when the spread between Nordic and German futures prices reaches a given level.

Research question: Are the Nordic and German front month electricity futures prices cointegrated, and, if so, is it possible to develop a trading strategy based on this finding?

In order to answer our research question, we will use the Engle-Granger method and the Johansen and Juselius method to check if the front month futures on Nordic and German electricity prices are cointegrated. If we find that the prices are cointegrated, we will exploit that relationship to develop trading strategies.

The thesis is organized as follows: In chapter 2 we briefly describe the power market and electricity price determination. Relevant literature regarding cointegration and trading strategies is presented in chapter 3. The methods we have used to answer our research question is described in chapter 4. Chapter 5 consists of data description. In chapter 6 and chapter 7 we show the empirical results for the cointegration analysis and the trading strategies respectively. In chapter 8, the results are discussed considering the literature presented in chapter 3. Finally, we conclude the thesis in chapter 9. Appendices are given in chapter 10.

2 The Power Market

In this chapter we will describe the power market more in detail. We provide a brief description of how the electricity prices are determined focusing on the Nordic market. Further, the energy mix in the Nordic and German area is given. Knowledge about this could give us a clue about what could affect the prices in the two areas, and hence eventual cointegration.

2.1 Price Formation

Electricity is not possible to store in large quantities and therefore differs from other commodities. It requires that production equals demand at any time. Day-ahead price formation is decided in the wholesale market, based on the actors' supply and demand, given available capacity. As a result of the short-term market adaptation, the cheapest production resources will be used first.

Every day, Nord Pool computes the system price for electricity in the following day. This is a theoretical price that is computed based on a prerequisite that there are no bottle necks in the Nordic transmission network. The system price is common for the Nordic market and works as a reference price for the price formation of the futures prices.

The producer's report how much they want to produce given a certain price level and the end users report how much they want to use given different price levels. The price is decided by the equilibrium between supply and demand in the day-ahead market.

Nord Pool also computes area prices that takes bottle necks in the transmission network into account. Area prices are those prices which creates a balance between supply and demand offers from the actors within the different bid areas in the Nordic market. The reason why bottle necks and different electricity prices between areas can occur is because of different regional power situations that can vary between seasons and years (EnergifaktaNorge, 2019).

General price determination can be described by the *merit order curve (Omland, 2018)*. The curve shows the distribution of marginal costs from different power production technologies. Hydropower has almost no marginal costs due to the input (water) being simply free. On the other hand, production from fossil fuels have higher marginal costs because of the need to buy commodities like coal, natural gas and oil to drift the power plants. The merit order curve shows that in periods with low demand, the cheapest production technologies will be used, like hydropower in the Nordic market. When the demand is high, one must start up more expensive production methods like coal or gas turbines. In case of high demand in the Nordic area, we must import electricity from European power plants drifted by e.g. coal and gas. Therefore, the system price in Nord Pool will be affected by the European market. In addition to this, electricity supply will go from low price areas to high price areas, increasing the integration between areas. If energy input like coal will be the marginal energy input used to cover the demand, it is natural to assume that electricity prices in Nordic and Germany will converge.

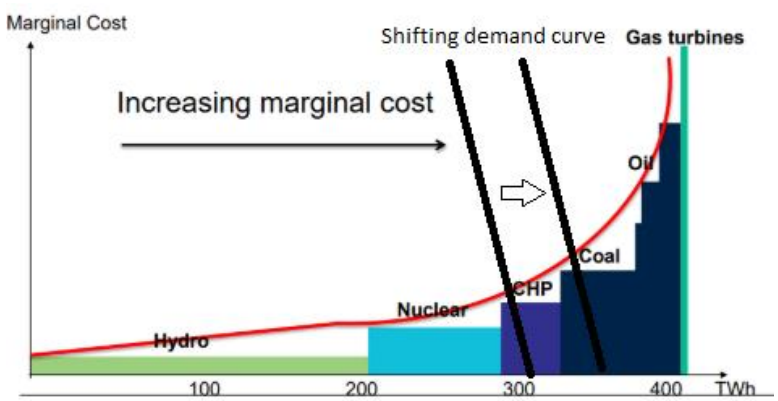

Figure 2.1: The merit order curve with shifting demand curves. As demand increases more expensive electricity production methods will be used to cover it. Figure shows a merit order curve from the Nord Pool area (Stavseth, 2014).

2.2 The Physical Power Market

The power market can be divided into a physical market and a financial market as mentioned earlier. In the Nordic region, Nord Pool AS is the main exchange for trading, while EPEX SPOT SE has the same role in Germany. We will now shortly describe these exchanges.

2.2.1 Nord Pool AS

Nord Pool AS is the physical power exchange for the Nordic countries including Norway, Sweden, Denmark, Finland, and the Baltic states. The establishment of Nord Pool started with the deregulation of the Norwegian electricity market in 1991. In 1993 Statnett Marked, the origin of Nord Pool, was established. The name Nord Pool was invented in 1996 when Norway and Sweden started a joint power exchange. The other countries in Nord Pool have joined thereafter with Latvia being the last country in 2013. Nord Pool's spot exchange is divided into a day-ahead market and an intraday market. As explained above, the system price for the following day is decided based on the market participants bid and offers. The day-ahead market is called Elspot (Electrical Spot Market). In addition to the Elspot, Nord Pool offers an intraday market called Elbas (Electrical Balancing Adjustment System) with continuous trading up to one hour before delivery. The Elbas market helps balancing between supply and demand. If the market participants do not produce and/or consume what they have decided in the Elspot market, this causes an imbalance. This is where the Elbas market comes into play, giving the opportunity to rebalance supply and demand (Stavseth, 2014).

2.2.2 EPEX SPOT SE

EPEX SPOT is the exchange for physical power in Germany, France, UK, the Netherlands, Belgium, Austria, Switzerland and Luxembourg. The company was founded in 2008. The power trading is organised in a similar way like Nord Pool with a day-ahead market and an intraday market. In the day-ahead market, the members specify the quantity and price for which they are interested to buy and sell for each hour the next day. EPEX SPOT then match the supply and demand and the spot price is determined by the equilibrium. The intraday market is organised by continuous trading. Here the participants get the opportunity to buy and sell electricity which is not determined day-ahead (EpexSpot, 2019).

2.3 The Financial Power Market

In the financial power market, the trades are cash settled, and the spot prices works as a basis for the derivative prices. In the futures market, one receives or pay, dependent on the type of position, the difference from yesterday's settlement price to today's settlement price. This is the *mark-to-market* principle. Market participant use the financial power market to hedge their positions. Traders can use the market to try making profit. In the Nordic region, NASDAQ OMX Commodities is an important exchange, while EEX is central in Germany.

2.3.1 NASDAQ OMX Commodities

The story behind the financial power market on NASDAQ OMX Commodities, started with Nord Pool establishing an exchange for trading and clearing financial power contracts in 1996 (Nasdaq, 2019). In 2008, Nord Pool's financial power exchange was acquired by NASDAQ OMX. The exchange offers a range of products, including futures contracts and options with different maturities, and contracts for difference (CFDs) used to hedge against area price differences.

2.3.2 EEX

The European Energy Exchange AG (EEX) was founded in 2002 and is Germany's energy exchange and the leading one in Europe. EEX owns 51 percent of EPEX SPOT. The company offers trading in several products including power derivatives, natural gas and emission allowances. For power contracts like futures, it is possible to trade contracts up to six years in the future (*European Energy Exchange*, 2018).

2.4 Nordic and German Power Production

The energy mix in the Nordic countries and in Germany is different. In the Nordic area, renewable energy is a major part of the power generation, and hydropower is the production method that generates the most electricity. Dams and reservoirs are often used in hydropower production, but rivers can also be applied. Figure 2.2 shows that 52 % of the Nordic energy mix came from hydropower in 2013. Wind power and other renewable energy sources represented 3 % and 7 % respectively. This means that more than 60 % of the energy mix is renewable (Stavseth, 2014). This is a distinct contrast from Germany's energy mix where approximately 32 % of the power production comes from renewable energy sources (Amelang and Wehrmann, 2019). Figure 2.3 shows that in 2018, about 50 % of the energy mix in Germany was thermic, including lignite and hard coal, natural gas, and mineral oil. Because of the high share of fossil fuels in the power production, German electricity prices will be affected by the carbon emission price. One can expect a higher share of renewable energy sources going forward. The EU has a directive called The Renewable Energy Directive, where the goal is to fulfil minimum 20 % of EUs energy needs with renewables by 2020. This directive was revised in 2016 with a new goal for 2030 where 27 % of the energy need comes from renewables (*Renewable energy directive*, 2018).

Focusing on our research question whether Nordic and German electricity prices are cointegrated, the energy input described in this section will be important. The merit order curve discussed in section 2.1 shows that electricity production using coal and gas are more expensive than e.g. hydropower. Looking separately at the two areas, we would expect that in general the Nordic electricity prices will be cheaper than the German electricity prices. This is due to the heavy use of hydropower, which we could see from the merit order curve are one of the cheapest production methods. The fact that the energy mix in the two areas are different could be an argument in favour of the prices *not* being cointegrated. But the markets do not operate in a vacuum.

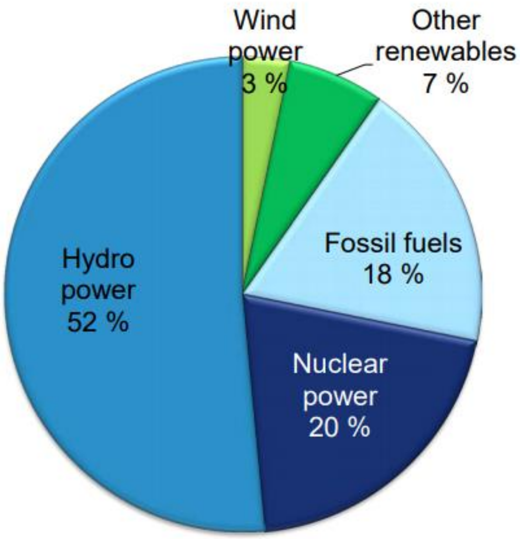

Figure 2.2: Nordic energy mix (Stavseth, 2014)

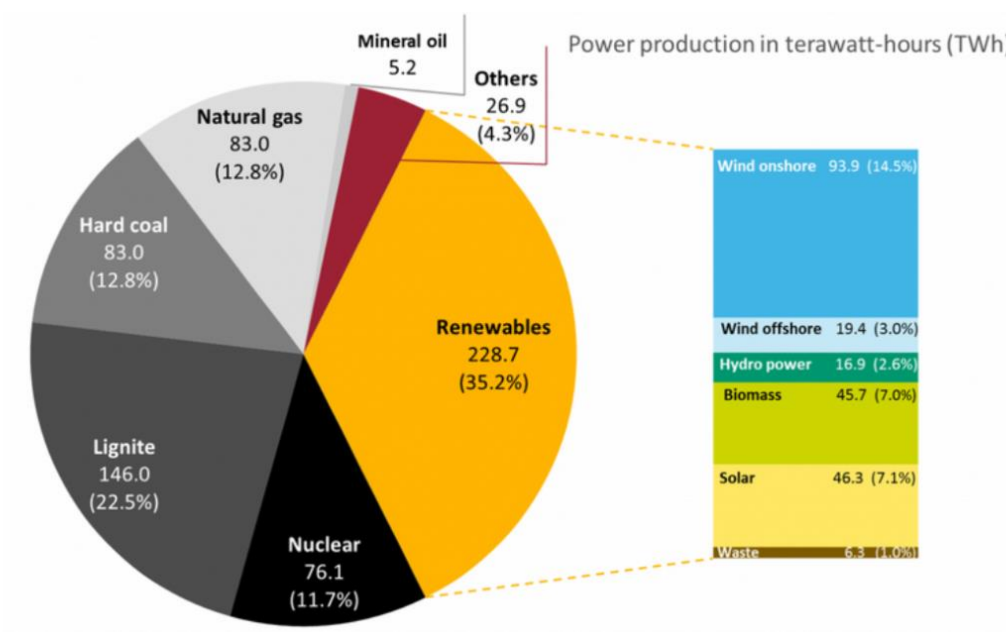

Figure 2.3: German energy mix (Amelang and Wehrmann, 2019).

3 Literature

This chapter provides a brief overview of research that have investigated similar questions as we will in this thesis. To the authors knowledge there are not so much research in the field of cointegration between Nordic and German electricity *futures* prices, except the articles by Aatola, Ollikainen and Toppinen (2013) and Povh and Fleten (2009) which will be discussed below. However, cointegration in the spot market is discussed to a greater extent in the literature.

We have not succeeded in finding any literature that investigates trading strategies between Nordic and German electricity futures in the two markets (or other electricity pairs for that matter). Therefore, we highlight literature that investigates trading strategies using other kinds of spread trades.

3.1 Literature Review – Cointegration Analysis

If two prices are cointegrated, it means that they are connected in the long run. In our case we will look especially on the cointegration between Nordic and German front month futures prices. One important question is: Why should these prices be cointegrated? The EU has for a while attempted to create a European wholesale market for electricity. The first step towards this was taken in 1996 with EU Directive 96/92/EC. Here EU defined common rules for the generation, transmission and distribution of electricity aimed at creating an efficient European market (Gebhardt and Höffler, 2007). Since then several cross-border interconnectors have been developed. Extended market coupling will lead to electricity flowing from low to high price areas, increasing the convergence in electricity prices across areas. More interconnections will be built. An interconnection between Norway and UK called Northconnect is on the way. Also, a direct power cable between Norway and Germany will begin operations in 2020. The project is called NordLink and is a 1.4-gigawatt interconnector which will export hydro power from Norway to Germany, but also import power from Germany to Norway (Karagiannopoulos, 2018).

A classic explanation on market integration is the Law of One Price (LOP) (Fetter, 1924). This theory states that in an efficient market, homogeneous products (like electricity) will trade for the same price. Electricity markets are not fully efficient. For example, capacity restrictions create different prices across areas. Price convergence can, on the other hand, be partially, i.e. the prices approximate each other, but are not always the same (Gugler, Haxhimusa and Liebensteiner, 2018). Similar studies are done by e.g. Chen and Knez (1995) who argues that integrated markets should have closely related prices, like a law of *similar* prices rather than the Law of One Price. Gugler, Haxhimusa and Liebensteiner (2018) says that electricity markets originally were designed to meet national demands, which causes complications when trying to interconnect different markets. Good interconnections between markets is a prerequisite for prices being cointegrated.

We will present some of the literature that highlights the question if cointegration between Nordic and German electricity prices exists. Bower (2004) looks at integration in daily spot prices across Europe in 2001 using both correlation and cointegration analysis. He finds that daily price changes were correlated within Nord Pool locations, but not between other areas. The correlation between the Nord Pool system price and the German EEX/LPX (the EEX and LPX markets are now merged) system price was low with 0.19 during the period. The cointegration analysis using the Engle-Granger method shows that there is no significant cointegration on a 10 % level between Nord Pool and EEX in the period. There is significant cointegration between Nord Pool and LPX on a 10 % level, but not on a 5 % level.

de Menezes and Houllier (2016) performs a fractional cointegration analysis including daily spot price analysis in the Nordic and German/Netherland area in the time period February 2000 to March 2013. They find that the cointegration between Nord Pool and the other markets were low with only 28 % of the days with the German market. However, they find an increase in cointegrated days from the second half of 2008 and wonder if this could be due to the NorNed interconnector between Norway and Netherland, which opened on May 6, 2008. In addition, the authors find that most forward prices they investigated were more cointegrated than spot prices. However, they did not look at forward price cointegration between Nord Pool and Germany.

Aatola, Ollikainen and Toppinen (2013) study the impact of the carbon price on the integrating electricity market in the EU using daily forward data from February 2003 to August 2011. They find that the carbon price has a positive, but uneven impact on the integration of the prices. In addition, they find that price convergence across the markets have increased in recent years.

Dividing the period into the three sub-periods 2003-2004, 2005-2007 and 2008-2011, they use both correlation and cointegration analysis to study the convergence. Focusing on the relationship between Nordic and German forward electricity prices, Aatola, Ollikainen and Toppinen (2013) find that the correlation between the time series shifts from -0.429 in the first sub-period, to 0.906 and 0.923 in the last two sub-periods. Using a VECM approach they find increasing market integration between Nordic and Germany during the sub-periods. The last cointegrating vector between Nordic and Germany shows that a 1 % increase in German forward prices leads to an 0.71 % increase in Nordic forward prices, showing a clear deepening in integration from earlier sub-periods. The vector also indicates a significant stationary relationship between Nordic, Germany and CO2 emission allowances.

Povh and Fleten (2009) used a VECM approach when they modelled long-term electricity forward prices. They modelled Nord Pool and EEX electricity forwards using weekly data of far-maturity forwards (maturity > 1 year). The model included forward prices for coal, gas, emission allowances and aluminium. There were some substantial shocks during the period. However, they do not find any evidence of a structural break. The cointegration analysis revealed two stationary long-run relationships between all variables except gas. They highlight one of the cointegrating vectors as especially interesting, representing a linear combination of Nord Pool, coal, emission allowances, EEX and aluminium prices. The relationship show that Nord Pool weekly forward prices fall almost one to one with an EEX price increase. The reason for this, according to Povh and Fleten (2009), is that since these two prices are strongly positively correlated, a positive shock occurring in the EEX price in the last period would most likely also have happened in the Nord Pool price. The cointegrating vector will then pull the Nord Pool price back down in the next period. The adjustment parameter, α, for this equation is -0.18 and significant. This means that 18 % of the disequilibrium will be reverted each week, ceteris paribus.

Looking more specifically at the price formation in Nordic and Germany, Redl et al. (2009) try to explain year-ahead forward prices at EEX and Nord Pool using an econometric analysis from December 2004 to April 2008. They find that although the EEX and Nord Pool market are physically weakly interconnected, main characteristics regarding price formation on the forward markets are alike. The prices depend to a high degree on generation costs, also in the Nord Pool area. In general, Nord Pool forward prices are lower than EEX forward prices due to heavy use of hydro power.

The findings by Redl *et al.* (2009) is comparable to an analysis conducted by Emery and Liu (2002). They find that electricity and natural gas future prices are cointegrated in a study using daily settlement prices from March 1996 to March 2000 for the first near-by natural gas futures, and California-Oregon Border (COB) and Palo Verde (PV) electricity futures. They find that there are no significant differences in sensitivities of electricity prices in the areas COB and PV to changes in natural gas prices. These two areas are comparable to Nordic and Germany regarding energy mix. In the PV market, a great amount of the power is generated using natural gas and coal, while in the COB market, about 65 % of the energy mix consists of hydropower. The findings by Emery and Liu (2002) show that fossil fuels often will be the marginal fuel used to generate power.

Summarizing this section, the literature is not coherent about if Nordic and German electricity prices are cointegrated. Especially earlier studies, as the one by Bower (2004) show no significant cointegration. de Menezes and Houllier (2016) found cointegration 28 % of the time. Aatola, Ollikainen and Toppinen (2013) and Povh and Fleten (2009) on the other hand found that the markets were cointegrated. However, the link between the articles seems to be that the markets have become increasingly integrated the last years.

3.2 Literature Review – Spread Trading

As mentioned, we have not succeeded in finding any literature regarding spread trades using two or more electricity futures. Therefore, we present literature investigating other commodity spread trades.

An important background when discussing trading strategies is the efficient market hypothesis (EMH). This hypothesis is formulated by Malkiel and Fama (1970), and states that if financial markets truly are efficient, prices absorb and reflect all available information as soon as it reaches the market. This is shortly discussed in Girma and Paulson (1999) where they state that any trading strategy should not generate profits that are significantly greater than zero, given an efficient market. However, both Girma and Paulson (1999) and Emery and Liu (2002) investigates spread trading strategies that yield profits significantly greater than zero. A reason for this is debated by Gatev, Goetzmann and Rouwenhorst (2006) where they argue that any abnormal returns from spread trading could be a compensation to arbitrageurs for enforcing the "Law of One Price".

Girma and Paulson (1999) investigates risk arbitrage opportunities in three traded petroleum futures spreads using daily futures prices of crude oil, heating oil and unleaded gasoline from April 1983 to December 1994. The article builds on cointegration as a statistical background for investigating spread trading opportunities. Furthermore, they discuss the problem regarding return calculations on future positions, concluding that it is more convenient to use dollar returns rather than percentage returns. The authors use a rolling 5- and 10-day moving average and standard deviations from ± 1.50 to 2.50 to identify "extreme" spreads. The results show that historically profitable risk arbitrage opportunities existed and were statistically significant between the mid-1980s and mid-1990s. Even though they focused on dollar returns rather than percentage returns, they performed a quick analysis of possible percentage returns. The lowest profits for the three spreads they investigated resulted in a 15.58 %, 17,55 % and 17.82 % annual rate of return after transaction costs.

Emery and Liu (2002) investigate the relationship between electricity futures in the California-Oregon Border (COB) and Palo Verde (PV) and natural gas futures prices and develops trading strategies between the spreads. This is known as the *spark spread*. Data are daily settlement prices from March 1996 to March 2000. Their trading strategy is implemented by regressing electricity on gas and using the residual from the equation to determine when the electricity price is different from its equilibrium value. They define the "extremes" using standard deviations from 0.25 to 1.00. The results show that the trading model proved profitable both in- and out-of-sample. Long positions in the spread proved more profitable than short positions.

Cummins and Bucca (2012) investigate trading in oil-based markets, with focus on WTI, Brent, heating oil and gas oil. They considered 861 spreads. The profits presented are aggregated by long and short positions in the spread. Cummins and Bucca's strategy yield average daily returns within the range of 0.07–0.35 % with Sharpe ratios that mostly exceed 2, and even in some cases are close to 4. The lowest Sharpe ratio they find is 1.73.

Gatev, Goetzmann and Rouwenhorst (2006) performed pairs trading with daily data of stocks from 1962-2002. Pairs are opened when they diverge by more than two historical standard deviations and are closed at the next crossing of prices. Their best-performing pairs yield average annualized excess returns up to 11 %, and an annualized Sharpe ratio (using daily data) of 2.14. Using the risk factors introduced by Fama and French (market, small-big, high-low etc.) (Fama and French, 1996), they find that the returns generated is not explained by these factors, but they link it to the presence of a latent risk factor abovementioned of compensating arbitrageurs for enforcing the Law of One Price.

4 Method

This chapter consists of relevant methods we have used for answering our research question. First, we go through our research methods used for exploiting eventual cointegration between Nordic and German electricity futures (in addition to other variables). The two methods we use are the Engle-Granger method and the Johansen and Juselius method. Second, we present the trading strategies, and we show how we have calculated the profits from the spread trades. The first trading strategy is based on the work by Emery and Liu (2002), while the second strategy is based on Girma and Paulson (1999). In the end we go through some possible error sources in this thesis. We first discuss the concept of stationarity, as it is important to understand cointegration.

4.1 Stationarity and Unit Root Tests

We are estimating and testing time series data, so the concept of stationarity is important. Performing a regression using non-stationary time series variables could lead to spurious regressions. This is because the variables can have a common stochastic trend giving significant results, even though there are no relationship between the variables. Often, economic time series are non-stationary in level form (price form), and stationary when differentiated. If this is the case, the variables are integrated of order one, I(1), in level form, and integrated of order zero, I(0), when differentiated.

The following requirements must hold for a stochastic process to be stationary:

1) $\mathrm{E}\left[X_t\right]$ = constant for all t (4.1)

   Constant mean across the time series. Fluctuations will be around the expected value.

2) $Var\left[X_t\right]$ = constant for all t (4.2)

   Constant variance across the time series.

3) $Cov\left[X_t, X_{t-s}\right]$ (4.3)

   Covariance only dependent on the time distance t-s, but not by t. In addition, we require that the autocorrelation approximates zero as s increases.

When testing for stationarity, we use the so-called unit root tests. The null hypothesis is that a time series is non-stationary, and the alternative hypothesis is that it is stationary. We get the following hypotheses:

$$\begin{aligned} H_0 &: X_t \sim I(1) \\ H_1 &: X_t \sim I(0) \end{aligned} \tag{4.4}$$

A common test for unit roots is the Dickey-Fuller test. The test procedure is described in Practical Financial Econometrics by Carol Alexander (Alexander, 2008), and it is based on the following regression:

$$\Delta X_t = \alpha + \beta X_{t-1} + \varepsilon_t \tag{4.5}$$

The test statistic is the t ratio on β , and tests for

$$\begin{aligned} H_0 &: \beta = 0 \\ H_1 &: \beta < 0 \end{aligned} \tag{4.6}$$

We can see why this test applies to the null and alternative hypotheses, assuming the data are generated by an AR(1) process of the form

$$X_t = \alpha + \rho X_{t-1} + \varepsilon_t, \qquad \text{with } \varepsilon_t \sim I(0). \tag{4.7}$$

Then, $\beta = \rho - 1$, and the hypotheses above are equal to

$$\begin{aligned} &H_0 : \rho = 1 \\ &H_1 : \rho < 1 \end{aligned} \tag{4.8}$$

where the null hypothesis imply that the time series are non-stationary, and the alternative hypothesis imply that the time series are stationary.

A common problem in the Dickey-Fuller test, is that their critical values could be biased if there is autocorrelation in the residuals from the regression. Therefore, Dickey and Fuller developed the Augmented Dickey Fuller test, where one includes lagged dependent variables to get rid of any residual autocorrelation. This test is based on the following regression:

$$\Delta X_t = \alpha + \beta X_{t-1} + \gamma_1 \Delta X_{t-1} + ... + \gamma_q \Delta X_{t-q} + \varepsilon_t \tag{4.9}$$

, where q is the number of lags required to get rid of the autocorrelation. The test proceeds as above, but the critical values are different.

4.2 Cointegration

We are interested in checking if the spread between Nordic and German futures prices are mean reverting, i.e. that the spread between the prices will revert to mean in the long run. A method commonly used for this purpose is cointegration analysis. When defining cointegration, we use Practical Financial Econometrics by Carol Alexander (Alexander, 2008). Cointegration is a way to determine if two or more prices have a common stochastic trend. If so, the prices will be connected in the long run. But they can drift apart in the short run. It is important to state that even though prices historically have been cointegrated, this can stop being the case. One must be aware that cointegration and correlation is not the same. High correlation does not necessarily imply cointegration, and vice versa. Correlation reflects co-movements in returns, which are liable to great instabilities over time. Return have no “memory” of a trend, so correlation is intrinsically a short-term measure (Alexander, 2008).

If we have a case of two integrated series, X and Y, which both are integrated of order one, i.e. I(1), they are cointegrated if there exists an α such that Z = X – αY is stationary.

One implication of finding cointegrated relationship in the financial market is that we can create a trading strategy based on mean reversion, where we short the highest priced security and go long the lowest priced security if the spread is significantly different from its mean. This kind of trading is called *statistical arbitrage*.

A cointegrating vector is the vector of constant coefficients in Z. There can be a maximum of n-1 vectors, where n is the number of variables in the system. Each stationary linear combination acts like "glue" in the system. This means that the more cointegrating vectors there is, the greater the long-term association between the series (Alexander, 2008).

Below we go through the two methods used to determine if there is a cointegrating relationship between Nordic and German electricity futures. The explanations are based on Alexander (2008).

4.2.1 The Engle-Granger Method

The Engle-Granger methodology is a simple test for cointegration. The idea is to perform an OLS regression of one integrated, I(1), variable on the other integrated variables. After this is done, a unit root test to the residuals is applied. The unit root test is described in section 4.1.

Let $X_1, \ldots, X_n$ denote the integrated variables, e.g. a set of (log) prices. We choose one of the variables as a dependent variable and perform a regression of the form:

$$X_{1t} = \beta_1 + \beta_2 X_{2t} + \ldots + \beta_n X_{nt} + \varepsilon_t \tag{4.10}$$

This is called the Engle-Granger regression and the test for unit roots is done to the residuals from the above regression. If the test indicates stationary residuals, then the variables $X_1, \ldots, X_n$ are cointegrated with the cointegrating vector $(1, -\hat{\beta}_2, \ldots, -\hat{\beta}_n)$. Then $Z = X_1 - \hat{\beta}_2 X_2 - \ldots - \hat{\beta}_n X_n$ is a stationary linear combination of integrated variables whose mean represents the long run equilibrium.

If we have a significant stationary linear combination of integrated variables, we can develop an error correction model (ECM). Below we illustrate ECMs for two cointegrated prices:

$$\Delta X_t = \alpha_1 + \sum_{i=1}^{m} \beta_{11}^{i} \Delta X_{t-i} + \sum_{i=1}^{m} \beta_{12}^{i} \Delta Y_{t-i} + \gamma_1 Z_{t-1} + \varepsilon_{1t}$$
$$\Delta Y_t = \alpha_2 + \sum_{i=1}^{m} \beta_{21}^{i} \Delta X_{t-i} + \sum_{i=1}^{m} \beta_{22}^{i} \Delta Y_{t-i} + \gamma_2 Z_{t-1} + \varepsilon_{2t} \quad (4.11)$$

where Z_{t-1} is the disequilibrium term shown in equation 4.11 and describes the long-term dynamics of the model. The magnitude of the gamma coefficients determines the speed of adjustment back to the long-term equilibrium. The short-term dynamics are given by the differenced variables.

Alexander (2008) describes two problems with the Engle-Granger test. When the number of variables is greater than two, the result of the test will depend on the choice of dependent variable. If we use another variable as dependent, the cointegrating vector will be different. Second, the test allows us to just estimate one cointegrating vector, even though there could be up to n-1 cointegrating vectors in a system of n integrated series. Only when n = 2 it does not matter which variable is chosen as a dependent variable. Because we have several integrated prices, we choose to use the Johansen and Juselius methodology to find on the number of cointegrated vectors.

4.2.2 The Johansen and Juselius Method

Johansen and Juselius' test can be thought of as a multivariate generalisation of the unit root test. The variables $\{Y_1, Y_2, ..., Y_n\}$ can be represented as a first order vector autoregressive process (VAR):

$$\mathbf{Y} = \alpha + \beta \mathbf{Y}_{t-1} + \varepsilon_t \quad (4.12)$$

If we take the first difference on both sides, we have the setup for an ADF test with multiple variables.

$$\Delta \mathbf{Y} = \alpha + \prod \mathbf{Y}_{t-1} + \varepsilon_t \quad (4.13)$$

Here, $\prod = \mathbf{B} - \mathbf{I}$, where I is the n x n identity matrix. In the ADF test we can add the number of lagged dependent variables required to get rid of any residual autocorrelation. Likewise, we can add lags of differenced observed variables to control for serial correlation. We then get the following equation:

$$\Delta \mathbf{Y} = \alpha + \prod \mathbf{Y}_{t-1} + \Gamma \Delta \mathbf{Y}_{t-1} + \Gamma \Delta \mathbf{Y}_{t-2} + ... + \Gamma_m \Delta \mathbf{Y}_{t-m} + \varepsilon_t \tag{4.14}$$

In this equation, m is the number of lags needed to correct for residual autocorrelation. If each of the variables $\{Y_1, Y_2, ..., Y_n\}$ is integrated, each equation in (4.14) has a stationary dependent variable so the right hand-side must also represent a stationary process. Then, $\prod \mathbf{Y}_{t-1}$ must be stationary. To determine how many linear relationships between the variables that are stationary, one must find the rank of $\prod$. The trace test is recommended by Johansen and Juselius to test for the number r of non-zero eigenvalues in $\prod$:

$$\begin{aligned} &H_0 : r \leq R \\ &H_1 : r > R \end{aligned} \tag{4.15}$$

With test statistics:

$$Tr = -T \sum_{i=R+1}^{n} \ln(1-\lambda_i) \tag{4.16}$$

Where,

R = rank number

T = sample size

n = number of variables in the system

Eigenvalues of $\prod$ are real numbers such that $1 > \lambda_1 > ... > \lambda_n \geq 0$.

Critical values of the trace (Tr) statistics are found in Johansen and Juselius (1990).

4.3 Trading Strategies

The first practice of statistical pairs trading is attributed to Wall Street quant Nunzio Tartaglia, who worked for the American investment bank Morgan Stanley in the mid-1980s. He assembled a group of mathematicians, physicists, and computer scientists. Their mission was to develop quantitative arbitrage strategies using state-of-the-art statistical techniques. The strategies developed by the group were automated to the point where they could generate trades in a mechanical fashion and, if needed, execute them seamlessly through automated trading systems. One of the techniques they used for trading involved trading securities in pairs. The process involved identifying pairs of securities whose prices tended to move together. Whenever an anomaly in the relationship was noticed, the pair would be traded with the idea that the anomaly would correct itself. This came to be known on the street as "pairs trading" (Vidyamurthy, 2004). Tartaglia justified the pairs trading strategy in a psychological way and claimed: "… Human beings don't like to trade against human nature, which wants to buy stocks after they go up not down" (Hansell, 1989).

We want to examine if it is possible to gain profits by spread trading in Nordic and German front month future prices. This prerequisite that the prices are cointegrated. If so, we could develop a trading strategy where we hope for convergence in the prices. We will then go short in the highest priced futures price and go long in the cheapest futures price. We have used two pairs trading strategies described below.

4.3.1 Trading Strategy Based on Emery and Liu

This trading strategy is built on the rules described by Emery and Liu (2002). If two prices are cointegrated, the spread between them tends to revert to the equilibrium given by the following equation (here using Nordic and German futures prices as an example):

$$ElNP_t = \beta_0 + \beta_1 ElGer_t + \varepsilon_t \tag{4.17}$$

where $ElNP_t$ is the front month electricity futures price in Nordic at time t, and $ElGer_t$ is the corresponding futures price in Germany at time t.

We define our spread as ElNP - ElGer. When the spread is positive, we go short (sell) ElNP and go long (buy) ElGer, and when the spread is negative, we go long (buy) ElNP and short (sell) ElGer. The positions are opened when the spread reaches a given size, while the positions are closed when the spread reaches equilibrium.

A position that is open when the first near-by contract stops trading is closed that day and reopened the following day when the new first near-by contract starts trading in Emery and Liu's strategy. We will follow the same strategy as we set the return on a rollover date to be zero as explained in section 4.5.1. We assume that all trades are done at the settlement price of the day the appropriate trading rule is satisfied. This also means that the settlement price is used when calculating profits.

As Emery and Liu (2002), we considered the spread between Nordic and German electricity futures to be different from its equilibrium value when the residual from the equilibrium equation 4.17 is more than φ standard deviations (denoted by σ) away from its mean of zero.

Our trading rules is summarized as:

Long positions:
Buy 1 contract (1 MWh) of ElNP and sell β_1 contracts (β_1 MWh) of ElGer when the residual $< -\varphi\sigma$.
Close position when the residual ≥ 0.

Short positions:
Sell 1 contract (1 MWh) of ElNP and buy β_1 contracts (β_1 MWhs) of ElGer when the residual $> \varphi\sigma$.
Close position when the residual ≤ 0.

$\varphi = 0.25, 0.50, 0.75$ and 1.00; β_1 = the number of ElGer contracts per contract of ElNP; σ = std. deviation of residuals from equation 4.17.

The profit calculation is described in section 4.4.

4.3.2 Trading Strategy based on Girma and Paulson

This strategy is based on Girma and Paulson (1999). The idea is to enter a position if the spread is e.g. above or below two standard deviations from the moving average. If it is, the spread is "extreme". What distinguishes our method from theirs is that we enter a position the *second* time the spread breaks through the moving average, in the same way as Herlemont (2003). This will hopefully help us to avoid riding an e.g. upward-trending spread if we are short and vice versa for long positions. Herlemont (2003) closed his positions when 20 % of initial size of the position were lost and no position were kept more than fifty days. We choose to not include these restrictions as this will vary depending on how risk averse the trader is. Using a snapshot from our time series, our trading strategy can be illustrated like this:

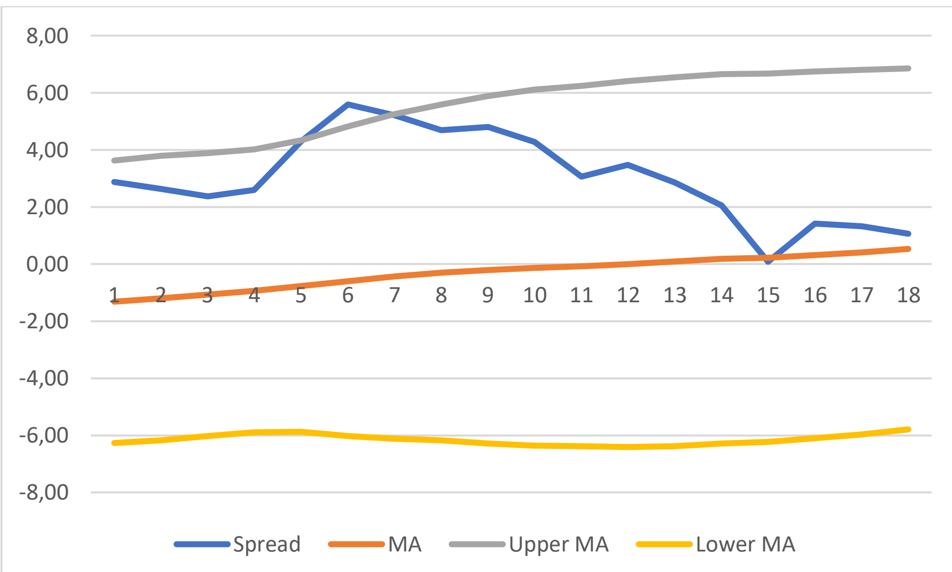

Figure 4.1: Snapshot from our time series showing the spread, the moving average, and the upper and lower moving average. Time is on the x-axis and spread difference in Euros is on the y-axis. A short position is opened when the spread breaks through the upper/lower moving average for the second time. The position is closed when it breaks through the moving average. In this figure a short position in the spread will be opened appr. on time 7, and it will be closed on time 15.

We open a short position in the spread on time t if

$$P_{t-1} > \mathrm{MA}_{t-1} + \mathrm{B} \cdot SD_{t-1} \text{ and } P_t < \mathrm{MA}_t + \mathrm{B} \cdot SD_t \tag{4.18}$$

Likewise, we open a long position in the spread on time t if

$$P_{t-1} < \mathrm{MA}_{t-1} - \mathrm{B} \cdot SD_{t-1} \text{ and } P_t > \mathrm{MA}_t - \mathrm{B} \cdot SD_t \tag{4.19}$$

where P_t is the spread at time t, MA_t is the moving average at time t, B is the number of standard deviations chosen, and SD_t is the standard deviation at time t.

The position is closed when the spread breaks through the moving average.

The moving averages are calculated in the following way:

$$\mathrm{MA}_t = \frac{1}{L}\sum_{l=0}^{L} P_{t-l} \tag{4.20}$$

The standard deviation is calculated in the following way:

$$SD_t = \frac{1}{L-1}\sqrt{\sum_{l=0}^{L}(P_{t-l} - \mathrm{MA}_t)^2} \tag{4.21}$$

where L is the number of trading days used for calculating the moving average and the standard deviation.

The method for return calculation is presented in section 4.4.

4.4 Calculating Profits in Futures Spread Trading

A problem arising when using future contracts in trading is how to calculate the return. Girma and Paulson (1999) discuss this problem. There is no cash outlay when buying or selling futures, unlike when investing in e.g. shares. The problem is what to be chosen as the appropriate investment. Could this be the margin required, or the required capital? Their paper measures profits in terms of dollars rather than returns. Like both Girma and Paulson (1999) and Emery and Liu (2002), we will calculate the percentage of profitable returns and use a t-test to check if the average profit per trade is significantly greater than zero. Girma and Paulson (1999) state that no trading strategy should generate profits that are significantly greater than zero in an efficient market.

When trading futures contracts at Nasdaq it is possible to trade with a margin account. This allows the trader to buy securities by borrowing money from a broker, which means that a trader can buy more securities than he could without the margin. The leverage implies a possibility for greater profits, but also greater losses, because the profit is calculated by the total value of a contract, not only the margin. In other words, the trader pays a given margin, the broker lends the trader the remaining amount to buy a contract, the trader receives the total return of the contract, and then pays the loan back to the broker. The margin is calculated as the difference between the market value of a security and the loan a broker makes (Nasdaq). There is a risk associated with this; if the price of the security moves in the opposite direction of what the investor thought, the investor could receive a margin call. A margin call is a demand for additional funds because of adverse price movement (Nasdaq).

To calculate a correct margin and the correct return in percentage is difficult for several reasons. First, the margin will vary depending on trading days left until closing day. Second, it varies according to the volatility at the given time. Even though we manage to find the right margin that is required, we do not know how much of the capital an investor is willing to invest. Trading in spreads like these means that an investor can choose the degree of leverage almost as he like. The reason is because the margins from the long and short position offset each other. This means that we need to know if the investor is risk-seeking or risk-averse. One investor with 1 million USD can buy ten contracts, while another investor with the same amount of money available can choose to buy five contracts. These two investors will experience different return on their investments.

In order to avoid making any preconditions about the risk associated with the investment or the investors willingness of taking risk we choose not to focus on percentage returns. However, to get a clue about the return, we have done a rough approximation of the margin requirement and calculated the annual return for our best trading rules. We also consider transaction costs in this analysis. This is shown in section 7.2.1.

The main part of our profits is presented only in Euros. It is generated by the price movements in the contracts from opening day to closing day. When we are in long position in the spread, i.e. go long ElNP and go short ElGer, this is calculated by:

$$\pi_l = \alpha_1(\mathrm{EINP}_{t+k} - \mathrm{EINP}_t) - \alpha_2(\mathrm{EI}Ger_{t+k} - \mathrm{EI}Ger_t) \tag{4.22}$$

And vice versa for a short position in the spread:

$$\pi_s = -\alpha_1(\text{EINP}_{t+k} - \text{EINP}_t) + \alpha_2(\text{EI}Ger_{t+k} - \text{EI}Ger_t) \tag{4.23}$$

, where π_l and π_s are profits for a long and short contract respectively, α_1 and α_2 are the number of contracts long and short, time t+k is the closing date and time t is the opening date of the position.

4.5 Possible Error Sources

Below we have described some possible error sources. Some of these error sources are not possible to avoid fully, but we have tried to minimize them.

4.5.1 Roll Yield

A possible source of error is the so-called *roll yield* problem. If a trader wants to be exposed to a futures market over time, he must leave his position before the contract's maturity date, and re-position himself in the new contract (Bessembinder, 2018). With the use of time series data on futures contracts, the return calculations will be affected by the roll yield with the transition from one contract to another. This roll yield does not represent real cash flows, and therefore we try to adjust for it. To account for this, we have tried to curb the effect of the roll yields by averaging the price on the rollover dates with $\pm$ 4 days. There are though numbers of ways to deal with this problem (or not deal with it at all). Our choice of method can affect the results in this thesis.

When calculating returns from the trading strategies, we set the return on the rollover date to be zero. By doing this we avoid being affected by any price changes which do not imply cash flows after mark-to-market of the futures. The moving averages and standard deviations calculated will though be affected, to a certain degree, by our choice of handling the roll yield.

4.5.2 Punching and Model Errors

Another source of error is punching errors. With many calculations, there is a chance of errors, either in data or functions. To alleviate this, we have double-checked the calculations. The calculations are also compared with other papers.

4.5.3 Choosing Sub-Periods for Trading Strategies

We use our trading strategies to predict the spread movement in the future. We choose in- and out-of-sample periods in our trading strategies. It is difficult to know for sure that this is the best way to split the data set and therefore it could be a possible error source. Our choice of in-and out-of sample periods is inspired by Emery and Liu (2002).

5 Data Description

The data analyzed are electricity futures for Nord Pool and EEX, brent oil futures, natural gas futures, coal futures and CO_2 emission allowances futures. Gas prices are obtained from Datastream, while the others are gathered from Montel. The data cover the period from January 2, 2007 to February 11, 2019, altogether 3037 observations for each variable.

The choice of sample period and periodicity reflects the limitations in the availability of time-series data on electricity prices. The data are adjusted for non-trading days. These rows are deleted. It is also important to notice that the contracts have different rollover dates.

The data is not adjusted for foreign exchange differences (FX). The reason for that is to avoid potential impact of FX volatility. An investor who plans to invest in a foreign currency will keep his funds in the relevant countries, and not convert it back to his own currency for every trade due to transaction costs.

Nord Pool and EEX are front month future contracts quoted in EUR/MWh. Brent data are front month crude oil contracts (US$/barrel) (1 barrel = 31.5 US gallons), front month coal contracts (US$/metric tonne), December contract CO_2 emission allowances (EUR/metric tonne), continuous futures natural gas contracts (GB£/therms of natural gas) (1 therm = 29.3071 kWh).

The reason why we used December contract for CO_2 emission allowances instead of front month is that the December contract is the most liquid (Aatola, Ollikainen and Toppinen, 2013). The reason why we are using continuous futures natural gas contracts is because of lack of options.

When testing for cointegration using the Johansen and Juselius method, we have used log prices. For the Engle-Granger method we have used the regular prices. The reason is because we have used this method when developing trading strategies in which regular prices are used.

Further in this thesis we will refer to brent oil futures as brent, natural gas futures as gas, coal futures as coal, and emission allowance futures as CO_2. As stated earlier, futures on Nordic and German electricity prices will be referred to as ElNP and ElGer.

5.1 Variables

This master thesis examines the question whether ElNP and ElGer are cointegrated. We included important input factors in the electricity production to model the prices in a good manner and to see how they are affected by input factors in the electricity production. Including these variables, we can see if the price formation in the ElNP and ElGer have similar dynamics. Frydenberg *et al.* (2014) chose coal, oil and gas when they investigated the relationship between electricity prices in Germany, UK and the Nord Pool and input factors in the period 2006 to 2012. What distinguishes our work from their paper is that we are interested in checking the relationship between ElNP and ElGer. In addition, our time span is longer with daily time series of prices from 2007 to 2019. Finally, we include emission allowance futures in our model as Frydenberg et. al. (2014) recommend others to analyse potential energy price cointegration including this variable, as the cost of producing electricity is directly linked to emission costs.

5.1.1 Coal

Coal, with lignite or hard coal, is frequently used in German power production. The use of coal in electricity production is one of the methods that pollutes the most. The EU, with its emission allowances, is eager to decrease the share of coal in power generation. Using coal in power generation implies high costs in start-up and shut down of the production. High demand is therefore of importance.

5.1.2 Brent Oil

Oil is not a major input factor in the European power production. On the other hand, it could be a supplement for coal and gas if the demand for electricity is high. The oil price is an important price proxy for energy, affecting both coal and gas prices. In addition, the oil price could be a good proxy for economic activity. High oil price is often related to high economic activity, which leads to higher demand for power and increasing electricity prices, ceteris paribus.

5.1.3 Natural Gas

Of the fossil fuels, gas is the second most used fuel for electricity production in Germany. The pollution from gas is significantly lower than from coal, and with the price on CO2, one hope that there will be a shift from using coal to using gas in electricity production. Therefore, the price of gas can become more important looking forward when explaining electricity prices. It is easy to transform a coal driven power generator into a gas driven one. An advantage when using gas as input in electricity production is its relative easiness in adjusting the production, in contrast to coal.

5.1.4 CO2 Emission Allowances

The Kyoto protocol made the EU develop a market for pricing carbon emissions, and since 1st of January 2005, they have had a market for trading emission allowances. Power producers must buy these allowances to cover their carbon emissions. For the last couple of years, the CO2 emission allowance prices has increased. Since Germany use mostly thermic energy as input for electricity production (Evans and Pearce, 2016), the price of CO2 emission allowances will have an impact on the German electricity prices. An increase in emission costs will increase the marginal cost of production, leading to a higher point on the merit order curve which decides the electricity price.

Fezzi and Bunn (2009) found that CO2 emission prices has an impact on the short-run price equilibrium in the UK electricity market. They also found that in the short-run, the CO2 emission price and the gas price will correlate and changes in the CO2 price will affect the long-run UK electricity price. The electricity market in UK and Germany is in many ways similar and we will therefore add the CO2 price to our analysis.

5.2 Descriptive Statistics

In the graphs below we will look especially at the relationship between ElNP and ElGer in one single graph. ElNP and ElGer seem to comove (figure 5.1). The other variables, and especially coal, brent and gas, seem to move in the same direction. The CO2 price is more volatile and has some heavy spikes during the period. The emission allowances have a period with very low prices due to a transition from one phase to another in the European Emission Trading Scheme (EU-ETS).

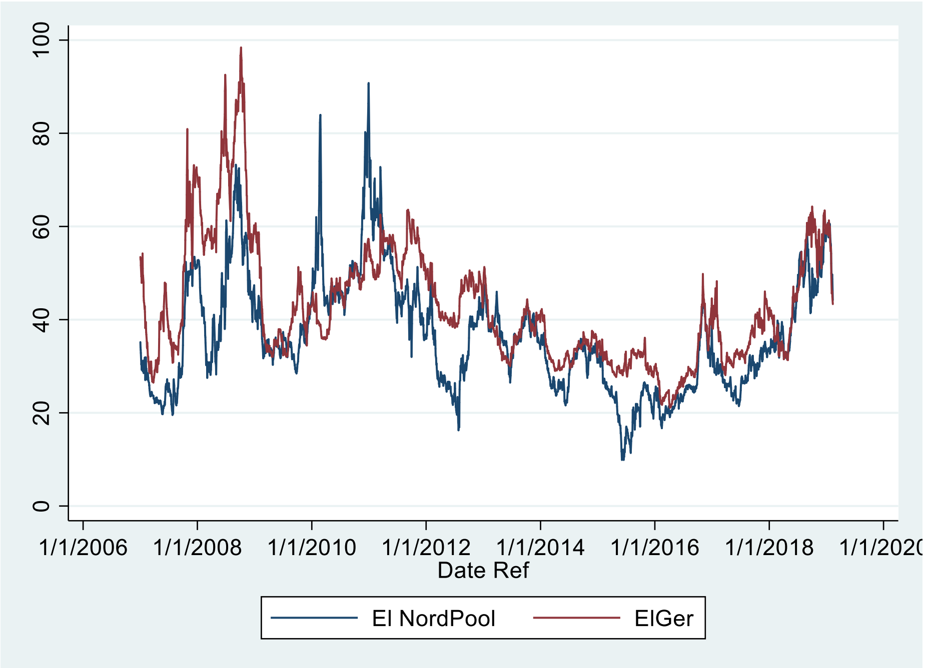

Figure 5.1: Graph of front month futures prices in Nord Pool area and Germany.

Figure 5.2: Graph of December futures contract carbon emission price

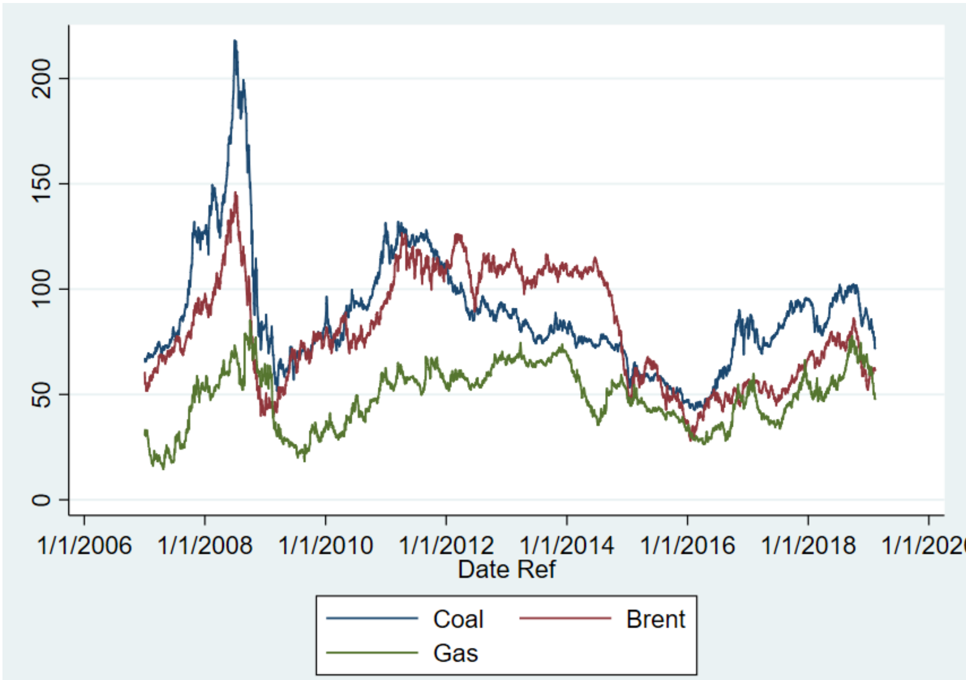

Figure 5.3: Graph of front month futures prices of coal, brent oil and gas.

To investigate if the prices comove and to what degree, we looked at the correlation matrix for the prices. Table 5.1 shows that ElNP is strongly correlated with ElGer, but also with CO2 and coal. ElNP also seems to correlate to some degree with brent and gas. For ElGer the picture looks alike. The correlation with CO2 and coal is stronger. This is expected because the electricity production is more reliant on coal, also making the electricity prices more sensitive to changes in the CO2 price. The correlation is quite strong between the three energy inputs coal, brent and gas. This is no surprise, all the time that they are close substitutes. Strong correlation between ElNP and ElGer does not necessarily mean that they are cointegrated, but it shows that the prices seem to comove. It is also interesting to see that they, approximately, correlate to the same extent with the other variables.

	ElNP	ElGer	CO2	Coal	Brent	Gas
ElNP	1.0000					
ElGer	0.7361	1.0000				
CO2	0.6302	0.7072	1.0000			
Coal	0.6303	0.8368	0.6017	1.0000		
Brent	0.3655	0.4370	0.2059	0.6429	1.0000	
Gas	0.4765	0.5639	0.3246	0.5309	0.5913	1.0000

Table 5.1: Correlation matrix between log prices of Nordic and German electricity futures, and futures for emission allowances, coal, brent oil and natural gas. The electricity futures show a strong correlation, and they correlate, approximately, to the same degree with the other variables. The input factors in electricity production, coal, brent oil and gas also seem to comove. 3037 observations for each variable from January 2007 to February 2019.

Table 5.2 shows the descriptive statistics for the time series of prices, log of prices and log differences. Comparing ElNP and ElGer, we see that on average, ElGer seems to have the highest prices with 42.88 EUR/MWh., compared to 36.64 EUR/MWh for ElNP. The standard deviation is almost the same with €12.95 and €12.44, respectively. Both prices exhibit positive skewness and excess kurtosis, implying a right-skewed distribution with fat tails compared to a normal distribution.

The average CO2 price is 10.01 EUR/Mt with a standard deviation of €6.35. The skewness is positive with 0.75 and the excess kurtosis is -0.10. Average prices of coal and brent are 88.12 US$/Mt and 80.68 US$/Barrel respectively. The standard deviation is quite similar with $28.05 and $25.95. Coal exhibits both positive skewness and excess kurtosis, while brent has positive skewness and negative excess kurtosis.

The average gas price in the period was 48.77 GB£/thm, with a standard deviation of £14.26. It exhibits negative skewness and negative excess kurtosis.

The prices excluding gas exhibit positive skewness. ElNP, ElGer and coal prices have positive excess kurtosis while the price of CO2, brent and gas all exhibit negative excess kurtosis.

To see if the prices are integrated of order one, I(1), we checked for stationarity using the Augmented Dickey-Fuller test with constant, trend and two control lags. All prices except ElNP are I(1) as the test statistics is above the critical value of -3.41. ElNP is though not significant on a 1 % level. For the log of prices, which we use in our VECM model, all the prices are non-stationary. The log differences are all significantly stationary. The data are therefore suited for cointegration analysis.

The Ljung-Box test shows significant serial correlation in the electricity prices, CO_2, coal, brent and gas.

The prices and the logarithm of the prices behave about the same, although there are some differences. Especially the CO_2 price seems to change in respect to skewness and kurtosis when it is log-transformed. This could be due to extreme price spikes, especially around the year-end of 2007.

Looking at the log differences, there is evidence of non-normality. The excess kurtosis is high, ranging from 3.96 for brent oil to 2300 for CO_2. The CO_2 price is a special case in our sample. Having excess kurtosis among our differenced variables implies fat tails. We have positive skewness for the electricity prices, CO_2 and gas, while the other variables exhibit negative skewness. As the critical value in the Ljung-Box test is 18.31, we have significant serial correlation for all the differenced log-prices.

Prices	No. obs.	Mean	Std. dev	Skewness	Kurtosis	ADF(2)	LB(10)
$Price_t$							
ElNP	3037	36.64	12.44	0.76	0.62	-3.483	28159
ElGer	3037	42.88	12.95	1.15	1.57	-2.980	28888
CO2	3037	10.01	6.35	0.75	-0.10	-1.803	29144
Coal	3037	88.12	28.05	1.51	3.50	-2.234	29714
Brent	3037	80.68	25.95	0.12	-1.21	-2.031	29816
Gas	3037	48.77	14.26	-0.25	-0.80	-2.652	29025
$ln(Price_t)-ln(Price_{t-1})$							
ElNP	3036	0.0075 %	0.034	0.53	5.97	-29.98	89.36
ElGer	3036	-0.0069 %	0.024	0.48	7.28	-31.27	139.12
CO2	3036	0.0457 %	0.140	44.40	2300	-35.39	39.54
Coal	3036	0.0023 %	0.015	-0.57	6.22	-28.07	107.46
Brent	3036	0.0006 %	0.021	-0.0030	3.96	-31.93	41.31
Gas	3036	0.0145 %	0.029	1.88	19.62	-33.62	40.92

Table 5.2: Descriptive statistics for price variables in levels and difference in log prices. The table shows the number of observations, mean, standard deviation, skewness and kurtosis. It also shows the augmented Dickey-Fuller test with constant trend and two control lags. Ljung-Box statistics with ten lags is also included. Critical value ADF is -3.41. and for LB(10) 18.31.

6 Empirical Results - Cointegration Analysis

In the following chapter we will present our results from our cointegration analysis. In section 6.1 we investigate if there exists a bivariate cointegrating relationship between ElNP and ElGer. This is done using the Engle-Granger method described in section 4.2.1. In section 6.2 we test for multivariate cointegrating relationships adding the variables presented in chapter 5. This is done using the Johansen and Juselius method described in section 4.2.2.

6.1 Bivariate Cointegration – The Engle Granger approach

In addition to the multivariate cointegration analysis performed with the Trace test and Johansen and Juselius method to determine the number of cointegrating relationships and VECM models, we will here shortly test for bivariate cointegration using the different futures prices (we do not use log prices in this analysis). The aim is not to describe full error correction models (ECMs) for all variables, but to run separate regressions for pairs of the variables and check if the residual from the equation is stationary, and hence if there exists cointegration as described in chapter 4. As our research question is if Nordic and German futures prices are cointegrated, we will calculate ECMs for these two variables.

For us, the relationship between ElNP and ElGer will be especially interesting. From table 6.1, we see that the test statistics from the ADF test using constant, no time trend[1] and two control lags is -4.984 from the regression consisting of ElNP and ElGer. This is lower than the critical value at 1 %, and we can therefore reject the null hypothesis that the residuals are non-stationary. Hence, ElNP and ElGer are cointegrated according to this test. We will develop error correction models for these prices below. Taking a quick look at the other relationships, we see that the ElNP is cointegrated on a 5 % significance level with CO2, coal and brent. ElGer is cointegrated with coal on a 1 % significance level, and with brent and gas, but only on a 10 % significance level. The Engle-Granger test shows no significant cointegrating relationship between the other variables CO2, coal, brent and gas.

[1] According to Frydenberg et al. (2014), earlier empirical work has concluded that energy prices show no clear deterministic trend. Looking at table 5.2 we also see that our differenced prices have roughly a mean of zero.

	ElNP	ElGer	CO2	Coal	Brent	Gas
ElNP	-					
ElGer	-4.984***	-				
CO2	-4.506***	-3.907**	-			
Coal	-4.125***	-5.422***	-2.322	-		
Brent	-3.590**	-3.262*	-1.773	-2.140	-	
Gas	-3.584**	-3.206*	-1.940	-2.175	-2.498	-

*Table 6.1: Test statistics for ADF test with constant, no time trend and two control lags. Row variables are the dependent variable in the regression of the pairs. * 10 % sign. ** 5 % sign. *** 1 % sign.*

Engle-Granger critical values are (Hill, 2012):

1 %	-3.96
5 %	-3.37
10 %	-3.07

Following the method described in section 4.2.1 we develop ECMs for ElNP and ElGer where the disequilibrium term Z_{t-1} is given by the residual where ElNP are regressed on ElGer. Further, we include lagged first differences of both variables which illustrate the short-term dynamics. The models include no trend. The results are given in table 6.2. The ECM for ElNP indicates a low explanatory power with a R^2 of 0.038. To fully explain the price, one could include other variables. The short-term dynamic with lagged first difference on itself is significant on a 1 % level, while the lagged difference of ElGer is not significant. The coefficient of the lagged difference of ElNP is 0.189. This indicates that an increase of 1 % yesterday leads to an increase of today's price of 0.189 %, ceteris paribus. Looking at the long-term dynamics we see that the coefficient is -0.012 and significant on a 1 % level. This indicates that the adjustment back to equilibrium following an exogenous shock takes ~ 57 days[2]. The prices could therefore stay out of equilibrium for a long time.

[2] Speed of adjustment (SA) is calculated in the following way using the example above: $SA = \frac{\ln(0.5)}{\ln(1-0.012)}$

The ECM for ElGer shows a low explanatory power of 0.040 indicating that important variables explaining ElGer are missing. We added two lagged differences for this equation to handle problems with autocorrelation. The short-term dynamics shows that both first- and second differences of ElGer is significantly different from zero on a 1 % level. The price of ElGer today is therefore impacted by price changes from the two previous periods. The first difference of ElNP is not significantly different from zero. The coefficient for the long-term dynamics is not significantly different from zero in this case, which indicates that ElGer is the driving force in this relationship. This is expected as Germany is a large market in the EU. Aatola, Ollikainen and Toppinen (2013) find that price shocks in the German forward price on electricity have a strong, positive and significant effect on other electricity prices in the EU (including Nordic), but not vice versa.

Tests for autocorrelation using the Lagrange Multiplier test in the ECMs are given in table 10.1 and 10.2. Durbin-Watson test statistics for autocorrelation are given in table 6.2.

Variable	Coefficient	t-statistic
ECM ElNP & ElGer		
Cons	0.002	0.11
LD_ElNP	0.189	9.77***
LD_ElGer	-0.016	-0.71
L_Z	-0.012	-4.31***
R squared		0.038
Durbin-Watson stat.		1.991

Variable	Coefficient	t-statistic
ECM ElGer & ElNP		
Cons	-0.003	-0.14
LD_ElNP	0.006	0.37
LD_ElGer	0.13	5.44***
LD2_ElGer	0.067	3.69***
L_Z	0.002	0.64
R squared		0.040
Durbin-Watson stat.		2.000

*Table 6.2: Bivariate error correction models between front month electricity futures prices for the Nordic (ElNP) and German (ElGer) area. ECM ElNP & ElGer is an error correction model with ElNP as the dependent variable, while ECM ElGer & ElNP is an error correction model with ElGer as the dependent variable. Z is the disequilibrium term from a regression where ElNP is regressed on ElGer. Data period: January 2, 2007 to February 11, 2019 (3036 observations). LD: Lagged first difference of variable. LD2: Lagged second difference of variable. L: Lagged variable. The table reports coefficients and t-statistics for the variables, the explanatory power of the model measured by r squared, and the Durbin-Watson test statistics. Critical values for the t-statistics is 1.96 for a two-sided t-test with a 5 % level of significance. A Durbin-Watson test statistic close to 2 indicates no serial correlation in the residuals from the regression. *** 1 % sign.*

Concluding the cointegration analysis based on the Engle-Granger method, we find significant cointegration between Nordic and German electricity futures prices. The error correction models show that the speed of adjustment to the equilibrium value for ElNP futures prices is low, with a half-life of ~ 57 days. The adjustment coefficient for ElGer is not significantly different from zero, which can imply that ElGer is the driving force in this relationship.

6.2 Multivariate Cointegration – The Johansen and Juselius Method

For this analysis, we have used logarithmic prices. The prices are quoted in the same way, except that "ln" is placed in front of the name.

The Johansen Trace test letting all variables be endogenous and two lags gives a maximum rank of three (see table 10.3), which will be the number of cointegrating vectors in the VECM model.

We expect that coal and gas prices influence the power prices positively, especially in Germany due to its high share of fossil fuels. An increase in the prices will increase the cost of producing electricity. Brent is seldom used in power generation, except when demand is high, because it is expensive. Therefore, we do not expect brent to influence the prices to the same degree as coal and gas. We believe that the CO2 price will have a positive impact on electricity prices because it increases the marginal cost of production in thermic power generation. Because of the Nordic areas high share of renewables, we expect the CO2 price will have less to say for this area's electricity price. One could argue that we should have included variables that better explained ElNP, like e.g. reservoir levels. But as we are developing a VECM model, we need the variables to be I(1), and variables like temperature, reservoir levels etc. are often I(0). In addition to this, thermic power input will often be the price setter in the market. The Nordic and European power markets are not independent. NVE states that the cost of producing in coal- and gas power plants hits the Nordic market (Amundsen, Bartnes and Øyslebø, 2017). This happens both through the Nordic thermic power plants, which represents approximately 18 percent of the energy mix, and the transmission connections to Europe. Redl *et al.* (2009) have shown that also Nordic electricity prices depend strongly on generation costs, and, that even though the EEX and Nord Pool market are weakly connected with each other physically, price formation is quite alike.

Table 6.3 shows the three cointegrating vectors as recommended from the Trace Statistics with coefficients (standard errors in brackets) and test statistics. The vectors are calculated using constant, a rank of three and two as the maximum lags to be included in the underlying VAR model.

Beta	Coeff.	Std. Error	z
_ce1			
lnElGer	1	.NA	-
lnCoal	0	.NA	
lnBrent	0	.NA	
lnGas	0.16	0.19	0.85
lnCO2	0.13	0.05	2.45**
lnElNP	-1.21	0.18	-6.67***
_Cons	-0.30	.NA	-
_ce2			
lnElGer	0	.NA	
lnCoal	1	.NA	-
lnBrent	-5.55e-17	.NA	-
lnGas	-0.17	0.20	-0.88
lnCO2	0.15	0.06	2.67***
lnElNP	-1.19	0.19	-6.16***
_Cons	0.15	.NA	-
_ce3			
lnElGer	0	.NA	
lnCoal	0	.NA	
lnBrent	1	.NA	-
lnGas	-1.88	0.35	-5.37***
lnCO2	0.04	0.10	0.43
lnElNP	0.03	0.34	0.10
_Cons	2.65	.NA	-

*Table 6.3: Error correction vectors estimated using the Johansen and Juselius method. ** 5 % sign. *** 1 % sign.*

The cointegrating vectors can be summarized in the following three equations showing stationary relationships between the variables:

$$\begin{aligned}
\ln \mathrm{El}Ger_{t-1} &= 0.30 - 0.16 \ln Gas_{t-1} - 0.13 \ln CO2_{t-1} + 1.21 \ln \mathrm{ElNP}_{t-1} \\
\ln Coal_{t-1} &= -0.15 + 0.17 \ln Gas_{t-1} - 0.15 \ln CO2_{t-1} + 1.19 \ln \mathrm{ElNP}_{t-1} \\
\ln \mathrm{B}rent_{t-1} &= -2.65 + 1.88 \ln Gas_{t-1} - 0.04 \ln CO2_{t-1} - 0.03 \ln \mathrm{El}N\mathrm{P}_{t-1}
\end{aligned} \qquad (6.1 - 6.3)$$

The first cointegrating vector, _ce1, is the most interesting because it shows a stationary relationship including lnElGer and lnElNP, in addition to lnGas and lnCO2. _ce2 and _ce3 do not include both lnElNP and lnElGer, hence they will not be our focus.

Table 6.3 shows that an 1 % increase in lnNP leads to an 1.21 % increase in lnElGer, ceteris paribus. As the coefficient is close to 1, this suggests that the markets are integrated. An 1 % increase in lnGas leads to a decrease of 0.16 % in lnElGer. The coefficient is not significantly different from zero on a 10 % level. An 1 % increase in lnCO2 leads to a decrease in lnElGer of 0.13 %. The explanation of this could be, since the two prices are positively correlated (see correlation matrix in table 5.1), that if a positive shock occurred in the CO2 price in the previous period it is likely to have occurred in the ElGer as well. The cointegrating vector would then pull lnElGer back down in the next period. A financial implication of this stationary relationship could be to develop a spread trading strategy including lnElGer, lnElNP and lnCO2 (lnGas was not significantly different from zero) and weighting the respective futures prices according to the coefficients given in the error correction vector. We have decided *not* to include CO2 in our trading strategies. The main reason is that market for emission allowances is volatile. Looking at the descriptive statistics in table 5.2 and figure 5.2 of the CO2 price, the uncertainty is high. In addition, the price is dependent on political actions, for example the number of allowances offered in the market. Because of the immaturity and uncertainty in the CO2 market, we do not take it into account in this thesis.

Further, we will roughly describe the two other cointegrating vectors. For _ce2, there exists a stationary relationship between lnCoal, lnGas, lnCO2 and lnElNP. Gas is though not significantly different from zero on a 10 % level. For _ce3, there exists a stationary relationship between lnBrent, lnGas, lnCO2 and lnNP, where lnGas is the only significant variable.

		D_lnElGer		D_lnElNP		D_lnGas		D_lnBrent		D_lnCoal		D_lnCO2	
		Coef.	*t-value*	*Coef.*	*t-value*	*Coef.*	*t-value*	*Coef.*	*t-value*	*Coef.*	*t-value*	*Coef.*	*t-value*
_ce1	*L1.*	-0.020	-6.04***	0.001	0.31	-0.006	-1.55	-0.010	-3.17***	-0.003	-1.49	-0.054	-2.73***
_ce2	*L1.*	0.020	-6.60***	0.007	1.70*	0.007	1.68*	0.008	2.83***	0.003	1.29	0.026	1.43
_ce3	*L1.*	-0.003	-2.39**	0.0004	0.28	0.003	2.06**	-0.00007	-0.07	0.002	2.22**	-0.015	-2.38**
lnGas	*LD.*	0.107	7.19***	0.108	5.05***	0.041	2.15**	-0.013	-0.92	0.008	0.84	0.252	2.80***
lnBrent	*LD.*	-0.007	-0.32	0.011	0.38	-0.006	-0.25	-0.076	-4.02***	0.006	0.46	-0.133	-1.08
lnCoal	*LD.*	0.004	0.15	0.060	1.40	0.077	0.71	0.024	0.89	0.149	7.60***	-0.295	-1.64*
lnCO2	*LD.*	0.006	1.89*	0.001	0.26	0.002	0.61	0.0063	0.22	-0.003	-1.69*	-0.091	-4.91***
lnElGer	*LD.*	0.152	7.46***	-0.540	-1.83*	0.025	0.95	-0.024	-1.28	0.013	0.98	0.179	1.45
lnElNP	*LD.*	0.002	0.14	0.159	8.13***	0.003	0.15	0.106	0.84	-0.005	-0.61	-0.033	-0.41
_Cons		-0.0001	-0.34	0.0001	0.25	0.0001	0.20	-0.00003	-0.08	5.61e-06	0.02	0.00004	0.02

*Table 6.4: VECM model for futures contract on German and Nordic electricity, natural gas, brent oil, coal and CO2 emission allowances. The table presents estimates for reversion to long term cointegrating vectors, ce1, ce2 and ce3 shown in table 6.3. The table also presents short term coefficients and their respective t-values. * 10 % sign. ** 5 % sign. *** 1 % sign.*

D_lnELGer:

Table 6.4 shows that both _ce1 and _ce2 are significantly different from zero on a 1 % level. _ce3 is significantly different from zero on a 5 % level. Both _ce1 and _ce2 have a speed of adjustment of nearly 2 % which implies a half-life of about 35 days. Speed of adjustment is lower for _ce3 with a half-life of 231 days.

Looking at the short-term dynamics in the model, the lagged difference coefficient of lnGas is positive and significant. This is expected, as increased gas prices will increase the cost of producing electricity. Since the lagged difference of lnGas has a significant impact on lnElGer, we say that lnGas Granger-causes lnElGer. We do not expect the relationship to go the other way around. Gas is important for electricity generation prices, but gas is used for other purposes than electricity alone. An 1 % increase in lnGas yesterday, implicates a 0.107 % increase in lnElGer today, ceteris paribus. lnCO2 is significant in this model, but just on a 10 % level, and we can interpret it in the same way as lnGas. As expected, the coefficient is positive. Increased tax on carbon emissions will increase the cost of producing electricity, leading prices to soar. Lagged differences on lnElGer is positive and significant, with an 1 % increase in yesterday's price leading to a 0.152 % increase in today's price, everything else being equal. Yesterday's return will have an impact on today's return. Lagged returns on lnElNP does not significantly explain todays return on lnElGer. In other words, there is no Granger-causality. Looking at the coefficients we see that among the input variables (lnGas, lnBrent, lnCoal and lnCO2) only lnGas and lnCO2 are significant (lnCO2 only on a 10 % level). With a coefficient of 0.107, lnGas seems to impact lnElGer quite much. We have expected that the price of coal influenced more, as this is the most important part of the area's energy mix. One possible explanation of this is that the price of gas often is the price setter in the market (especially during peak-hours[3]). Paraschiv, Erni and Pietsch (2014) argue that gas power plants often are price-setting during peak-hours when demand for electricity is high due to their high operational flexibility and short ramp-up time. This argument is based on a study by Sensfuß, Ragwitz and Genoese (2008) who find that variations in gas prices changes the merit-order effect more than other input factors coal, oil and nuclear. We also expected that the CO2 price would influence to a greater extent. The impact

[3] Peak-hours refers to the hours during a day with the highest demand for electricity.

could though have been greater if more recent data is explored as the market for emission allowances has developed during our data period.

D_lnElNP:

For D_lnElNP _ce2 is significant, but only on a 10 % level. This implicates that lnElNP is not as strongly intertwined with the variables in the error correction vectors as ElGer.

For the short-term dynamics of this model, we can see that the lagged difference coefficient of lnGas is positive and significant. This is expected as increased gas price will increase the cost of producing electricity. lnGas Granger-causes lnElNP. The coefficient is 0.108, which is similar as in lnElGer. It shows that variables affecting lnElGer also seem to impact lnElNP approximately to the same degree. In contrast to D_lnElGer the lagged difference coefficient of lnCO2 is not significant. A smaller part of electricity production in Nordic is based on fossil fuels. Furthermore, lagged returns on lnElGer has a negative, but not significant impact on lnElNP on a 5 % level. Lagged returns on lnElNP has a positive and significant impact on today's return on lnElNP, with a coefficient of 0.159, which implies that an increase in yesterday's return of 1 % leads to an increase in today's return of 0.159 %, ceteris paribus.

For lnGas and lnCoal, _ce3 is significant on a 1 % level. For lnBrent and lnCO2, _ce1 is significant on a 1 % level. None of the energy commodities, lnGas, lnBrent and lnCoal, Granger-cause each other, but the lagged return on itself is significant for all three variables. The _ce3 coefficient is significant on a 5 % level for lnGas, lnCoal and lnCO2, but not for lnBrent. The _ce2 coefficient is significant on a 1 % level for lnBrent, on a 10 % level for lnGas, but not for lnCoal and lnCO2. The speed of adjustment is low for the energy commodities, but for CO2, we have at most a mean reversion of about 5.4 % (_ce1).

Lagged lnCO2 returns have no significant effect on energy prices in our model. On the other hand, we see that an increase in lnGas seems to increase lnCO2. One reason for this could be that an increase in gas prices causes less substitution from coal to gas in electricity production, which leads to an increased demand for emission allowances due to much higher carbon emissions in electricity generation from coal versus gas. In addition to this, we see that an increase in lnCoal leads to a decrease in lnCO2. This is the opposite situation to an increase in lnGas. An increase in coal prices leads to substitution from coal to gas in electricity generation. Emissions from gas-based generators are less than from coal-based generators, which causes a lower demand for emission allowances.

We have performed diagnostics tests for normality and autocorrelation for the VECM models (see table 10.3 and 10.4). They show significant non-normality and autocorrelation. Non-normality is not likely to be a problem in this analysis as the Johansen ML estimator presents small sample properties consistent with the asymptotic values even if there is non-normality present (Gonzalo, 1994). Autocorrelation can on the other hand cause bias in our model. We have tested if the coefficients change significantly if we add another lag in the VECM models (and get rid of the autocorrelation), but this does not seem to be the case. None of the coefficients being significant on a 5 % level become non-significant adding another lag, except the adjustment parameter _ce3 for gas. However, the adjustment parameter for _ce1 for gas becomes significant on a 5 % level. Since the changes in the VECM model adding another lag are few, we continue to use one lag, as it makes the interpretations easier.

The explanatory power measured by R^2 for the VECM model is low, ranging from 0.001 for lnGas to 0.07 for lnElGer (see table 10.6). lnElNP has a R^2 of 0.04.

Concluding the cointegration analysis using the Johansen and Juselius method, we find significant cointegration between Nordic and German electricity futures prices. Further, we see that futures prices on emission allowances is included in this stationary relationship. The speed of adjustment is low, with a half-life of ~ 35 days. This coincides to some degree with the findings using the Engle-Granger method in section 6.1, but there the cointegrating vector only consisted of ElNP and ElGer. The effects of the short-term dynamics were to some extent expected. Gas was the most influential variable. Brent was as expected not an important variable. Looking at figures 2.2 and 2.3 of the Nordic and German energy mix, we see that a small fraction of the mix consists of oil. However, we had expected that coal would affect more, especially for ElGer since about 35 % of the energy mix in Germany comes from coal according to figure 2.3 (12.8 % of the energy mix comes from gas). CO2 did not influence either ElNP or ElGer much. The effect could have been greater not using data all back to 2007 as the influence and market of emission allowances has developed the recent years (different phases) (Clara and Mayr, 2018).

7 Empirical Results - Trading Strategies

Finding significant cointegration between Nordic and German electricity futures prices, we develop trading strategies based on the idea that the two electricity prices will move together. The trading strategies are based on the spread between the two electricity prices. In other words, when the spread reaches a given level, we will position ourselves in a way that can generate profit when the spread narrows. Finding good entry and exit points in the trade is important. Below we use the strategy based on Emery and Liu (2002) both in- and out-of-sample. Afterwards we implement the strategy based on Girma and Paulson (1999) using the same out-of-sample periods. For detailed information about the design of our trading strategies see section 3.5.

7.1 Results Strategy Based on Emery and Liu

<u>In-sample Trading Results:</u>

As we found that the Nordic and German front month electricity futures prices were cointegrated, we tried to develop a trading strategy to profit from the significant mean reversion. It is used daily data of front month electricity futures from January 2, 2007 to February 11, 2019. Table 7.1 shows the results from the trading strategy described in section 4.3.1. Panel A contains the results from a long position constructed by purchasing a Nordic futures contract and selling German futures contracts. The results in Panel B are from a short position where we sell a Nordic futures contract and buy German futures contracts. The number of German futures contracts to buy/sell per Nordic futures contract is determined by the following equilibrium equation:

$$\mathrm{EINP}_t = \beta_0 + \beta_1 \mathrm{EI}Ger_t + \varepsilon_t \qquad (7.1)$$

The result from equation 7.1 is summarized in table 7.1:

Fitted regression model for ElNP for the in-sample period		
	Coefficient	P-value
Intercept	6.33	0.000
ElGer	0.71	0.000
R^2	0.5419	
Std. dev. of residuals	8.4177	

Table 7.1: Estimated parameters from the regression $\mathrm{ElNP}_t = \beta_0 + \beta_1 \mathrm{ElGer}_t + \varepsilon_t$*. Data are daily settlement prices of front month electricity prices for Nordic and Germany from January 2, 2007 to February 11, 2019.*

Table 7.1 shows that the number of ElGer contracts we must acquire is 0.71 per ElNP contract. The standard deviation of the residuals of 8.4177 is used to determine when ElNP is not in equilibrium, and we enter a position in the spread.

Panel A	Open Long Position When			
	Residual < -0.25σ	Residual < -0.50σ	Residual < -0.75σ	Residual < -1.00σ
No. of trades	26	18	15	10
Av. dur (days)	58	69	72	88
% profitable	65 %	72 %	80 %	80 %
Max. profit (€)	18.64	18.64	18.64	18.64
Min. profit (€)	-14.96	-12.49	-8.75	-7.14
Av. profit (€)	0.99	2.47	3.40	5.60
Std. dev. (€)	5.52	6.25	6.00	7.17
Std. error	1.08	1.47	1.55	2.27
T-value	0.92	1.68*	2.20**	2.47**

Panel B	Open Short Position When			
	Residual > 0.25σ	Residual > 0.50σ	Residual > 0.75σ	Residual > 1.00σ
Number of trades	22	15	8	4
Average duration	58 days	69 days	99 days	132
Percent Profitable	59 %	60 %	63 %	75 %
Max. Profit (€)	7.23	7.23	7.38	3.82
Min. Profit (€)	-20.9	-17.12	-14.92	-14
Average Profit (€)	-0.27	0.612	0.655	-2.19
Std. dev. (€)	6.76	6.32	7.51	8.01
Standard Error	1.44	1.63	2.66	4.01
T-value	-0.19	0.38	0.25	-0.54

*Table 7.2: A long (short) position is opened by purchasing (selling) 1 MWh of Nordic electricity and selling (buying) β_1 MWhs of German electricity, where β_1 is the coefficient gathered from the equilibrium equation. β_1 is 0.71 in our case. A long (short) position is closed when the residual from the equil. equation ≥ (≤) zero. The probability that the average profit from the trades are greater than zero is computed using a T-test with n-1 degrees of freedom and the standard error is the sample standard deviation divided by the square root of n, where n is the number of trades. ** significantly greater than zero on a 5 % level. * significantly greater than zero on a 10 % level.*

Table 7.2 shows the in-sample results from our trading strategy. Profits are ex. transactions- and slippage costs. We have adjusted for roll yield as described in section 4.5.1. The main picture is that trades often are profitable, with the average profit per trade being greater than zero in all cases both long and short except short positions using $\varphi = 0.25$ and $\varphi = 1.00$. The percentage of profitable trades are all above 50 %. We used a t-test to check if the average profit per trade is greater than zero (t-values presented in the table). The average profit in the long positions was significant on a 10 % level when $\varphi = 0.5$, and on a 5 % level when $\varphi = 0.75$ and $\varphi = 1.00$. None of the average profits in the short trades were significant on a 10 % level. The average profit is low and often negative in these cases. The profits are therefore higher when we are long ElNP and short ElGer. In addition, the number of trades is often less than in the long trades. This is not surprising since the price of ElGer most of the time exceeds ElNP. When we require ElNP to be further from its equilibrium value before entering a trade by increasing the standard deviation, we see a reduction in number of trades. This also increased the average duration of the trades and increased the average profit for all specifications except for short position with $\varphi = 1.00$. This is in line with the findings from Emery and Liu (2002).

As these are in-sample results, an investor could not earn the amount specified above. We will therefore perform an out-of-sample test of the model below.

<u>Out-of-sample results:</u>

When Emery and Liu (2002) predict their out-of-sample results they divide their total data sample in two, with each part consisting of approximately 500 observations. Emery and Liu find that the half-life of the shock to the spark spread is short, approximately 15 days. This is less than our findings. In section 6.1 we found that half-life for ElNP is 57 days and that the adjustment coefficient for ElGer is not significant. Therefore, we choose to expand our formation period and out-of-sample period to 1000 observations each. This gives us the possibility to include more trades in our results. A disadvantage using greater periods could be that more and diverse "events" or shocks are included in the fitted regression model, making it less useful for prediction purposes. Using a longer out-of-sample period can cause bad fit for future data as new regimes can occur. But, as the tables below show, the average duration of the trades can be up to 300 days, so using the same out-of-sample window as Emery and Liu could lead to very few trades being executed during the trading period. In our trading models, we used three periods of in- and out-of-sample. The periods are generated randomly using a function in excel and ended up being the following periods consisting of 1000 trading days each (appr. 4 trading years):

	<u>In-sample period</u>:	*<u>Out-of-sample period</u>:*
Period 1:	10.10.2007 – 06.10.2011	07.10.2011 – 05.10.2015
Period 2:	01.02.2010 – 22.01.2014	23.01.2014 – 16.01.2018
Period 3:	05.01.2011 – 23.12.2014	29.12.2014 – 18.12.2018

The literature is not coherent about how to choose the share of in-sample vs. out-of-sample. According to Hansen and Timmermann (2012) it does not exist much guidance regarding choice of split point between in- and out-of-sample periods. The choice we make will have an impact on the results, and there is a danger of being accused for data mining. That is why we have used a random generator for choosing the periods. The number of days in the samples are though solely our choice.

Below we will go through the results generated for our three out-of-sample trading periods. The fitted regression models used are introduced before each result table. We assume that the prices are cointegrated during all three periods. It is also worth to notice that every profit presented in the results for this trading strategy is based on acquiring only one contract of ElNP and β_1 contracts of ElGer. The profits will be multiplied with the number of contracts a trader decides to invest in. Transaction- and slippage costs will reduce the total profit from each trade.

Using in-sample period 1 and regressing ElNP on ElGer, yields the following regression model which is used for out-of-sample prediction purposes:

Fitted regression model for ElNP for out-of-sample period 1		
	Coefficient	P-value
Intercept	28.23	0.000
ElGer	0.35	0.000
R^2	0.1810	
Std. dev. of residuals	10.4411	

Table 7.3: Estimated parameters from the regression $\mathrm{ElNP}_t = \beta_0 + \beta_1 \mathrm{ElGer}_t + \varepsilon_t$ *. Data are daily settlement prices of front month electricity prices for Nordic and Germany from October 10, 2007 to October 6, 2011.*

Using the model in table 7.3 in our trading strategy out-of-sample yields the following results:

	Open Long Position When (Period 1)			
	Residual < -0.25σ	Residual < -0.50σ	Residual < -0.75σ	Residual < -1.00σ
No. of trades	5	4	3	3
Av. dur. (days)	192	227	282	273
% profitable	60 %	50 %	33 %	33 %
Max. profit (€)	8.61	8.61	6.57	8.78
Min. profit (€)	-24.84	-19.81	-20.01	-17.87
Av. profit (€)	-3.99	-3.48	-6.01	-3.95
Std. dev. (€)	13.40	13.15	13.35	13.37
Std. error	5.99	6.58	7.71	7.72
T-value	-0.67	-0.53	-0.78	-0.51

	Open Short Position When (Period 1)			
	Residual > 0.25σ	Residual > 0.50σ	Residual > 0.75σ	Residual > 1.00σ
No. of trades	1	-	-	-
Av. dur. (days)	3	-	-	-
% profitable	0 %	-	-	-
Max. profit (€)	-1.62	-	-	-
Min. profit (€)	-1.62	-	-	-
Av. profit (€)	-1.62	-	-	-
Std. dev. (€)	-	-	-	-
Std. error	-	-	-	-
T-value	-	-	-	-

*Table 7.4: A long (short) position is opened by purchasing (selling) 1 MWh of Nordic electricity and selling (buying) β_1 MWhs of German electricity, where β_1 is the coefficient gathered from the equilibrium equation. β_1 is 0.35 in our case. A long (short) position is closed when the residual from the equilibrium equation $\geq$ ($\leq$) zero. The probability that the average profit from the trades are greater than zero is computed using a T-test with n-1 degrees of freedom and the standard error is the sample standard deviation divided by the square root of n, where n is the number of trades. ** significantly greater than zero on a 5 % level. * significantly greater than zero on a 10 % level.*

Table 7.4 shows the results for period 1. We see that none of the long trades yield positive average returns. The return is skewed negatively as the minimum return is higher than the maximum return in absolute numbers for all φ. None of the returns are significantly greater than zero on a 10 % level. A reason for this is that we have few numbers of trades which leads to few degrees of freedom. The average duration of each trade is long and often more than a year, assuming that a year consists of 250 trading days. This reduces the number of trades. Long trading periods indicates that once ElNP is out of equilibrium it takes a while before mean reverting. Percentage profitable trades are above 50 % just once, and even then, we get negative profits. The strategy does not work well for this period.

For trades based on a short position, we only execute one trade during the period. The only trade occurs when φ = 0.25 and lasts for three days. This indicates that ElNP rarely is significantly above its equilibrium value.

Using in-sample period 2 and regressing ElNP on ElGer, yields the following regression model which is used for out-of-sample prediction purposes:

Fitted regression model for ElNP for out-of-sample period 2		
	Coefficient	P-value
Intercept	7.07	0.000
ElGer	0.78	0.000
R^2	0.2443	
Std. dev. of residuals	10.3591	

Table 7.5: Estimated parameters from the regression $\mathrm{ElNP}_t = \beta_0 + \beta_1 \mathrm{ElGer}_t + \varepsilon_t$. *Data are daily settlement prices of front month electricity prices for Nordic and Germany from February 1, 2010 to January 22, 2014.*

Using the model in table 7.5 in our trading strategy out-of-sample yields the following results:

	Open Long Position When (period 2)			
	Residual < -0.25σ	Residual < -0.50σ	Residual < -0.75σ	Residual < -1.00σ
No. of trades	3	3	3	3
Av. dur. (days)	296	284	221	212
% profitable	67 %	67 %	100 %	100 %
Max. profit (€)	5.69	7.03	7.73	8.93
Min. profit (€)	-5.75	-2.97	0.08	1.35
Av. profit (€)	0.19	2.69	4.58	5.61
Std. dev. (€)	5.73	5.13	4.00	3.88
Std. error	3.31	2.96	2.31	2.24
T-value	0.06	0.91	1.98*	2.51*
	Open Short Position When (period 2)			
	Residual > 0.25σ	Residual > 0.50σ	Residual > 0.75σ	Residual > 1.00σ
No. of trades	-	-	-	-
Av. dur. (days)	-	-	-	-
% profitable	-	-	-	-
Max. profit (€)	-	-	-	-
Min. profit (€)	-	-	-	-
Av. profit (€)	-	-	-	-
Std. dev. (€)	-	-	-	-
Std. error	-	-	-	-
T-value	-	-	-	-

*Table 7.6: A long (short) position is opened by purchasing (selling) 1 MWh of Nordic electricity and selling (buying) β_1 MWhs of German electricity, where β_1 is the coefficient gathered from the equilibrium equation. β_1 is 0.78 in our case. A long (short) position is closed when the residual from the equilibrium equation $\geq$ ($\leq$) zero. The probability that the average profit from the trades are greater than zero is computed using a T-test with n-1 degrees of freedom and the standard error is the sample standard deviation divided by the square root of n, where n is the number of trades. ** significantly greater than zero on a 5 % level. * significantly greater than zero on a 10 % level.*

Table 7.6 shows the results from period 2. The strategy yields positive average profits for all long position. For φ = 0.25 and φ = 0.50 we get 67 % percent profitable trades, while when φ = 0.75 and φ = 1.00 we get 100 % profitable trades. This indicates that the strategy seems to work fine. The problem is that we get few trades and therefore only two of them are significantly greater than zero on a 10 % level and none on a 5 % level.

We do not get any trades for short positions during period 2. This indicates that ElNP never is significantly above its equilibrium value.

Using in-sample period 3 and regressing ElNP on ElGer, yields the following regression model which is used for out-of-sample prediction purposes:

Fitted regression model for ElNP for out-of-sample period 3		
	Coefficient	P-value
Intercept	3.52	0.002
ElGer	0.80	0.000
R^2	0.4741	
Std. dev. of residuals	7.4675	

Table 7.7: *Estimated parameters from the regression* $\mathrm{ElNP}_t = \beta_0 + \beta_1 \mathrm{El}Ger_t + \varepsilon_t$ *. Data are daily settlement prices of front month electricity prices for Nordic and Germany from January 5, 2011 to December 23, 2014.*

Using the model in table 7.7 in our trading strategy out-of-sample yields the following results:

	Open Long Position When (period 3)			
	Residual < -0.25σ	Residual < -0.50σ	Residual < -0.75σ	Residual < -1.00σ
No. of trades	8	5	5	5
Av. dur. (days)	80	117	93	90
% profitable	88 %	80 %	80 %	80 %
Max. profit (€)	5.23	7.05	6.21	8.98
Min. profit (€)	-5.09	-3.03	-3.20	-1.61
Av. profit (€)	1.84	2.68	2.60	5.04
Std. dev. (€)	3.17	3.72	3.71	4.37
Std. error	1.12	1.66	1.66	1.95
T-value	1.65*	1.61*	1.57*	2.58**
	Open Short Position When (period 3)			
	Residual > 0.25σ	Residual > 0.50σ	Residual > 0.75σ	Residual > 1.00σ
No. of trades	5	3	1	1
Av. dur. (days)	45	66	131	115
% profitable	60 %	33 %	100 %	100 %
Max. profit (€)	3.05	4.69	1.57	4.64
Min. profit (€)	-3.13	-3.11	1.57	4.64
Av. profit (€)	0.26	0.10	1.57	4.64
Std. dev. (€)	3.01	4.08	-	-
Std. error	1.35	2.35	-	-
T-value	0.19	0.04	-	-

*Table 7.8: A long (short) position is opened by purchasing (selling) 1 MWh of Nordic electricity and selling (buying) β_1 MWhs of German electricity, where β_1 is the coefficient gathered from the equilibrium equation. β_1 is 0.80 in our case. A long (short) position is closed when the residual from the equilibrium equation $\geq$ ($\leq$) zero. The probability that the average profit from the trades are greater than zero is computed using a T-test with n-1 degrees of freedom and the standard error is the sample standard deviation divided by the square root of n, where n is the number of trades. ** significantly greater than zero on a 5 % level. * significantly greater than zero on a 10 % level.*

Long positions in period 3 yield positive profits for all specifications. Period 3 has more trades for each φ, and each trade has a lower average duration. For all specifications we have 80 % or higher share of profitable trades. All average profits for the long positions are significant on a 10 % level, and for φ = 1.00 the average profit is significant on a 5 % level.

What makes period 3 differs from the two others is that we have more short trades. However, it is not enough for any of the profits being significantly greater than zero. All the average profits are greater than zero.

Summary:

For the in-sample period, long positions yield positive average profits. The profits of the short positions differ with two out of four specifications yielding negative average profits.

The out-of-sample periods vary in terms of profits. The strategy does not work well for period 1, with negative average profits for all specifications both long and short. The model used for this period shows a low explanatory power with a R^2 of only 0.1810. The regression coefficient for ElGer, β_1, is 0.35. It can seem like the model does not fit the data well. Since this period is modeled during the years 2007 to 2011, the integration between the Nordic and German market could have increased in the years after.

The strategy yields better results in period 2, with positive average profits for all long specifications. There were no short trades during this period. There are few numbers of trades, with only three for each specification. None of the average profits are significant on a 5 % level, and only two of them are significant on a 10 % level.

The best results are obtained in period 3. All average profits, both long and short, are greater than zero. In addition, the number of trades is higher, and the average trading duration is lower. Three of the average profits for long positions are greater than zero on a 10 % level. However, only one of them are significant on a 5 % level.

We conclude that the strategy seems to work fine in period 3. The results in period 2 seems good but having few trades we will not claim that the strategy works well. There is no doubt, however, that the strategy does not work for period 1, with all average profits being less than zero. In general, more trades are executed in long positions than in short positions. This indicates that most of the time German electricity prices is higher than Nordic electricity prices[4].

We think that increased integration between the Nordic and German market could be one of the reasons why the strategy works better in period 2 and 3, compared to period 1. The explanatory power of the model is higher, especially for period 3. With a beta-coefficient closer to one in both period 2 and 3, the market integration could have increased during the samples. In addition, we

[4] The spread is defined as ElNP – ElGer.

see that the average duration per trade has decreased, especially from period 2 to period 3, which could be a sign of a higher speed of adjustment to equilibrium value.

7.2 Results Strategy Based on Girma and Paulson

We did not do any in-sample testing for this strategy, but only tested is using the same periods which we used out-of-sample in the strategy based on Emery and Liu. These periods are:

Period 1: 07.10.2011 – 05.10.2015

Period 2: 23.01.2014 – 16.01.2018

Period 3: 29.12.2014 – 18.12.2018

We use the same specifications regarding choice of standard deviations as Girma and Paulson (1999). The only exception is that we do not include 2.5 standard deviations in our strategy. We choose standard deviations from 1.5 to 2.25 with an interval of 0.25. Further, Girma and Paulson (1999) settled on 5- and 10-days moving average with the argument that any mispricing should not consist for long period of time. We found that deviations in the spread can consist for a long time, with a half-life of about 57 days according to the error correction model presented in section 6.1. For that reason, we use 40- and 50-days moving averages in our trading model.

We focus more on this strategy as the results below show that it performs better than the strategy based on Emery and Liu. Hence, we have included a measure of risk called Coefficient of Variation (CV)[5]. The measure shows the extent of variability in relation to the mean. We have not included the CV when the average profit is negative. CV is used for risk measurements by Girma and Paulson (1999), but also by other literature on the topic of spread trading like e.g. Mitchell (2010), Simon (1999) and Ma and Soenen (1988). It is preferable that the CV is as low as possible because it implicates a better risk-return trade-off. We have tried to outline some calculations of percentage returns after transaction costs and Sharpe ratios for our best strategies in section 7.2.1.

[5] CV = Std.dev./Av. profit

Period 1	Long Position MA = 40				Long Position MA = 50			
	SD = 1.5	SD = 1.75	SD = 2.0	SD = 2.25	SD = 1.5	SD = 1.75	SD = 2.0	SD = 2.25
No. of trades	13	12	10	8	13	12	10	8
Av. dur. (days)	12	12	14	17	11	12	13	14
% profitable	69 %	75 %	60 %	62 %	92 %	83 %	80 %	75 %
Max. profit (€)	3.9	3.9	3.9	3.65	5.42	5.42	5.42	5.42
Min. profit (€)	-3.11	-2.99	-6.52	-6.52	-0.16	-4.55	-4.55	-4.79
Av. profit (€)	0.82	1.03	0.151	0.06	2.06	1.53	1.61	1.31
Std. dev. (€)	2.20	2.22	2.29	3.54	1.57	2.54	2.92	3.31
Std. error	0.61	0.64	1.04	1.25	0.43	0.74	0.92	1.17
T-value	1.34	1.61*	0.14	0.05	4.74**	2.09**	1.74*	1.12
CV	2.68	2.16	15.17	59	0.76	1.66	1.81	2.53
	Short Position MA = 40				Short Position MA = 50			
	SD = 1.5	SD = 1.75	SD = 2.0	SD = 2.25	SD = 1.5	SD = 1.75	SD = 2.0	SD = 2.25
No. of trades	12	9	8	5	9	9	4	4
Av. dur. (days)	21	29	22	22	27	28	44	40
% profitable	67 %	44 %	38 %	20 %	67 %	56 %	25 %	50 %
Max. profit (€)	11.75	11.75	2.73	2.73	4.02	4.02	1.69	3.94
Min. profit (€)	-5.92	-5.92	-5.92	-4.69	-15.79	-13.13	-14.17	-12.04
Av. profit (€)	0.81	0.35	-1.01	-0.92	-0.46	-0.67	-3.32	-1.61
Std. dev. (€)	4.28	5.28	3.44	2.83	5.60	4.99	7.31	7.14
Std. error	1.24	1.76	1.22	1.27	2.00	1.66	3.65	3.57
T-value	0.66	0.26	-0.83	-0.73	-0.23	-0.40	-0.91	-0.45
CV	5.28	15.09	neg.	neg.	neg.	neg.	neg.	neg.

*Table 7.9: Results from period 1 using the trading strategy based on Girma and Paulson. * 10 % sign. ** 5 % sign. CV is Coefficient of Variation. When CV is referred to as "neg." means that the average profit is negative, and the CV is not defined.*

Table 7.9 shows that in period 1 it is the long positions that yield the highest average profits. They yield positive average profit for all standard deviations for both moving averages. Using SD = 1.5 and SD = 1.75 based on MA = 50, the profit is significantly greater than zero on a 5 %-level, while using SD = 1.75 based on MA = 40 and SD = 2.0 based on MA = 50, the profits are significantly greater than zero on a 10 %-level.

When focusing on percentage of profitable trades SD = 1.5 and SD = 1.75 using MA = 50 stands out with 92 % and 83 % respectively.

Only two of the trades based on a short position yield positive average profit in this period, and none of them are significantly greater than zero on a 10 %-level. The highest percentage of profitable trades are 67 %. Objectively speaking, this may seem good, but none of the profits are significant, and for SD = 1.5 based on MA = 50 the average profit is even negative.

As expected, the number of trades is reduced when we increase the standard deviations for both short and long trades. This can be one of the explanations of why some of the trades are not significantly greater than zero on a 10 % level.

The Coefficient of Variation (CV) varies from a low 0.76 to 59 (when the average profit approximates zero). Most of the CVs are between 1 and 3 for long positions, while for the short positions they are higher with 5.28 and 15.09. The lowest minimum profit for the period is €-15.79 which is substantial relative to the price of the contracts.

Combining long and short positions, we get the following total return:

SD	Profit MA = 40	Profit MA = 50
1.5	€20.36	€22.52
1.75	€15.55	€12.96
2.0	€-6.57	€2.81
2.25	€-4.12	€4.03

Table 7.10: Accumulated profits from long and short positions in period 1 consisting of 1000 trading days.

Summarizing period 1, using 1.5 and 1.75 standard deviations seems to yield the highest and most significant profit. The share of profitable trades is also highest using these specifications, both for long and short positions.

Period 2	Long Position MA = 40				Long Position MA = 50			
	SD = 1.5	SD = 1.75	SD = 2.0	SD = 2.25	SD = 1.5	SD = 1.75	SD = 2.0	SD = 2.25
No. of trades	12	11	9	7	12	9	7	7
Av. dur. (days)	12	13	20	22	13	17	19	20
% profitable	67 %	64 %	44 %	29 %	83 %	56 %	43 %	43 %
Max. profit (€)	2.30	3.15	3.15	3.65	2.33	2.30	3.15	3.65
Min. profit (€)	-6.59	-5.17	-6.52	-6.52	-5.89	-5.89	-4.94	-4.94
Av. profit (€)	-0.13	-0.005	-1.34	-1.87	0.50	-0.69	-0.90	0.73
Std. dev. (€)	2.57	2.80	3.43	3.49	2.48	2.88	3.23	3.53
Std. error	0.74	0.84	1.14	1.32	0.72	0.96	1.22	1.27
T-value	-0.18	-0.01	-1.17	-1.42	0.70	-0.72	-0.74	-0.57
CV	neg.	neg.	neg.	neg.	4.96	neg.	neg.	4.84
	Short Position MA = 40				Short Position MA = 50			
	SD = 1.5	SD = 1.75	SD = 2.0	SD = 2.25	SD = 1.5	SD = 1.75	SD = 2.0	SD = 2.25
No. of trades	10	7	5	3	7	8	2	2
Av. dur. (days)	18	25	11	10	22	23	15	15
% profitable	90 %	71 %	80 %	67 %	86 %	88 %	100 %	100%
Max. profit (€)	11.75	11.75	2.73	2.73	4.02	4.02	2.16	2.16
Min. profit (€)	-0.48	-0.48	0.00	0.00	-0.89	-1.94	1.80	1.80
Av. profit (€)	2.27	2.59	1.74	1.63	1.32	1.00	1.98	1.98
Std. dev. (€)	3.43	4.19	1.03	1.44	1.52	1.67	0.26	0.26
Std. error	1.08	1.58	0.46	0.83	0.57	0.59	0.18	0.18
T-value	2.02**	1.64*	3.77**	1.96*	2.31**	1.69*	10.89**	10.89**
CV	1.51	1.62	0.59	0.88	1.15	1.67	0.13	0.13

*Table 7.11: Results from period 2 using the trading strategy based on Girma and Paulson. * 10 % sign. ** 5 % sign. CV is Coefficient of Variation. When CV is referred to as "neg." means that the average profit is negative, and the CV is not defined.*

For period 2, short positions yield the highest average profit. This is complete opposite from period 1. A reason for this can be that in period 2, the spread (see figure 10.5) has more significant drops than in period 1. In addition, most of the profits are significantly greater than zero on a 5 % level with three exceptions; SD = 1.75 and SD = 2.25 based on MA = 40, in addition to SD = 1.75 based on MA = 50. These three are though significantly greater than zero on a 10 % level.

Focusing on percentage profitable trades, six out of eight specification have a share of profitable trades above 80 % for short positions. The highest share of profitable trades is obtained using SD = 1.5 and SD = 1.75, except when MA = 50. On the other hand, there are only two short trades in this case.

None of the long trades are significantly greater than zero. The average profit per trade is mostly negative. Interestingly, using SD = 1.5 and SD = 1.75 seems to yield the best results for long trades as well, both in terms of average profit and share of profitable trades. Using MA = 50 and 2.0 and 2.25 standard deviations results in a share of profitable trades of 100 %. However, there are only two trades during the period.

The CV ranges from a low 0.13 to 4.96 in this period. Short positions show the lowest CVs between 0.13 and 1.67. The lowest minimum profit during the period is €-6.59. Compared to period 1, this is low. Looking at the short positions which yield the highest profits during this period, we also see that the minimum profits overall are low.

Combining long and short positions, we get the following total return:

SD	Profit MA = 40	Profit MA = 50
1.5	€21.12*	€13.27*
1.75	€18.06	€1.78
2.0	€-3.37	€-2.34
2.25	€-8.20	€-1.12

Table 7.12: Accumulated profits from long and short positions in period 2 consisting of 1000 trading days. Average profit per trade for long/short positions accumulated is sign. on a 10 % level.*

Summarizing period 2, we obtain similar results as in period 1. Using SD = 1.5 and SD = 1.75 yields the highest profits. On the other hand, short positions were the most profitable ones during this period.

Period 3	Long Position MA = 40				Long Position MA = 50			
	SD = 1.5	SD = 1.75	SD = 2.0	SD = 2.25	SD = 1.5	SD = 1.75	SD = 2.0	SD = 2.25
No. of trades	12	10	8	6	11	8	6	6
Av. dur. (days)	15	14	22	25	18	21	26	27
% profitable	67 %	60 %	50 %	33 %	73 %	38 %	17 %	33 %
Max. profit (€)	1.96	2.27	2.27	1.35	2.33	2.06	1.35	1.35
Min. profit (€)	-6.60	-5.17	-6.52	-6.52	-5.89	-5.89	-4.94	-4.94
Av. profit (€)	-0.15	-0.33	-1.57	-2.34	-0.08	-1.43	-2.27	-1.62
Std. dev. (€)	2.52	2.51	3.25	2.98	2.48	2.71	2.28	2.79
Std. error	0.73	0.79	1.15	1.22	0.75	0.96	0.93	1.14
T-value	-0.20	-0.42	-1.36	-1.93	-0.11	-1.50	-2.44	-1.42
CV	neg.	neg.	neg.	neg.	neg.	neg.	neg.	neg.
	Short Position MA = 40				Short Position MA = 50			
	SD = 1.5	SD = 1.75	SD = 2.0	SD = 2.25	SD = 1.5	SD = 1.75	SD = 2.0	SD = 2.25
No. of trades	9	8	7	4	6	7	4	2
Av. dur. (days)	22	25	14	10	26	23	19	15
% profitable	78 %	75 %	71 %	75 %	83 %	86 %	75 %	100 %
Max. profit (€)	11.75	11.75	5.13	5.13	4.02	4.02	5.13	2.16
Min. profit (€)	-8.00	-8.00	-6.72	0.00	-7.12	-3.92	-6.50	1.80
Av. profit (€)	1.58	1.65	1.00	2.51	0.64	1.01	0.65	1.98
Std. dev. (€)	5.03	5.37	3.73	2.11	3.96	2.53	5.00	0.26
Std. error	1.67	1.90	1.41	1.05	1.62	0.95	2.50	0.18
T-value	0.95	0.87	0.71	2.38**	0.39	1.05	0.26	10.89**
CV	3.18	3.25	3.73	0.84	6.19	2.50	7.69	0.13

*Table 7.13: Results from period 3 using the trading strategy based on Girma and Paulson. * 10 % sign. ** 5 % sign. CV is Coefficient of Variation. When CV is referred to as "neg." means that the average profit is negative, and the CV is not defined.*

Period 3 in table 7.13 shows weaker results overall than the two previous periods. We only get two profits that are significantly greater than zero on a 5 % level and none of the others are significantly greater than zero. These two are both short trades. All the average long trades are negative, while all the average short trades are positive during the period. Few trades and high standard deviations of profits could be a reason for none of the long trades being significantly greater than zero.

The overall share of profitable trades is lower than in the previous periods. Still 1.5 and 1.75 standard deviations seem to stand out for both moving averages.

The CV is only present for short positions during this period as all the average profits are negative for long positions. It varies from 0.13 to 6.19. The lowest minimum profit is €-8.00.

Overall, the results for period 3 is in line with the other periods. Using 1.5 and 1.75 standard deviations yields the best results. This is reassuring as it shows that these specifications seem to work well during different regimes.

Combining long and short positions in period 3, we obtain the following total return:

SD	Profit MA = 40	Profit MA = 50
1.5	€12.51	€2.95
1.75	€9.81	€-4.41
2.0	€-5.44	€-11.04
2.25	€-4.05	€-5.73

Table 7.14: Accumulated profits from long and short positions in period 3 consisting of 1000 trading days.

<u>Summary:</u>

The results from our trading strategy based on Girma and Paulson were better than the strategy based on Emery and Liu. The profits generated were mostly greater, and the amount of trades executed were significantly higher. Two specifications seemed to stand out during all three periods: Using 1.5 and 1.75 standard deviations yields the highest return for both moving averages, with a combined profit greater than zero for all periods except period 3 with MA = 50 and SD = 1.75. Though, the profits were not necessarily significantly greater than zero in all cases. As discussed earlier we have not included transaction costs and slippage costs. The profits generated here, will therefore not be obtainable in real life. Concluding this trading strategy, it seems like there is a chance for generating positive profits using the recommended specifications. There can be some variation in the results, and for other periods there is no guarantee that the strategy will function in a similar way.

We have included Coefficient of Variation (CV) as a measure of the risk. Our CVs vary during our periods. There is often one side of the trade that yields profits during the three periods, whether it is long or short positions. When the average profit is negative, the CV is not defined in our thesis. The CVs reported vary. This indicates that there is a certain risk associated with the trading. Compared to Girma and Paulson (1999), our CVs are higher and more volatile. Their strategy yields positive average profits both long and short. However, the short positions show CVs that varies from 0.688 to 9.257. When our average profit is positive, our CVs are not *that* high related to Girma and Paulson (1999). Ma and Soenen (1988) investigate the gold-silver spread and find positive risk-adjusted profits. Their average CV is 3.04 according to Mitchell (2010), and the strategy results in 61 % profitable trades. Mitchell (2010) reports CVs from a low 4.28 and up in his soybean crush spread trade. He also reports CVs from Simon (1999) who investigates the crush spread. There, the CV ranges from 2.46 to 15.04 for long positions and from 1.96 to 8.61 for short positions. Compared to these last three articles, our CVs seem satisfactory. However, some of them are not defined since the average profit is negative. Also, we have not included transaction costs to our analysis, which means that the CVs will be somewhat higher in reality.

Even though the CV is a tool for considering the risk-adjusted profits (here using profits in Euros), a litmus test in finance is to generate returns in percentage and estimate for example a Sharpe ratio or value-at-risk. We found that 1.5 and 1.75 standard deviations using 40-days moving average seemed to yield the highest return. Using these trading rules, we will outline some calculations of annualized returns and standard deviations, and the corresponding Sharpe ratios in section 7.2.1.

7.2.1 Risk and Return Calculations for the Strategy Based on Girma and Paulson

Traders are interested in comparing results from trading strategies. To verify the risk and return from trading strategies, an estimate of the percentage return and the risk is important for comparing the quality of the returns. Therefore, we highlight the best-performing rules in the strategy based on Girma and Paulson, and outline some calculations of the percentage return, and the risk using Sharpe ratio. The calculations are based on a rough estimate of margin requirements of €20.00 per spread contract. According to the Chicago Mercantile Exchange (CME) the futures margin is typically 3-12 % of the notional value of the contract (CME, 2019a). In addition, there is often a margin discount when trading spreads because the positions offset each other (CME, 2019b). Therefore, a margin of €20.00 per spread contract seems sufficient in most cases. We included transaction costs in this analysis. According to Nasdaq (Nasdaq), trading European power contracts implicates a trading fee of 0.0045 EUR/MWh (one contract is 1 MWh) and a clearing fee of 0.0045 EUR/MWh. In total 0.009 EUR/MWh will be charged for every transaction. When trading spreads we need to multiply this with two because we acquire both long and short positions. This means that for every trade, a transaction cost of 0.018 EUR/MWh will be charged. We have also added transaction costs when rolling from one contract to another.

For our calculations we have assumed that one year consists of 250 trading days. Formula for the Sharpe ratio are shown in the appendix (section 10.7). The Sharpe ratio is calculated using the average annual 3-month Norwegian treasury bills from 2007 to 2018 (which is our total period of data) as risk-free rate. The data are collected from Norges Bank (NorgesBank, 2019). The average annual risk-free rate turned out to be 1.88 %.

We will do a quick comparison of Sharpe ratios with spread trading literature as well as Sharpe ratios for S&P 500 during our three periods. The Sharpe ratios for period 1-3 were the following for S&P 500 (using the same 3-month interest rate):

Period 1 Sharpe ratio: 0.93

Period 2 Sharpe ratio: 0.78

Period 3 Sharpe ratio: 0.30

Period		Av. daily return	Annualized return	Daily std. dev.	Annualized Std. dev	Sharpe ratio (annual)
1	1.50 std.dev.	0.23 %	77.0 %	3.8 %	59.7 %	0.93
	1.75 std.dev.	0.18 %	56.1 %	3.9 %	61.1 %	0.70
2	1.50 std.dev.	0.30 %	112.7 %	3.6 %	57.7 %	1.28
	1.75 std.dev.	0.27 %	95.0 %	3.7 %	58.8 %	1.11
3	1.50 std.dev.	0.20 %	65.9 %	4.8 %	75.6 %	0.65
	1.75 std.dev.	0.13 %	39.0 %	4.4 %	69.9 %	0.44

Table 7.15: The key numbers average daily return, annualized return, daily standard deviation, annualized standard deviation and Sharpe ratio shown for 1.50 and 1.75 standard deviations using on 40-days moving average for all three periods. The calculations of the Sharpe ratios are based on the average daily returns and daily standard deviations and are annualized (see formula in appendix section 10.7). Calculation annualized return (AR): $AR = (1+r)^{250} – 1$, where r = daily average return. Calculation annualized standard deviation (ASD): $ASD = \sigma(250)^{0.5}$, where σ = daily standard deviation.

Table 7.15 shows the returns, standard deviations and Sharpe ratios we have obtained for period 1-3. The Sharpe ratios vary from 0.44 in period 3 using 1.75 standard deviations to 1.28 in period 2 using 1.5 standard deviations. Compared to Cummins and Bucca (2012) our Sharpe ratios are smaller. This means that their risk-adjusted return is higher. As mentioned, we have included Sharpe ratios for S&P 500 which we have calculated for exactly our three periods using the same risk-free rate. For period 1, S&P 500's Sharpe ratio was 0.93, while we had 0.93 and 0.70. For period 2, S&P 500's Sharpe ratio was 0.78, and we had 1.28 and 1.51. The Sharpe ratio for period 3 was low for S&P 500 with 0.30. Our strategy resulted in a Sharpe ratio of 0.65 and 0.44 in this period. Overall, our Sharpe ratios is competitive with the ones for S&P 500. However, they are calculated using the rules that performed best. In addition, the estimated margin requirement of €20.00 is a rough approximation.

8 Discussion

Having presented the results, we will now discuss our findings in light of the literature presented in chapter 3 and make suggestions for further research. First, we discuss our results from the cointegration analysis, before we move over to the trading strategies.

8.1 Discussion – Cointegration Analysis

We found that Nordic and German front month electricity futures prices were cointegrated. This was indicated by both the Engle-Granger method and the Johansen and Juselius method. The multivariate cointegration analysis using the Johansen and Juselius method also showed a cointegrating vector between ElGer, ElNP and CO2. We focus on this vector (_ce1) when comparing with other literature on the subject.

We started the literature chapter (chapter 3) with referring to the Law of One Price (Fetter, 1924). In an efficient market, homogenous products like electricity should trade for the same price. It is no doubt that this law does not hold between the Nordic and German power markets. But as we have found cointegration, this could be evidence of partial convergence, or similar relative prices, described by Gugler, Haxhimusa and Liebensteiner (2018), and Chen and Knez (1995) respectively. EU has a goal to create a European wholesale market for electricity. New interconnections between European countries, could lead to a more efficient market. Jamasb and Pollitt (2005) argues that to increase the integration across Europe, governments must facilitate for competition. Increased competition will reduce market power for big suppliers (like e.g. Statkraft in Norway). Increased transmission capacity across Europe will expand the relevant market, and the individual supplier will lose its share of the total market because of higher competition. Moreover, different distribution and transmission charges between countries is also elements working against a development of efficient markets. If the EU succeed with their goal, we expect a tighter integration between the Nordic and German electricity market. It would be interesting to investigate any cointegrating relationship after the NordLink interconnector between Norway and Germany will begin operations. We expect that this could lead to a higher speed of adjustment to equilibrium than we have found for our data.

As discussed in chapter 3, Bower (2004) found no significant (5 % level) cointegration between Nord Pool and German EEX/LPX spot prices using data from 2001. In addition, the correlation between the markets was low. None of these findings coincide with our results. One explanation for this could be that while we use futures prices, Bower use spot prices. Different price dynamics in futures/forwards versus spot prices can give different results. Povh and Fleten (2009) argue that the forward-price dynamics is different from the spot-price dynamics when there is some time left until delivery (t). As the time to delivery closes ($T \approx t$), the dynamics in spot and forward prices will become more similar. de Menezes and Houllier (2016) found that most forward prices they investigated were more cointegrated than the respective spot prices. However, they did not investigate this using Nordic and German electricity futures. The most important reason for our different findings could though be the data period used for testing. While Bower tested using daily data from 2001, we have used daily data from January 2007 to February 2019. First, our time span differs quite heavily. Second, but maybe most importantly, much has happened regarding the market integration in Europe since 2001, with e.g. increasing physical interconnections between areas.

The fractional cointegration analysis by de Menezes and Houllier (2016) using daily spot data from 2000 to 2013 including Nord Pool and Germany showed cointegration only 28 % of the time. However, they find that this share increased during the sample period. Aatola, Ollikainen and Toppinen (2013) find similar results using futures prices. Both correlation and market integration, investigated using a VECM approach, between Nordic and German futures prices increased during their sub-periods. These results could support our theory that the findings by Bower (2004) are not *that* comparable with ours.

Going more in-depth in the article by Aatola, Ollikainen and Toppinen (2013) is interesting because their article coincides to a greater extent to our thesis than the articles by Bower (2004) and de Menezes and Houllier (2016). They investigate cointegrating relationships between European electricity markets using daily forward data from 2003 to 2011 and find stationary relationships with both Nordic and German forward prices, and Nordic forwards, German forwards and forwards on CO_2 emission allowances. We also found a cointegrating vector showing strong integration between Nordic and German futures prices, and a low, but significant impact from futures on CO_2 emission allowances. The coefficients obtained are quite similar to the findings by Aatola, Ollikainen and Toppinen (2013). As discussed earlier, an implication of this could be to develop spread trading strategies between Nordic futures, German futures and futures on the CO2 price. This could have improved our trading results, especially for the strategy based on Emery and Liu (2002). One reason for this is that the in-sample regression between Nordic and German futures prices used for prediction purposes out-of-sample, showed a low explanatory power, at least for period 1 and 2. Adding other variables to the trading strategy could therefore increase the fit of the regression model and improve our out-of-sample results. However, we chose not to include the CO2 price in out trading strategy based on the argumentation in section 6.2.

Povh and Fleten (2009) analyzed cointegrating relationships between weekly forward prices on Nordic and German electricity, and coal, gas, emission allowances and aluminum. They found a cointegrating vector showing a stationary relationship between Nordic futures, coal, emission allowances, German futures and aluminum. In sharp contrast to us, they find that Nordic prices fall almost one to one with an increase in German prices. Since the prices are strongly positively correlated, like we find in our data as well, they argue that if a positive shock occurred in the German prices last period (last week), then a similar shock is likely to have occurred in the Nordic prices also. Further, they find a small, but significant impact from the CO2 price, like us, but also cointegration between Nordic prices, coal and aluminum. We found that the gas price was insignificant in our cointegrating vector normalized on Nordic prices. This coincides with the findings by Povh and Fleten (2009). We think the use of weekly forward prices is an important explanation for the differences in the cointegrating vector between our results and the ones by Povh and Fleten (2009). The cointegration analysis by Aatola, Ollikainen and Toppinen (2013) shows a cointegrating vector with the same sign as us using daily data, which supports our thoughts that using weekly data will lead to a somewhat different dynamic in the cointegration analysis. However, both our results and the results by Povh and Fleten (2009) show significant cointegration between Nordic and German futures/forward prices.

Finally, regarding price formation in the Nordic and German area, Redl *et al.* (2009) found that price formation in the Nordic and German area was similar, and that the prices depend on generation costs, also in the Nordic area. Emery and Liu (2002) discovered that the sensitivity to natural gas prices was almost similar in two areas in the US which have energy mixes quite similar to the Nordic and German power markets. Looking at the short-term dynamics in our VECM model, we saw that the sensitivity to gas prices was almost the same for both futures prices in Nordic and Germany. As mentioned in section 6.1 this could be because gas often is the price setter in the electricity market, especially during peak-hours.

8.2 Discussion – Trading Strategies

Emery and Liu (2002) found that traders using their strategy would have earned profits both in- and out-of-sample. They also found that trades based on a long position yield higher profits than those based on a short position for both samples.

Our findings show that long positions yield higher profits than short positions. Our problem is that we did not get enough trades in the out-of-sample period to get a good empirical foundation. We think the main reason for that is the speed of adjustment to equilibrium value for the spread. Emery and Liu (2002) found an adjustment to equilibrium value with a half-life of approximately 15 days, while our test revealed a half-life of ~ 57 days. The difference is significant, and the result is that Emery and Liu obtain more trades than us.

We struggle with recommending our trading strategy based on Emery and Liu (2002) to traders. This is because we execute few trades, and hence we do not get a good empirical foundation. The strategy fails in period 1 but seems to work better for period 2 and 3. We think this could be due to increasingly integrated markets during the periods, as the explanatory power increases, and that the beta-coefficient approaches 1. It could be interesting to do the same analyzes on Nordic and German electricity prices in the future. As mentioned, it is planned to build more interconnectors between the Nordic countries and the rest of Europe, included Germany. This could lead to a tighter integration between the Nordic and German electricity markets. The time span for adjustment to equilibrium could shorten. Out fitted regression models used in this trading strategy showed low to moderate explanatory power measured by R^2. Emery and Liu's (2002) fitted regression models showed greater explanatory power, which could be another reason for that they succeed to a greater extent with their strategy. Including futures on emission allowances in the trading, as the cointegration analysis showed a stationary relationship between futures on Nordic and German electricity, and CO2, could have improved our results.

Our trading strategy based on Girma and Paulson (1999) using 1.5 and 1.75 standard deviations yields the highest profits overall. Girma and Paulson (1999) found that using 1.50 and 1.75 standard deviations yields the highest profits in absolute numbers. The reason for this seems to be that the amount of trades is much higher than if they increased the standard deviation. Looking at average profit per trade, the picture is opposite with highest profits per trade obtained (mostly) using the upper standard deviations (2.00 up to 2.50 standard deviations). This is not the case for us, with both absolute profits and average profits per trade being highest using 1.50 and 1.75 standard deviations. Our expectations were that average profit per trade would be highest for the upper standard deviations, so this finding was surprising. One explanation can be that if the spread manages to break the highest standard deviations, the drift in the spread continuous for a time, dragging up/down the moving average which is where the positions are closed. We hoped that our method of entering a position the *second* time the spread broke the moving average would prevent being long/short a downward/upward drifting spread. In some cases, this probably has worked, but it is inevitable that the spread will break the MA the second time, but then continue its drift before reversing to the mean. We also know from our cointegration analysis that that the spread can be different from its equilibrium value for a long time.

Girma and Paulson (1999) found that historically profitable risk arbitrage opportunities existed and that they were statistically significant. We cannot compare our absolute profits with theirs because our time spans are different. Their profits are less volatile, and more or less all their trading results showed profits significantly greater than zero. This was not the case for us. Our results vary, both in terms of absolute profits and significance. There could be several reasons for this. For example, there is a possibility that this is not the optimal strategy for our spread. The specifications chosen regarding length of moving averages and size of standard deviations could be different. Another explanation can be that the market is efficient, which implies that any trading strategy should not generate profits significantly greater than zero, as discussed by Girma and Paulson (1999). The risk associated with the trading measured by Coefficient of Variation (CV) shows that Girma and Paulson (1999) generally generate better risk-adjusted returns than us. However, comparing to other literature on the topic of spread trading, our CVs seem to be satisfactory when the average profit is positive. But on a general basis, we conclude that the profits seem to be unstable based on the CVs obtained.

Cummins and Bucca (2012) found Sharpe ratios mostly exceeding 2 and often close to 4. This is higher than our findings, meaning that their risk-adjusted profits were better. However, the analysis of our best trading rules showed that our risk-adjusted returns outperform S&P 500 if we focus on the Sharpe ratio. We must take into consideration that we only calculated the Sharpe ratio for our best returns. It is hard to say exactly *why* Cummins and Bucca's risk-adjusted returns are better than ours. Their volatility in returns is lower than ours. This may be because they performed spread trades in different oil and oil products. These kinds of products are often highly integrated and will not wander far apart before reversing to equilibrium since they are all based on oil and different refining processes. As shown in the cointegration analysis, the drift from equilibrium value between Nordic and German electricity futures could be substantial and last for a long time. It is therefore natural to believe that differences in these kinds of spreads can be less volatile.

Gatev, Goetzmann and Rouwenhorst (2006) found that the excess return from their spread trading strategy could not be explained by the Fama and French factors (market, small-big, high-low etc.) (Fama and French, 1996), and concluded that profits can be described by a latent risk factor in which arbitrageurs are compensated for enforcing the Law of One Price (LOP). We have not done any analysis of our returns, but this could be one possible reason for our best strategies yielding excess returns. Further, Gatev, Goetzmann and Rouwenhorst (2006) report that their best pairs yield average annualized returns up to 11 %. The Sharpe ratio (annualized) for their highest yielding portfolio of pairs was 2.14 (using their reported daily excess return and standard deviation). Our highest Sharpe ratio turned out to be 1.28. Since our excess returns generally are higher, it is the risk associated with the electricity futures trading that drags down the Sharpe ratio, compared to this article.

Future research can investigate risk management in spread trading using some sort of stop loss. In this strategy one could e.g. close the position if the spread continued to drift up/down to φ standard deviations. Other tips for future investigation could be to do a thorough analysis of how to calculate percentage returns from a (spread) trading strategy using futures. A deeper analysis of the risk-adjusted return is also relevant.

9 Conclusion

This thesis examines if the Nordic and German front month futures on electricity prices are cointegrated, and, if so, if it is possible to develop a spread trading strategy between the prices. The cointegration analysis conducted using the Engle-Granger method and the Johansen and Juselius method both showed significant cointegration between the futures prices. The Johansen and Juselius method also revealed that the futures prices on emission allowances is a part of this relationship. The speed of adjustment was shown to be low by both methods. This indicates that the prices can stay out of equilibrium for a long time.

The results from our trading strategies varied. The strategy based on Emery and Liu (2002) resulted in few trades out-of-sample and few significant profits. The profits increased during the three periods, which we think can be due to a better fit of the model from period 1 to period 3. The trading strategy based on Girma and Paulson (1999) resulted in varying profits but proved to be better than the one based on Emery and Liu, both regarding number of trades and overall profitability. Using 1.5 and 1.75 standard deviations stands out as the best specifications. It results in positive average profits during all three periods using both moving averages. The Sharpe ratio proved to be competitive with the corresponding Sharpe Ratios for S&P 500 during the investigated periods. However, few of the profits proved to be statistically significant. Based on this, the market could seem to be efficient since no significant profits was generated using statistical arbitrage strategies.

The results could be different with a higher speed of adjustment. Increasing amounts of interconnections in the European electricity wholesale market makes it interesting to develop trading strategies between electricity markets looking forward. Future research can include a price for emission allowances in the trading strategies since one of our cointegrating vectors showed a stationary relationship between futures on Nordic electricity, German electricity and emission allowances. One of the reasons Einar Aas' spread trade went bust was because the cost of carbon emissions spiked, pushing up the German electricity price (Ewing and Schreuer, 2019). Hence, including this variable when modeling a trading strategy could have prevented this loss from occurring.

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10 Appendices

10.1 Tests for Autocorrelation for Bivariate Error Correction Models

Error Correction Model for ElNP:

The Lagrange Multiplier test:

Lags (p)	chi2	df	Prob > chi2
2	3.774	2	0.1515

Table 10.1: The Lagrange Multiplier test for the Error Correction Model where ElNP is the dependent variable.

Error Correction Model for ElGer:

The Lagrange Multiplier test:

Lags (p)	chi2	df	Prob > chi2
2	0.725	2	0.6960

Table 10.2: The Lagrange Multiplier test for the Error Correction Model where ElGer is the dependent variable.

H_0: no serial correlation

STATA command: ‘ estat bgodfrey, lags(2) ‘

10.2 The Johansen Trace Test

Trend: constant	Number of obs. = 3035
Sample: 3 – 3037	Lags = 2

Max. Rank	**Parms**	**LL**	**Eigenvalue**	**Trace Statistics**	**5 % Critical Value**
0	42	37818.998	-	140.3071	94.15
1	53	37851.082	0.02092	76.1388	68.52
2	62	37865.397	0.00939	47.5100	47.21
3	69	37875.605	0.00670	27.0940*	29.68
4	74	37883.328	0.00508	11.6468	15.41
5	77	37886.579	0.00214	5.1464	3.76
6	78	37889.152	0.00169	-	-

Table 10.3: Johansen Trace Statistics for 2 lags and no trend for all variables. Critical values at 5 % are given.

STATA command: ‘ vecrank lnNP lnElGer lnCo2 lnCoal lnBrent lnGas, trend(constant) ‘

10.3 Test for Autocorrelation and Normality for VECM model

Test for autocorrelation:

Lag	chi2	df	Prob > chi2
1	80.1629	36	0.00003
2	88.6094	36	0.00000

Table 10.4: Test for autocorrelation.

H_0: no autocorrelation at log order

STATA command: ‘ veclmar ‘

Test for normality (Jarque-Bera):

Equation	chi2	df	Prob > chi2
D_lnNP	4174	2	0.0000
D_lnCo2	5.8e+08	2	0.0000
D_lnBrent	2113	2	0.0000
D_lnCoal	3333	2	0.0000
D_lnElGer	6118	2	0.0000
D_lnGas	7.7e+04	2	0.0000
ALL	5.8e+08	12	0.0000

Table 10.5: Jarque-Bera test for normality.

STATA command: ‘ vecnorm, jbera ‘

10.4 Explanatory Power for VECM Models

Equation	R^2
D_lnElGer	0.070
D_lnCoal	0.035
D_lnBrent	0.011
D_lnGas	0.010
D_lnCo2	0.016
D_lnNP	0.041

Table 10.6: R squared for the VECM models.

10.5 Spread Between Nordic and German Front Month Futures Price

Figure 4.1: Spread between Nordic and German front month futures prices for the whole data period. X-axis: Date. Y-axis: Spread in Euros. Spread is defined as Nordic – German.

10.6 Calculating the Sharpe Ratio

Sharpe ratio is a measure of risk-adjusted returns. It measures the excess return (return in excess of risk-free rate) per unit of volatility (measured in standard deviations). The higher the Sharpe ratio, the better. The formula of the Sharpe ratio is:

Sharpe Ratio = $(r_p - r_f) / \sigma_p$

Where r_p is the portfolio return, r_f is the return of the risk-free asset, and σ_p is the volatility of the portfolio (standard deviations). We use daily average return and daily standard deviation as input for calculating the daily Sharpe ratio. Converting the risk-free rate to daily rate is done by dividing it on the number of trading days per year (which is assumed to be 250 per year). Annualizing the Sharpe ratio is done by multiplying it with the square root of 250. This assumes that daily returns are independent and identically distributed (i.i.d.).

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