Joonas Vaissalo

Volatility dynamics between EU ETS and Nordic electricity market

School of Accounting and Finance
Master’s thesis in Finance
Master’s Degree Programme in Finance

Vaasa 2021

UNIVERSITY OF VAASA
School of Accounting and Finance
Author: Joonas Vaissalo
Topic of the thesis: Volatility dynamics between EU ETS and Nordic electricity market
Degree: Master of Science in Economics and Business Administration
Programme: Finance
Supervisor: Anupam Dutta
Year: 2021 **Pages:** 72

ABSTRACT:

Due to the increasing awareness towards climate change scholars have been displaying growing interest towards emission trading. European Union emission trading scheme is an EU-wide establishment in which corporations trade emission allowances. One of the largest individual sectors participating in the European emission trading is the electricity market. Thus, it is important to investigate the complex connection between emission and electricity markets. So far, the existing literature has been focusing on the price and return relationship between the two markets. The main focus of this study is to shed light to the scarcely studied volatility connection between European emission trading and electricity prices.

In order to study the volatility connection between the markets this study conducts a DCC-GARCH analysis. Such modelling enables the investigation of return and volatility connection as well as the time-varying correlation between assets. Thus, the model is able to provide valuable information about the constantly changing European emission market. The data utilized in this study ranges from January 2009 to March 2019 and includes daily prices from EU ETS and Nord Pool electricity market. The data is gathered only from the second and third phase of EU ETS as carbon price was practically zero at the end of the first trading phase.

The main empirical findings suggest that the volatility and returns flow only from Nordic electricity market to European emission market. No evidence of information or return flows of opposite direction is found. This could be due to Nordic countries developing their production mixes to include more carbon-free generation. Thus, the carbon price has a lower impact on region’s electricity price formation. Further, electricity’s volatility could affect EUAs volatility as rapid changes in demand of electricity may force producers to ramp up carbon-intensive facilities. Finally, analysis of hedging effectiveness proves that Nordic electricity market participants can lower their downside risk by including carbon assets in their portfolios.

KEYWORDS: Volatility spillovers, Hedging, EU ETS, Nordic electricity, DCC-GARCH

Vaasan Yliopisto
Laskentatoimen ja rahoituksen yksikkö
Tekijä: Joonas Vaissalo
Tutkielman nimi: Euroopan päästökaupan ja Pohjoismaisen sähkömarkkinan välinen volatiliteettiyhteys
Tutkinto: Kauppatieteiden maisteri
Koulutusohjelma: Rahoitus
Työn ohjaaja: Anupam Dutta
Valmistumisvuosi: 2021 **Sivumäärä:** 72

ABSTRACT:

Ilmastonmuutoksen vääjäämätön uhka on kasvattanut yritysten sekä tutkijoiden mielenkiintoa markkinaehtoista päästökauppaa kohtaan. Euroopan päästömarkkinat ovat yksi vanhimmista ja suurimmista päästöoikeuksien kauppapaikoista, jonka vuoksi siihen kohdistuu erityistä huomiota useilta tahoilta. Energian tuotannon ja kulutuksen synnyttämät markkinat puolestaan ovat yksi suurimmista yksittäisistä päästökaupan alaisista toimialoista. Tämän vuoksi on tärkeää tutkia ja ymmärtää energiamarkkinoiden ja päästökaupan välistä yhteyttä. Aikaisemmat tutkimukset keskittyvät hintojen ja tuottojen väliseen yhteyteen ja jättävät usein näiden volatiliteettiyhteyden huomioimatta. Tämä tutkimus pyrkii täyttämään tämän aukon tutkimalla Pohjoismaisen sähkömarkkinan ja Euroopan päästökaupan välistä volatiliteettiyhteyttä.

Tutkiakseen sähkömarkkinoiden ja päästökaupan välistä volatiliteettisuhdetta tämä tutkimus hyödyntää DCC-GARCH-mallia. Malli mahdollistaa markkinayhteyksien analysoinnin sekä tuotto- että volatiliteetti tasoilla. Tämän lisäksi mallin avulla on mahdollista tutkia myös markkinoidenvälisen korrelaation kehitystä tutkimusperiodin aikana. Tutkimuksessa käytetty aineisto on kerätty tammikuun 2009 ja maaliskuun 2019 väliseltä ajanjaksolta ja se koostuu päivittäisistä havainnoista Euroopan päästömarkkinoilta sekä Pohjoismaisilta sähkömarkkinoilta. Tutkimusperiodi alkaa Euroopan päästökaupan toisen jakson alusta, sillä ensimmäisen jakson lopussa päästöoikeudet olivat käytännössä arvottomia.

Tutkimustulosten mukaan volatiliteetti- ja tuottovirrat markkinoiden välillä ovat yksisuuntaisia. Tulokset indikoivat, että Pohjoismainen sähkömarkkina vaikuttaa molemmilla tasoilla Euroopan päästökauppaan, mutta päästökaupalla ei ole tilastollisesti merkittävää vaikutusta sähkömarkkinoihin. Tämä saattaa johtua vähäpäästöisen energiatuotannon määrän kasvusta Euroopan ja erityisesti Pohjoismaiden alueella, jonka vuoksi päästöoikeuden vaikutus sähköntuotantoon laskee. Lopuksi tutkimus analysoi onko Pohjoismaisen sähkömarkkinatoimijan mahdollista laskea riskiään sisällyttämällä portfolioonsa päästöoikeuksia. Tutkimustulosten mukaan portfolio, jossa yhdistyvät päästöoikeudet sekä Pohjoismainen sähkö on matalariskisempi kuin vastaava portfolio, joka koostuu ainoastaan sähköstä.

KEYWORDS: Volatiliteettiyhteys, Riskien hallinta, EU ETS, Pohjoismainen sähkömarkkina, DCC-GARCH

Table of Contents

1 Introduction 8
  1.1 Research motivation and hypotheses 9
  1.2 Structure of the thesis 11
2 Literature Review 12
3 Electricity markets 18
  3.1 Deregulation of electricity markets 18
  3.2 Characteristics of competitive electricity markets 20
  3.3 Electricity price formation 22
    3.3.1 Effects of carbon trading to electricity price formation 23
  3.4 Nordic power markets 26
    3.4.1 Nord Pool 26
    3.4.2 Bidding areas 28
4 Emission trading in Europe 31
  4.1 Kyoto Protocol 31
  4.2 European Union Emission Trading Scheme 32
  4.3 Implementation of EU ETS 35
    4.3.1 Phase I 35
    4.3.2 Phase II 35
    4.3.3 Phase III and the future of EU ETS 36
  4.4 EUA price formation 37
5 Volatility estimation 41
    5.1.1 ARCH models 41
    5.1.2 GARCH models 42
6 Data & empirical methodology 45
  6.1 Data description 45
  6.2 Empirical methodology 49
7 Empirical results 52

7.1 DCC-GARCH estimation 52
  7.1.1 Mean and variance equations 52
  7.1.2 Time-varying correlation 55
7.2 Hedging effectiveness 57
7.3 Robustness check 58

8 Conclusions and discussion 61

References 64

Figures

Figure 1. Merit order curve. 22

Figure 2. Pass-through rates under a change in merit order. (Sijm et al., 2006). 23

Figure 3. Electricity production mix in Scandinavian countries. 26

Figure 4. Formation of area prices. (Junttila et al., 2018). 28

Figure 5. Equilibrium of supply and demand of EUAs. (Rickels et al., 2015). 36

Figure 6. Price development of EUA and Nordic electricity. 43

Figure 7. Logarithmic returns of EUA and Nordic electricity. 45

Figure 8. Time-varying conditional correlation. 54

Tables

Table 1. Summary statistics for price series. 44

Table 2. Summary statistics for price series. 46

Table 3. Augmented Dickey-Fuller stationarity test results. 47

Table 4. Results from DCC-GARCH model. 51

Table 5. Summary statistics of time-varying correlation. 53

Table 6. Results from ADCC-GARCH model. 56

Abbreviations

UNFCCC	United Nations Framework Convention on Climate Change
CO_2	Carbon Dioxide
EU ETS	European Union Emission Trading Scheme
EUA	European Emission Allowance
ARCH	Autoregressive Conditional Heteroskedasticity
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
DCC	Dynamic Conditional Correlation
OECD	Organization for Economic Co-operation and Development
BAU	Business-As-Usual
HE	Hedging Effectiveness

1 Introduction

By the time of writing this thesis it is well known that climate change is among the most severe threats not alone to the global economy or the environment but also to humankind as a whole. Emitting greenhouse gases, especially carbon dioxide (CO_2), to the atmosphere is found to be the main driver behind accelerating global warming and changing climate (Luo & Wu, 2016). To tackle the threat of climate change organizations and governments over the globe have implemented programs to mitigate greenhouse gas emissions. In 1997 the Kyoto protocol was introduced and set into action by the United Nations framework convention on climate change (UNFCCC). The initial goal of the Kyoto protocol was to decrease the amount of greenhouse gases emitted on average by 5.2% compared to the year 1990 (UNFCCC, 2003). In order to provide member countries and corporations incentives to follow the goals set in the Kyoto protocol European union introduced the first broad trading scheme for carbon emissions at the beginning of 2005. European Union emission trading scheme (EU ETS) sets a maximum cap of greenhouse gas emissions emitted by participating corporations and facilities. This cap is decreased annually with the target of carbon neutrality by the year 2050. Under this cap the participants are able to trade the allowances freely. Hence, the allowance to emit carbon dioxide is considered to be a tradeable asset with a price that is determined by market forces. (European Commission, 2015).

Equilibrium of European emission allowances (EUA) supply and demand is broadly influenced by the electricity sector which is among the largest individual industries participating in the emission trading scheme. Utilities make decisions regarding their need for emission allowances and buying strategies based on their power production mix. These decisions have a major influence on how carbon prices evolve in both long- and short-term (World bank, 2012). However, research between emission and electricity markets remain scarce when compared with other commodities such as oil and coal. So far existing studies on the connection between electricity markets and emission trading have mainly focused on the price and return dynamics. For example, in their research Daslakis and Markellos (2009) study the linkage between EU ETS and European electricity risk premia. Their results argue that the relationship is positive due to the producers strategizing with the over-allocation of emission allowances in the early phases of EU ETS. Moreover, Huisman & Kiliç (2015) prove that the pass-through rates of carbon prices to European wholesale electricity prices are not stable over time. Thus, the selection of the time frame from which pass-through rates are calculated is important for policy makers. Additionally, Hammoudeh et al. (2014) study how the relationship between the two commodities changes in different quantiles of distribution. Authors argue that changes in electricity price have the largest impact in the right tail of carbon distribution or in other words when the carbon price is high. This could be due to a lack of clean energy to substitute fossil fuels in energy production.

Contrary to the effect of emission trading on electricity price and returns, literature on volatility dynamics between the two markets is almost non-existent. According to my knowledge, only one prior study includes the volatility spillovers between electricity prices and emission prices. As a part of his broad research Castagneto-Gissey (2014) investigates the volatility transmission from carbon prices to different European electricity forward prices. By means of multivariate GARCH modelling author reveals that carbon price volatility has positive and significant effects on electricity price volatilities in France, Germany and especially in Nordic countries. Notably, they state that the most significant factor affecting the electricity volatility during EU ETS phase II was the volatility of coal prices.

1.1 Research motivation and hypotheses

The purpose of this thesis is to shed light on the scarcely studied volatility relationship between carbon emission trading and electricity prices. Additionally, also the return connections between the asset markets and evolution of correlation over the observation period are under the scope of the study. The geographical focus of this thesis is Europe and especially its Nordic region. Power production mix in Europe’s Nordic areas relies heavily on carbon-free methods which is why it is interesting to study its volatility dynamics with emission trading. Data regarding emission allowance price is retrieved from daily EU ETS allowance prices while electricity market data is gathered from the Nordic electricity exchange, also referred as Nord Pool. By including the latter years of the third trading phase this study is able to contribute to the existing literature by extending the reach of current research between energy and emission markets. Also, no studies exist that have investigated the time-varying nature between EUA and Nordic electricity. This additional information regarding the evolution of the risk connection is vital information for market operators and corporate managers that are responsible for managing risks and hedging market exposures.

The main research question is whether there exists any significant relationship between EU ETS and Nordic electricity prices. Based on this research question the following null hypothesis is formed:

> *H_0: There exists no significant relationship between EU ETS and Nordic electricity markets.*

Then, the following alternative hypotheses are derived based on the null hypothesis and the capabilities of the selected empirical modelling:

> *H_1: There exist significant volatility spillovers between EU ETS and Nordic electricity markets,*
>
> *H_2: There exist significant return spillovers between EU ETS and Nordic electricity markets,*
>
> *H_3: The correlation between EU ETS and Nordic electricity prices is significant and time-variant.*

To investigate the research question and test hypotheses this thesis utilizes a dynamic conditional correlation generalized conditional heteroskedastic (DCC-GARCH) model which is originally proposed by Engle (2002). DCC-model enables non-constant conditional correlation matrices with which analysis of time-varying relationships is possible. Additionally, DCC-GARCH produces parameters that allow the investigation of return and volatility spillovers between asset markets.

1.2 Structure of the thesis

The research is conducted in eight chapters as follows: the second chapter includes a brief glimpse into the latest literature about emission trading and its connection with stock- and commodity markets. In the third chapter, the European deregulated electricity markets and the characteristics of electricity as a commodity are discussed. Chapter four presents the history and evolution of the European emission trading scheme as well as the price formation of emission allowances. The fifth chapter includes a brief look into the volatility modelling and the family of different GARCH-models. Chapter six illustrates the data being used in this study and goes through the empirical methodology step-by-step. Results from empirical modelling are presented in chapter seven, followed by conclusions and discussion in chapter eight. Additionally, the final chapter links the results with theory and existing literature while also providing possible subjects for future research.

2 Literature Review

In recent years the literature on the carbon market has received a growing amount of interest from scholars, policy makers and investors. Branches of literature include especially studies regarding return and volatility dynamics between EU ETS and stock or commodity markets. The purpose of the following chapter is to briefly summarize the latest research regarding interrelationships between the market for emission allowances and other marketplaces.

Among the first ones to study return dynamics between stock markets and EU ETS are Oberndorfer (2009) and Veith et al. (2009). Both studies are limited to analyse only Phase I of emission trading which has been considered as a learning period. Employing a multifactor framework including firm specific EUA effects Oberndorfer (2009) studies the connection between emission trading and market performance of European electricity companies. The author finds a significant positive correlation between EUA price changes and stock performance of European electricity firms. Notably, this effect is proven to be time- and country-specific. In line with the findings of Oberndorfer (2009), Veith et al. (2009) also report a somewhat counterintuitive positive correlation between EUA price and electricity producers. According to both studies, the root cause of the positive correlation is the over-allocation of free emission allowances during the trial period.

Further investigations on return linkages are carried out by Oestreich et al. (2015) and Tian et al. (2016). By extending the study period to also cover Phase II of emission trading authors are able to complement initial studies. Oestreich et al. (2015) explain the positive correlation between German stock returns and EUA with excess abnormal returns or in other words, carbon premium. Evidence of carbon premium is stronger for companies receiving more free allowances in the initial allocation. However, as the trading of emission allowances was largely transferred to auctions during phase II significance of the carbon premium disappeared. Moving forward, elements of effect between EU ETS and electricity producers is studied by Tian et al. (2016). Results from simple ordinary least squares, time series and panel data regressions indicate that two main drivers of EUA market impact on electricity producers are carbon intensity of production and the overall market volatility in the European Union. Therefore, as the carbon price increase producers with larger green energy portfolios will face less risk and lower costs. Correspondingly, a decrease in carbon prices has harms these companies because of the relatively lower cost efficiency.

Besides the power sector, other industries have been addressed in the literature as well. Demailly and Quirion (2008) study the effects of EU ETS on the competitiveness of iron and steel industries in the European Union. Empirical evidence from the study indicates no major negative impacts on production levels or profitability of iron and steel industries arising from emission trading. Chan et al. (2013) verify these results as they also fail to find significant effects between carbon trading and competitiveness of iron, steel and cement industries. Notably, they are able to identify higher material costs and revenues in the power sector. Hence, power generators seem to be able to shift higher costs nearly directly to power prices. Meleo (2014) reports that the Italian paper producing sector faces a limited risk for decreasing competitiveness due to carbon trading. However, due to market structure and competition coming from subsidiary products such as plastic Italian paper industry is not able to pass risen environmental costs to product end prices. Overall, according to prior studies EU ETS does not seem to have a major impact on the profitability of the industries under its influence.

Moreover, Moreno and Silva (2016) utilize a multifactor panel data model in order to gather comprehensive information regarding EU ETS and stock returns of Spanish companies from industries under the influence of the trading scheme. Research’s period of interest ranges from the beginning of Phase II to the first two and a half years of Phase III. Thus, the study provides a rare view into the relationship between stock performance and third phase emission trading. The authors’ empirical results suggest that the impact of EU ETS price on stock prices was positive in Phase II while a negative correlation was found in Phase III. This effect was found to be sector specific. According to the authors the underlying reason for varying effects between sectors is the difference in initial allocation of emission allowances. Notably, size, direction and sector dependency vary between different phases of carbon emission trading.

To extend the literature Kumar et al. (2012); Dutta (2017) and Dutta et al. (2018) investigate how EU ETS impacts the performance of clean energy indices. Kumar et al. (2012) apply a vector autoregressive model in order to study the effects of oil and carbon price changes on alternative energy stocks. Instead of carbon returns, which do not have a significant effect on alternative energy stocks, the main return drivers are proven to be movements in oil prices, the performance of technology companies and interest rates. Especially oil prices are proven to have a positive effect on clean energy indices (Kumar et al., 2012). Similarly, Dutta (2017) and Dutta et al. (2018) are able to identify the insignificancy of the effect of carbon emission prices to clean energy companies' returns in both European and US markets.

In addition to stock returns, another aspect receiving attention from scholars is the volatility dynamics between EUA price and stock markets. However, despite the rising interest the number of individual studies from this viewpoint remains rather scarce. Tian et al. (2016) study the existence of volatility linkage between carbon market and stock prices of electricity companies with a multivariate DCC-GARCH model. Results of this analysis suggest the model including dynamic conditional correlations is an appropriate fit for the data as correlations were volatile during the whole second phase of emission trading. However, the stage including Phase I failed to yield any significant results regarding EUA price returns. Results from Phase II show positive and significant effects considering past variability and volatility spillovers for both EUA price returns and returns from electricity stocks. Dutta et al. (2018) utilize a bivariate VAR-GARCH model to demonstrate volatility linkages between clean energy stocks and emission trading. Notably, Phase I is excluded from the sample period as carbon prices were close to zero at the end of the trading phase. Evidence from VAR-GARCH analysis suggests that volatility transmission from the emission market to European clean energy stocks exists. Additionally, the authors fail to find significant volatility linkages between EUA and the US market. This indicates that the effect is market-specific.

Also the cointegration of spot and futures markets for EUA has been addressed in the literature. Among a few others, Uhrig-Homburg and Wagner (2009) study the cointegration of spot and futures markets during the initial phase of emission trading. In Phase I the relationship between spot and futures prices can be explained by the cost-of-carry framework. However, the efficiency of the cost-and-carry model remains unclear as evidence from Daslakis and Markellos (2009) suggests that such a relationship would not exist. Evidently, the futures market seems to lead to the formation of EUA price (Uhrig-Homburg & Wagner, 2009). Allowing effects of structural breaks in vector autoregressive analysis Chevallier (2010) is not able to identify a cointegration between spot and futures prices in the early years of Phase II. According to Rittler (2012), this is due to only using daily data. Based on high-frequency intraday data clear evidence of cointegration is found. Also, the price-determining status of futures compared against spot markets is verified by high-frequency analysis (Rittler, 2012).

Recent literature regarding carbon emission trading also includes a number of studies considering return and volatility dynamics between EUA and different commodities. Recent studies have been focused on commodities such as coal, gas and crude oil with which electricity and heat are often being produced. Additionally, ingredients used in biofuel production such as rapeseed oil have received interest as well. The main focus in these studies has been on the effects of primary energy prices, for instance, oil, gas and coal on EUA prices. Primary energy prices are stated to be the most important determinant of carbon prices since energy generators are able to switch between different production inputs (Alberola et al., 2008).

Furthermore, the effects of energy prices on carbon pricing are studied by Alberola et al. (2008); Creti et al. (2012) and Aatola et al. (2013). The research period of Alebrola et al. (2008) ranges from 2005 to 2007. Thus, their results reflect how carbon prices were determined in the initial phase of trading. Utilizing data from the whole period yields results in which oil does not have a role in carbon price determination. The effect of coal is negative and significant while natural gas affects EUA price positively. However, the authors prove that the structural trading breaks change carbon price determination significantly. For example, from June 2006 to October 2006 all energy prices except oil are completely disconnected from EUA price. These results are complemented by Creti et al. (2012) who study whether the price determinants change between Phase I and Phase II by utilizing data from EUA futures. To identify long- and short-term impacts the authors use the cointegration methodology framework. Moreover, the authors suggest that oil plays a significant role in both trading phases while factor illustrating the effect of switching from coal to natural gas is significant only in the second phase. Also Creti et al. (2012) confirm the importance of structural breaks in the fundamentals of carbon prices. The importance of energy fundamentals is also emphasized by Aatola et al. (2013) who suggest that approximately 40% of EUA price changes are explained by changes in energy price. Furthermore, they address the importance of German electricity price changes as an explanatory variable.

In the literature, variations of GARCH models are often used to describe volatility dynamics and risk spillovers between EUA and certain commodities. Chevallier (2012) compares results from three different GARCH family models. According to the authors' findings, DCC-GARCH is the most efficient in modelling time-varying correlations of emission allowances and energy commodities. Additionally, the results from a such model indicate significant co-movements between EUA, gas and oil. Furthermore, Dhamija et al. (2018) study the effects of coal in addition to gas and oil. By means of a BEKK-GARCH model authors identify significant effects from gas and oil while the no volatility relationship between coal and EUA is found. However, the BEKK-GARCH model is unable to identify any long-term effects (Dhamija et al., 2018). However, findings regarding the effect of oil on EUAs effect are contractionary as Reboredo (2014) is unable to find a significant interrelationship between oil and EU ETS.

Among recent literature, also interrelations of electricity and carbon allowances have been addressed in part of the research. As this study focuses on the interplay between EUA and Nordic electricity price and volatility this branch of literature is particularly interesting. In the study by Daslakis and Markellos (2009) connection between the carbon spot market and electricity risk premia is studied. Authors state electricity risk premia as the separation between futures prices and the estimated spot price of electricity. After regressing realized percentage risk premia against logarithmic EUA returns a positive connection between EUA returns and electricity risk premia is detected. The study suggests that the connection is based on carbon market uncertainties and trading of initially allocated free allowances. Utilizing a Granger causality framework Keppler and Mansanet-Bataller (2010) propose that electricity prices affect carbon allowances through spreads between the sum of electricity production and carbon price, and the spot price of electricity. Finally, by means of the GARCH model Castagneto-Gissey (2014) is able to identify significant volatility spillovers from carbon prices to electricity price volatility in France, Germany and in particular Nordic region.

After the observation of past literature regarding the relationship between EU ETS and other securities and commodities markets it is clear that the over-allocation of free allowances during the early phases has severely affected the efficiency of the European carbon market. Furthermore, it has to be addressed that EU ETS has not yet had a trading phase without severe disruptions. Phase I as an exploratory period included a massive overallocation of emission allowances while economic movement during Phase II was affected by the global financial crisis (Keppler & Mansanet-Bataller, 2010). Finally, the end of the third EU ETS trading phase saw the rise of the COVID-19 pandemic that also severely affected the economic activity globally. Thus, further research regarding the return and volatility dynamics between European emission trading, stock markets and other commodities is vital for policy makers, risk managers and investors.

3 Electricity markets

This chapter explains the unique characteristics of electricity markets in general and presents the specifications of European electricity markets. According to the publication of World Bank (2012) utilities are the largest individual participant in the European emission trading scheme and thus have a significant impact on carbon prices. Moreover, the impact of emission trading to a certain electricity market is defined by the carbon intensity of the production mix (Castagneto-Gissey, 2014). Thus, it is important to acknowledge the unique characteristics and generation methods of electricity if one desires to understand the interconnections between the European electricity and carbon markets.

The chapter begins with a brief introduction to the deregulation of electricity markets. In brief, the deregulation opened energy markets with intention to gain efficiency benefits. Further the unique characteristics of electricity markets are presented. Moving forward the chapter takes a look into the complex price formation process of electricity and how carbon trading affects this process. Finally, as the main focus of this study is on the Nordic electricity market, the Nordic electricity exchange Nord Pool is introduced in detail.

3.1 Deregulation of electricity markets

In the recent decades the electricity markets in Nordic Europe have gone through a liberalization process where market power was withdrawn from monopolies and government owned utilities and the markets were opened for competition. This liberalization process introduced conditions under which special characteristics of electricity were developed. Before the process all operations including generation, transmission and sales of electricity were strictly regulated. Introducing competition to the markets was expected to result in efficiency gains from which the end consumers of electricity would benefit via lower costs (Kirschen & Strbac, 2004, p. 1-2). Before the restructuring process electricity producers were allowed to earn predefined rate of return that was linked to their cost of capital. After the investment was accepted by the regulators the costs would be transferred to consumers via the regulated electricity prices hence transferring the risk of failed investment from producers to consumers. In other words, a significant amount of efficiency gains from the deregulation comes from long-run investments in electricity generating facilities. (Deng & Oren, 2006).

However, after the deregulation there has been difficulties in achieving the ideal risk segmentation because of market imperfections. In the ideal situation the risk included in investments is addressed to the generators while the operators procuring electricity from the wholesale markets bare the price risk. Most of the markets that have gone through the deregulation process have already given up on the pursue towards the ideal market structure and have utilized procedures such as different price gaps and capacity payment mechanisms in order to find the most efficient market model. These regulating actions allocate the risks by limiting price volatility for consumers while making sure that the investment costs get recovered for the generators. (Deng & Oren, 2006).

The first phase in the deregulation process was the formation of power pools. In a power pool a transmission grid connects the neighbouring utilities which enables the trade of energy between certain regions. Region wide trading produces both cost and reliability benefits for the market operators although it also exposes them to the differences between area prices and the system price (Ernstén et al., 2017). Lowered costs are acquired as the larger fleet of generators is able produce larger amount of energy with fuels with lower marginal cost. Reliability, in other hand, is acquired by allowing utilities the access to production capacity in other areas. This makes it easier to supply energy if the market is struck by a demand spike or a critical generating unit falls apart. However, the absence of a strong spot market in the early power pools limited the benefits achieved by region wide connections. (Cramton, 2017).

According to Cramton (2017) the final step in reaching the competitive markets was the establishment of the wholesale energy markets which allows the real time trading and pricing of electricity. In the wholesale markets retailers buy the electricity produced by generators from the centralized markets. These markets can be power pools or bilateral transactions. The wholesale price of electricity is determined by the equilibrium of demand and supply which exposes the market participants to the price risk if the prices can’t be predicted accurately. In the modern electricity wholesale market small consumers are also able to choose the specific retailer which introduces the competition separately to the retail markets as well. Large consumers such as producing companies can buy their electricity straight from the wholesale markets without retailers intermediating the process. (Kirschen & Strbac 2004, p. 5-6).

Even though majority of the electricity markets these days are considered to be competitive the companies running the transmission and distribution networks still remain as natural monopolies as it is not effective to have two similar but competitive transmission grids running parallel. In order to achieve economically effective and reliable transmission all the components of the transmission grid should be attached to the same entity. This way, if there is a failure somewhere in the system balancing resources can be adapted into the grid quickly. (Kirschen & Strbac 2004, p. 8).

3.2 Characteristics of competitive electricity markets

Electricity as a commodity has characteristics due to which it differs substantially from other commodities and financial assets. Due to these characteristics the seasonal behaviour of electricity price process is among the most complicated commodity price discovery processes. Short-term demand of electricity is highly volatile as it is affected by extreme weather conditions as well as business activity. Moreover, as efficient storage of electricity is not yet possible the inelasticity in demand cannot be smoothed leading to extreme price spikes and different cyclical price patterns. Extreme price movements cause difficulties to power generators as stopping the production or changing the output of a large generation facility is expensive and it could even cause damage to the unit (Paraschiv et al., 2015). Furthermore, recent developments in policies promoting sustainable energy production introduce another factor increasing the complexity and volatility in electricity price formation. As inflexible production from renewables is combined with non-storable nature of the commodity the number and magnitude of extreme prices has grown. In certain areas even negative prices have occurred during windy periods with business activity. Thus, negative prices are consequence of producers accepting a fee rather than driving down their facilities (Paraschiv et al., 2014).

In more detail, the supply and demand in electricity markets need to be balanced in real time in order to avoid possible failures that in a worst-case scenario could cause blackouts in the grid. As electricity cannot be stored in an efficient manner severe weather conditions produce difficulties in balancing the market. Also, during periods with abnormal demand the energy exceeding the estimated load needs to be procured from the spot market with an unknown price. The need for constant balanced in the markets has introduced a demand for additional market participants and ancillary services for market balancing. These additions are defined to identify disturbances in the market and take action in balancing the supply and demand of electricity during periods of distress. Eydeland & Krzysztof 2003, p. 5).

Finally, to illustrate a clear picture of competitive electricity markets one needs to understand the functions and purposes of all different market operators. Electricity producers generate energy in their facilities and sell it through the power exchanges. Producers can own one single production unit or a portfolio of units operating with different fuels. In some cases, power producers also sell ancillary services such as reserve capacity to protect the balance of supply and demand. Distribution companies own and operate the networks utilized to distribute the electricity to a certain region. In addition of owning the networks distribution companies are also responsible for maintaining and developing their transmission assets. Retailers of electricity buy energy from power exchanges and sell it forward to end-consumers. Customers of retailers are called retail consumers as they cannot buy electricity directly from the exchange. Large consumers such as forestry companies, on the other hand, are allowed to buy electricity straight from the exchange and thus take an active role as a market participant. Transmission companies own assets used in the transmission of electricity in their respective transmission region. These assets can be lines, cables, transformers and reactive compensation devices. Transmission companies use their assets in a way that the independent system operator instructs. Furthermore, independent system operator has the final responsibility to maintain the balance over the entire system. The system must be operated in a way that every market participant gets treated equally. (Kirschen & Strbac 2004, p. 2-4).

3.3 Electricity price formation

In the power exchanges electricity price is determined by the equilibrium of supply and demand. In the context of electricity exchanges this equilibrium price is referred as market clearing price. All lower offers from producers with lower price than market clearing price are accepted and respectively all higher bids from electricity retailers or large companies are accepted as well (Kirschen & Strbac 2004, p. 52-56). The offers made by producers are based on the costs of producing a specific amount of electricity. The merit order is used to describe how the marginal cost is determined. According to the merit order curve power plants are used in order beginning with the production facility with lowest marginal costs. After this power plants producing energy with higher costs are connected to the network step-by-step until the demand of electricity is met. So as the demand of electricity grows the commodity must be produced with higher marginal costs. These marginal costs are reflected directly to the price with which electricity is traded in exchanges. (Wolff & Feurriegel 2017.) The merit order curve is illustrated in the figure 1. The dispatching order can change along with fuel price changes. Fuel prices could be affected by for example geographical crises and increases in emission prices. As can be observed from the figure, the marginal cost of renewable production is often found to be lower than corresponding cost for fossil fuels. Thus, utilities aim to use renewable production methods as often as possible as in addition to being sustainable it is often also cheaper.

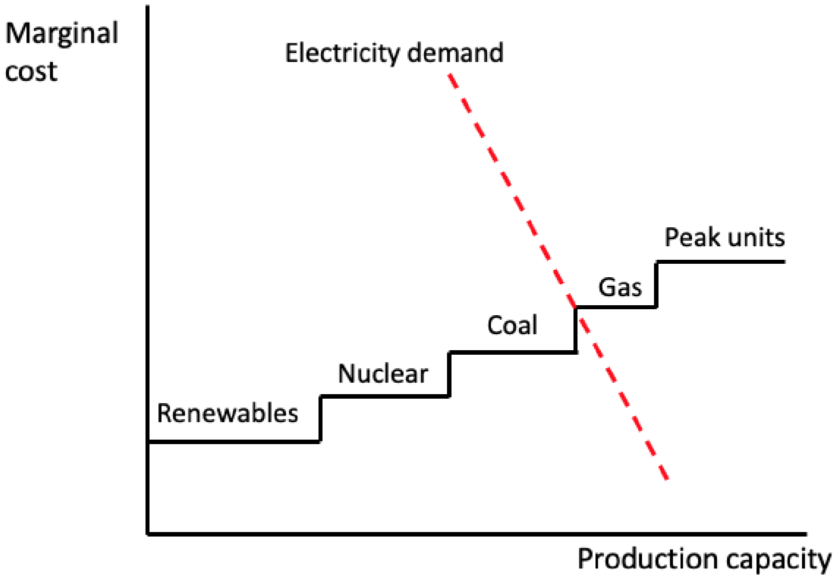

Figure 1. Merit order curve.

The consumption, or demand in other words, of electricity is found to be highly seasonal as various different factors affect the need for power. The consumption and thus also the price of electricity strictly follows factors such as temperature and the amount of daylight. During extremely cold periods households use electricity to in order to heat their apartments and correspondingly cool them during heat waves. Consumption levels differ also between working days and weekends due to business activity. The hours with higher electricity consumption are called On-Peak Power while correspondingly hours with lower consumption levels are considered as Off-Peak Power. Many electricity exchanges price On-Peak Power and Off-Peak Power differently. (Eydeland & Krzysztof, 2003, p. 8).

3.3.1 Effects of carbon trading to electricity price formation

Launch of carbon emission trading and specially EU ETS has introduced a new emission related cost to electricity producers. As producers are allowed to either use the allowances to cover emitted CO_2 or sell them to other emitters, usage of an allowance represents an opportunity cost. According to the basic economic theory a company will most likely include the CO_2 related costs with its other marginal costs. As companies in different regions have varying production mixes also the pass-through rates of carbon costs are not fixed but rather, they depend on a level of demand and a marginal production unit at certain point of time. Hence, pass-through of carbon prices is described as average increase in energy price over a certain time period due to increase in the price of emission allowances. Also, possible changes in the merit order curve affects the pass-through rate. If there is no change in the merit order the change in electricity price is equal to carbon allowance cost of a marginal production method. Furthermore, when there is a switch in the merit production order the carbon costs are not transferred to power prices in full extent. (Sijm et al., 2006).

Figure 2 illustrates a simplified example of changing merit order with only two power production methods A and B. The leftmost part of figure captures the situation where merit order does not change. Hence the change in electricity price Δp_1 is equal to the change in production cost of marginal production technology denoted by $\Delta p_{2.}$ The right-hand side of the graph captures the situation where the impact from emission prices forces the merit order to change. Now, the marginal production method is A as the carbon cost is higher. As can be observed, the effect from carbon pricing in marginal production Δp_3 is now higher than increase in electricity price Δp_4. As carbon pass-through rates differ between production methods pass-through rates for certain markets are calculated as averages from all methods of energy generation. (Sijm, et al., 2006).

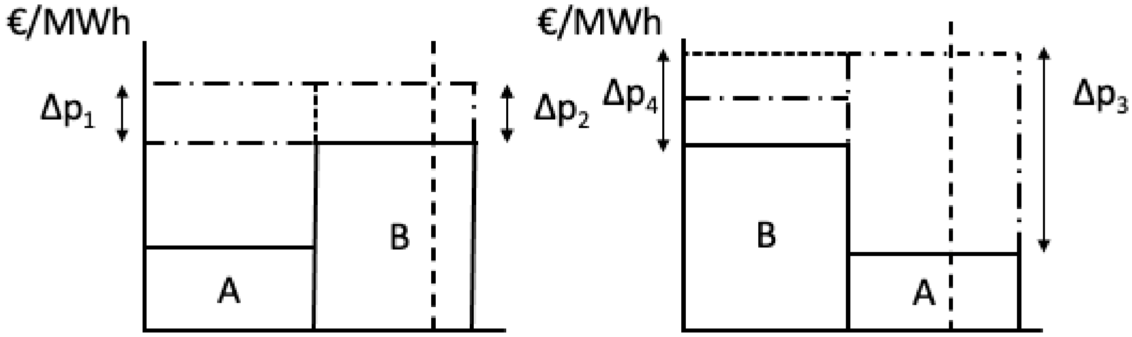

Figure 1. Pass-through rates under a change in merit order. (Sijm et al., 2006).

In more detail, the pass-through ratio for an electricity producer depends on the interrelations ship of three factors: volume effect, price effect and emission intensity. Volume effect describes how production mix and volume change due to carbon costs. For example, if production volume is significantly reduced producer may face losses in net revenue regardless the high pass-through rate. Producer with highly flexible capacity is able to capture the profits from peak hour electricity prices despite high carbon costs. Price effect illustrates the spot price profile change due to carbon costs. Finally, emission intensity indicates the amount of carbon emissions related to production volume. Emission intensity is closely related to losses in production volume as production facilities with high emission intensity could end up producing less power. (Kim & Chattopadhyay, 2010).

As already mentioned, emission intensity of energy markets in different geographical regions varies which leads to differences in CO_2 pass-through rates. For example, in Nordic region power is mainly generated with hydropower. In this area the effect from the cost of carbon is on average 0.74€ per every 1€/tCO_2 emitted (Kara et al., 2008). For means of comparison, in central Europe the pass-through rate varies between 60% and 100% depending on the CO_2 emission intensity of the marginal production unit. Germany is among countries which electricity prices are affected the most from emission prices. It is estimated that on carbon price level of 20€/tCO_2 the German electricity prices will likely increase by €13-19/MWh. On corresponding emission price levels, the effect on French power market is estimated to be € 1-5/MWh which is the lowest in Europe. This small impact in France is due to commanding share of Nuclear power in the production mix. (Sijm, et al., 2006).

3.4 Nordic power markets

Nordic power markets have one dominating exchange for energy, referred as Nord Pool. Nord Pool is one of the oldest marketplaces for electricity in the world. The market covers most of the Europe as market operators from 20 different countries take part in it. This chapter provides a brief introduction to the Nord Pool, the Nordic electricity market.

3.4.1 Nord Pool

Multinational Nordic power exchange took its first steps in 1991 following the deregulation of Norwegian domestic electricity market. Integration of Nordic markets begun in 1996 as the Swedish system operator became a co-owner in the Nordic power exchange establishing an integrated market between Norway and Sweden. As the millennium changes the market becomes fully integrated with Finland and Denmark joining Nord Pool exchange. Since then, the Nordic electricity market has continued to expand as it nowadays is the principal marketplace of electricity in 13 countries. In addition to those already mentioned Nord Pool provides electricity for Estonia, Latvia, Lithuania, Belgium, Germany, the Netherlands, Luxemburg, France and the United Kingdom. As a whole, trading in Nord Pool region contains 360 companies in 20 countries. The overall volume electricity being traded in the exchange was 494 TWh during year 2019. (Nord Pool, 2021).

Scandinavian countries, that is Finland, Sweden, Norway and Denmark, accounted for total generation of 401,07 TWh out of the total 494 TWh traded in the Nord Pool power exchange during the year 2019. Figure 3 illustrates how the power production mixes in these countries are constructed in corresponding year. In the Nordic region hydro power is considered to be the dominant method of energy production. For example, in Norway 93% of all electricity is due to hydro generation. Other popular method of production which accounts for 35% of power production in Finland and 40% in Sweden. The amount of wind power has grown in the recent years and nowadays it is considered to produce a substantial proportion to match the energy demand in Scandinavia. As can be observed from the figure, countries in Nord Pool already rely on production methods that are capable of generating electricity without or with only low carbon emissions. (International Energy Agency, 2021).

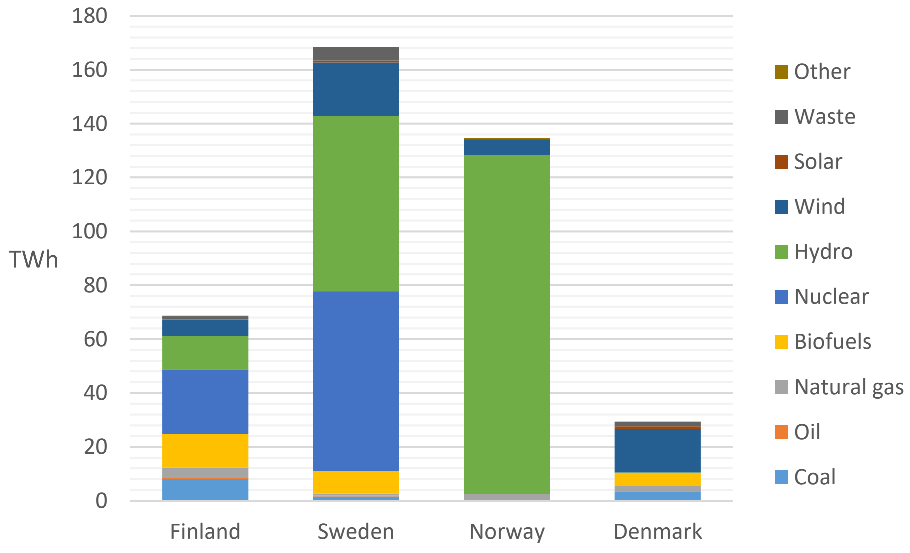

Figure 3. Electricity production mix in Scandinavian countries.

Electricity trading in the Nord Pool power exchange is divided into short-term physical trading and longer-term trading operated through financial markets. Furthermore, the physical marketplace has three separate markets. Day-ahead market which are the spot market of Nord Pool, intraday market which operates the hourly balancing auctions of electricity and the ancillary market maintained by the transmission system operators. In the day-ahead markets market participants take part in the auctions of electricity for every hour the next day. The market parties leave their bids and offers before 12:00 CET after which independent supply and demand curves for each hour (00:00-24:00) are formed from these sell and purchase orders. Hourly equilibriums of the curves determine the hourly market clearing price which is referred as system price. The prices are announced at 12:42 CET and the physical delivering of electricity begins at 00:00 CET. In order to efficiently discover the equilibrium in every situation Nord Pool has determined also the minimum and maximum day-ahead MWh prices. The maximum price is set at 3000 € and the minimum price is considered to be -500 €. (Nord Pool, 2021; Junttila, Myllymäki & Raatikainen, 2018).

The day-ahead market is complemented by the intraday market which maintains the important balance between supply and demand in the electricity market of Northern Europe. Incidents such as generator failures can happen between the price declaration at 12:42 and the physical delivery at 00:00. To maintain the balance in spite of generator failures or other incidents, trading in intraday markets is possible almost real time. Capacities available for intraday trading are published at 14:00 CET. Trading in this market is continuous and does not stop until one-hour prior delivery. Prices of the intraday market are determined on the principle of first-come, first served where the best prices are considered first. As more wind power enters the grid the importance of intraday market grows as the wind power is considered to be unpredictable source of power. So as the amount of wind power grows the need for balancing acts in the market grows simultaneously. Consequently, balancing markets such as Nord Pool’s intraday market play a remarkable role in decreasing the amount of carbon emissions by permitting more growth opportunities for renewable production. (Nord Pool, 2021).

3.4.2 Bidding areas

The Nord Pool market region is divided into 21 different bidding areas. Different bidding areas help market operators to detect bottlenecks in energy transmission while ensuring that different geographical production mixes are reflected to the price. Furthermore, daily calculation of area prices secures the transparent treatment of each market operator which is considered to be a corner stone of a liberal marketplace. Bidding areas are determined by the domestic transmission system operators separately for each country. Currently, Norway is separated into five bidding areas while Sweden is represented by four separate areas. Denmark is divided into two price regions as Western and Eastern parts of the country are considered as separate bidding areas. Finland, Estonia, Lithuania, Latvia, the Netherlands, Belgium, France, Austria and the United Kingdom are constructed from one pricing region each. Finally, Germany consists of four bidding areas which, however, have always the same price. (Nord Pool, 2021).

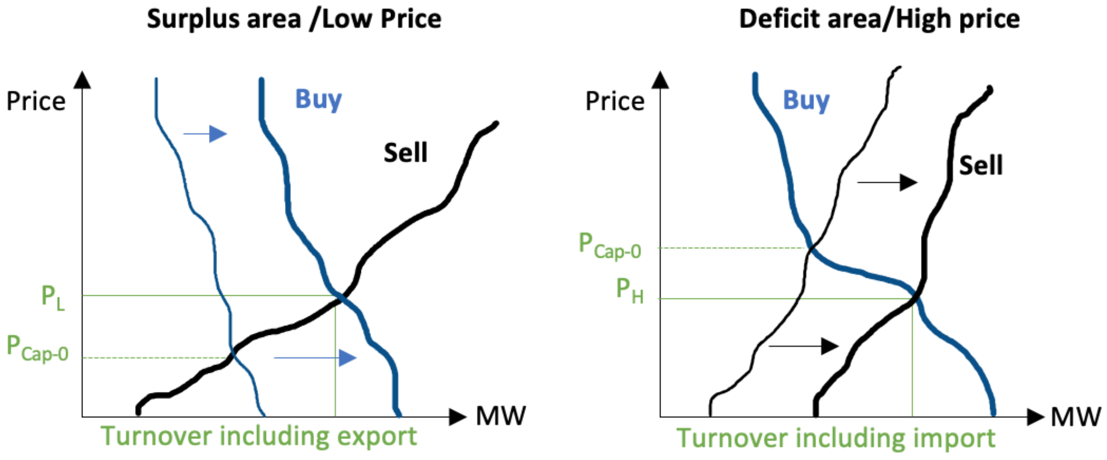

Figure 4. Formation of area prices. (Junttila et al., 2018).

As the area price is formed from an equilibrium including the congestions in the transmission network it should assure that electricity is produced in the most efficient way in every region. To ensure this the flow of electricity is directed from the regions with lower price to the higher price areas with the maximum transmission capacity. This effects the price equilibrium as the supply curve in the high price areas moves towards right while correspondingly the demand curve in the low-price regions shifts to right as well. The changes in the equilibrium increase the area prices in regions with lower price and vice versa. This movement is illustrated in the figure 3 in which P_L and P_H stand for prices in each area when the transmission capacity is fully in utilization and P_{Cap-0} marks the area prices in a situation without the possibility of transmission. Thus, bidding areas importing beyond their ideal capacity are able to reduce importing while the deficit regions can procure electricity from areas with lower price. Consequently, in the market equilibrium minimum marginal costs are ensured by the fact that the bidding areas with low marginal costs are exporting at the full transmission capacity meanwhile the areas with high marginal costs are importing at the full capacity. (Junttila, Myllymäki & Raatikainen 2018; Ernsten et. al 2017.)

4 Emission trading in Europe

The purpose of this chapter is to describe the different phases and functionalities of the European Emission Trading Scheme. To understand the volatility linkage between electricity prices and carbon prices one is ought to have basic knowledge regarding the European Emission trading scheme. The chapter begins with a look into the commitments made following the Kyoto Protocol. After which reader is guided through an overall description of the trading scheme, different implementation phases and finally price formation for European emission allowances.

4.1 Kyoto Protocol

After climate change and greenhouse gases were identified to be among the most severe threats to individual’s health, environment and biodiversity United Nations took action in order to tackle the rising threat. In December 1997 United Nations held a convention in which Kyoto Protocol was first introduced. Initially the protocol included 37 industrialized countries who committed to battling climate change by lowering their greenhouse gas emissions. The program’s original goal was to mitigate greenhouse gas emissions by 5.7% per year compared to the emission levels of the year 1990. The mitigation was originally ought to be done by the year 2012. The protocol was first put into action in 2005 while the first commitment period officially begun a few years later in 2008. (Luo & Wu, 2016.)

The Kyoto protocol divides member countries into three separate groups based on commitment levels. Annex I groups consist of developed countries who are also members of organisation for economic cooperation and development-organisation (OECD). Also, Annex I includes regions that are going through an economic transformation. These countries are granted additional flexibility in completing the environmental demands. Annex II countries include OECD countries that are not considered to be in the midst of an economic transfer process. These countries are demanded to give financial assistance to developing countries in order to assure that they are ready for the issues caused by climate change. Non-Annex I groups are formed from developed countries. A specified group of Non-Annex I parties are identified to be extremely defenceless against global warming and climate change. These countries are mentioned to get additional attention in order to ensure their environmental wellbeing. (UNFCCC, 2003).

The implementation of the Kyoto protocol introduced practical tools for fighting climate change. These methods are joint implementation, emission trading and the clean development mechanism. Joint implementation permits Annex I countries to introduce projects on emission reduction in different Annex I regions and gain emission removal units from such projects. Emission trading, on the other hand, allows groups from Annex I to receive assigned amount units from corresponding Annex I groups who are more able to lower their carbon intensity. As allowances are tradable, carbon prices are to be set based in the markets by supply and demand. Thus, countries are able to identify the cheapest methods of lowering emission amounts and acquire allowances based on a certain method. The purpose of the clean development mechanism is to provide sustainable investments, especially in developing countries. However, to be implemented the project needs to be approved by all authorities and projects must yield actual long-term benefits for the environment. In order to ensure the transparency and accountability of the trading system Kyoto protocol introduced so-called tracking units. Units and transactions are registered by Annex I groups. In addition to emission reduction units and assigned amount units, these tracking units include certified emission reductions and removal units. (UNFCCC, 2003).

4.2 European Union Emission Trading Scheme

After the implementation of the Kyoto protocol European Union was willing to fulfil the emission reduction targets. Thus, few of the EU member countries arranged individual and experimental emission trading schemes. The issue with different individual arrangements was the incompatibility of separate systems. Hence, the European commission decided to introduce an EU-wide emission trading scheme that included the whole continent (Watanabe & Robinson, 2005). Nowadays, the European Union emission trading scheme has grown to be the largest emission market in the world. The implementation of EU ETS was arranged in separate phases. The first phase ranged from 2005 to 2007, the second trading phase covered years from 2008 to 2012 while the third phase ranged from 2013 to 2020. The commission has agreed that the current fourth trading phase will include years 2021-2030. The structure of the scheme is based on a cap-and-trade framework in which the EU sets a cap on maximum emissions. Member countries estimate the amount of emissions that should be covered by allowances and present these calculations in national allocation plans. Then, allowances are allocated based on the emission presented in national calculations. After allocation countries and companies are able to trade permits freely which ensures that market participants lower emission with low as possible costs as the allowance price is determined by the market forces. (Keppler & Mansanet-Bataller, 2010).

In more detail, allowances are also allocated for free to certain parties. These parties are considered to be under a higher risk of carbon leakage. Carbon leakage is defined as a scenario where companies under threat of paying a high price on carbon emissions shift their production to countries with less demanding environmental regulation. The most notable driver behind carbon leakage is competition arising from countries that are not subject to emission restrictions. Notably, the number of allowances allocated freely has to be carefully calculated in order to keep the trading scheme as efficient as possible (Oberndorfer, 2009). After free allocation, the remaining allowances are acquired mostly from auctions. During the latter years of the EU ETS auctions are considered to be the main allocation method for allowances. Companies are also able to acquire allowances by means of over-the-counter trading after the initial allocation has been made. Every year member parties have to return a number of allowances that depend on the CO_2e tonnes they have emitted through the year. If the number of allowances owned by a company is insufficient it needs to take action in lowering its emission or acquire missing allowances from the exchange. However, if a party is unable to submit a correct number of allowances it needs to pay a penalty in addition to acquiring the allowances. In 2013 the penalty was 100€ per every missing allowance. The penalty is linked with EU inflation level and thus it will increase yearly. (European Commission, 2015).

Since the introduction of EU ETS, the scheme has included all EU member countries. Moreover, also Norway, Island and Lichtenstein are included in the trading scheme. Thus, the system covered the whole European Economic Area. The last geographical addition to the scheme has been Croatia in January 2013. EU ETS has covered the most carbon-intensive sectors from the beginning of Phase I. Industry-wise EU ETS has included the most polluting sectors from the beginning of Phase I. Since then, sectors such as carbon capture and storage, aviation and chemicals have been added to the trading scheme. Overall, since the beginning of Phase III EU ETS the scheme includes over 11 000 highly carbon-intensive entities such as power stations and oil refineries. (European Commission, 2021).

The European commission's goals for future emission mitigation are ambitious. According to the EU's Green Deal, it should achieve carbon neutrality by 2050. In addition to region-wide regulation and emission trading, national carbon pricing plays a significant role in reaching carbon neutrality. Despite ambitious planning, the carbon price in the European trading scheme remains low when compared with the Kyoto Protocol commitments. The fundamental reason behind this is the global COVID-19 pandemic which has ravaged the earth in 2020. The global economic downturn caused by the pandemic has caused negative pressure to carbon prices as amount of emissions is lower which yields in a lower demand for emission allowances. In comparison, the price of EU ETS allowance was €25/CO_2t in the first quarter of 2019 while the corresponding price in 2020 is €17/CO_2t. (World Bank, 2020).

4.3 Implementation of EU ETS

4.3.1 Phase I

Implementing EU ETS begun in 2005 with the first trading phase. The fundamental purpose of Phase I was to ensure that EU ETS is able to support member countries in reaching their commitments from Kyoto Protocol. Between 2005 and 2007 price structure, emission tracking and verification were tested in order to be ready for the first Kyoto commitment period which would start in 2008. Moreover, as there were no data available at the beginning of Phase I most of the decisions were based solely on assumptions and forecasts. In Phase I majority of emission allowances were allocated for free based on national allocation plans. Finally, European Commission accepted the national allocation plans and allocated the first European emission allowances based on them. (European Commission, 2015).

As caps for carbon emissions were designed solely with forecasted emissions during Phase I over-allocation of free allowances was an issue during the period. Due to the introduction of new European environmental governance policies led to two structural breaks severely affecting carbon prices. The first structural break appeared in April 2006 after the publication of verified emissions of 2005. The price reaction after this compliance break provided information regarding that the Phase I emission cap was not stringent enough to lead to abatement of emissions. The second break occurred in October 2006 and it led the carbon price to nearly zero was caused by the European Commission announcing notable restrictions to validating national allocation plans in second phase of EU ETS. (Alberola et al., 2008).

4.3.2 Phase II

Phase II of EU ETS was designed to cover the first Kyoto Protocol commitment period which ranged from 2008 to 2012. The second phase was the first time when firms were able to utilize emission reduction units they had produced to reach their emission targets. During the latter years of the second trading phase the European Commission decided to include the aviation sector in the trading scheme as well. After this development scheme covers all EU and non-EU carriers that fly either from or to airports located in countries under EU ETS. Allocation of allowances in Phase II was similar to Phase I. Thus, most of the allowances were laid out for free regarding national allocation plans produced by member countries. Phase II introduced functionalities that enabled market participants to bank their surplus allowances for future use without any additional costs. Banked allowances are taken into account when determining the emission cap for upcoming trading phase. (European Commission, 2015).

At the beginning of Phase II of EU ETS most parties estimated that carbon price would be approximately €35/tCO_2. However, as the global financial crisis decreased economic activity and simultaneously demand for emission allowances EU ETS prices encountered negative pressure. In addition to the financial crisis, the trading scheme was affected by severe frauds in 2008 and 2009 that affected the system's prominence. After being confronted by these challenges the carbon price was below €10/tCO_2 instead of the originally forecasted price levels at the end of the second trading phase. Yet again, the unexpected price development fuels conversations regarding the effectiveness of the European carbon market as an incentive to reduce emissions. (Perthuis & Trotignon, 2014).

4.3.3 Phase III and the future of EU ETS

The third phase of European emission trading is set to range from 2013 to 2020. Phase III is designed to cover the second Kyoto Protocol commitment period. During the third trading period European Commission has decided to lower the emission cap in a linear fashion in order to tighten the environmental policy that has faced criticism of being too loose. The reduction is set to be 1.74% compared to 2010 emission levels and the reduction is done on yearly basis. Cap reductions will continue as such until the year 2025 when the operation will be under further revision. Another major change made in the EU ETS in phase III is introducing auctions as a fundamental method for allowance allocation. In practise, this means that at the beginning of Phase III approximately 50% of the allocations will be acquired from auctions and the rest will be allocated freely similarly that in earlier phases. The allocation method will depend on the industry in which an individual company operates. For example, the power sector is demanded to operate fully through auctioning while other industries such as heating will continue to receive free allowances. (European Commission, 2015).

The operations of EU ETS continue after 2020 with a period that is referred as Phase IV. This phase has begun at the beginning of 2021 and will end in 2028. Moreover, European Commission has introduced structural changes to the trading scheme in order to enhance the carbon mitigating effect. According to the propositions of the commission the linear emission cap reduction will be further tightened from 1.74% to 2.2% for each year between 2020 and 2030 to achieve the emission reduction of 43% when compared to 2005 levels. Another proposed mechanisms were the automatic set-aside mechanism. This mechanism works as a price floor for emission included with a yearly reboot of prices and the market stability reserve that is designed to change the amount of emission allowances traded yearly in auctions based on the total number of allowances being traded in the system. The purpose of the reserve system is to settle the imbalances of carbon supply and demand. (Dhamija et al., 2018).

4.4 EUA price formation

The pricing of emission allowances plays a significant role in maintaining an efficient emission trading scheme. If allowance prices are too low carbon trading fails to work as an incentive to mitigate emissions. Moreover, the whole system might be unsuccessful in preventing global environmental issues as buying an allowance and still using carbon-intensive fuels might be the most cost-efficient way. On the other hand, too high price levels might also cause difficulties, as well as especially impoverished countries, could be reluctant to join the scheme (Chung et al., 2018). Hence, understanding the dynamics of emission price formation is crucial if one desires to learn the process of controlling emissions via cap-and-trade systems.

As with other market-based assets, also the price of European emission allowance is based on the equilibrium of supply and demand. The demand is determined by the level that emitting companies are willing to pay for emitting one tonne of CO_2. Corresponding supply levels are set by the international decisions regarding environmental policies. Thus, the total supply of allowances is based on national allocation plans and the climate policy and it is represented as the total number of allowances allocated to companies. Additionally, the EU-wide regulations also determine the amount of carbon credits acquired from joint implementation and clean development mechanisms that are allowed to be used to comply emissions and also the maximum rate with which certified emission reductions and emission reduction units are to be traded for EUAs. Later developments of EU ETS have introduced possibilities to bank or borrow allowances that affect the long-term supply. Option to bank surplus allowances limits the supply in the short-term and thus has an increasing effect on allowance prices. Correspondingly, the possibility of borrowing allowances has an inverted effect on the price. (Rickels et al., 2015). Hence, as the supply of EUAs is fixed following environmental policy decisions, changes in the price of the asset are mostly explained with the factors affecting demand.

Figure 5 illustrates how the equilibrium of supply and demand changes along with the maximum amount of allowance or in other words, the emission cap. The supply is illustrated as two vertical lines since the maximum amount of greenhouse gases emitted is fixed with the cap. In the first scenario, the equilibrium price P_1 is determined by the intersection of demand (D) and supply in period one (S_1). The market equilibrium shifts among the emission cap as is described by P_2 in the figure. If it is assumed that the demand remains fixed the effect of lowering the emission cap is then determined by the difference between two equilibrium prices P_1 and P_2.

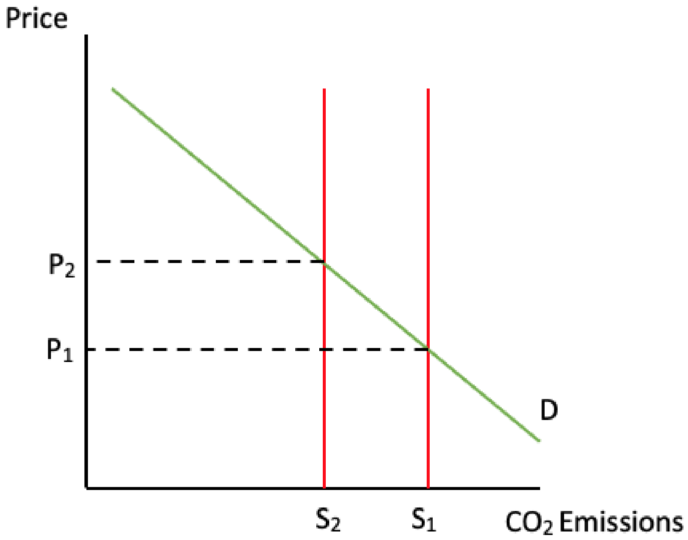

Figure 5. Equilibrium of supply and demand of EUAs. (Rickels et al., 2015).

After the total supply of allowances is determined by the European Commission the EUA price is determined by business-as-usual (BAU) carbon emissions and marginal abatement cost of carbon. BAU emissions and marginal abatement costs are identified to be the main factors affecting the demand for allowances. BAU emissions describe the level of carbon emissions in the absence of an emission trading scheme and thus to what extent the EUAs are considered to be scarce. In a case where BAU emissions are lower than the total cap of EUAs the price is influenced by negative pressure. In a situation where carbon markets work efficiently, and allowances are scarce the main drivers behind the demand are economic activity and fuel switching costs. The relationship between emission prices and economic activity is rather intuitive. During positive economic environment production levels and thus also the amount of carbon emissions rises which increases emission prices and vice versa. (Rickels et al., 2015).

In general, marginal abatement cost is an estimate of the possible costs a company would suffer from reducing its carbon emissions at a certain point in time. Marginal abatement costs are affected by the prices of fuels used in energy production. Currently in most cases, the cost of switching between gas and coal as the fuel of producing energy is considered to illustrate the marginal abatement cost. The cost difference is often illustrated with dark- and spark spread. The dark spread is the margin between the cashflow acquired by selling one MWh of energy produced with coal while spark spread determines the spread between revenue and production costs of one MWh of energy produced with natural gas. If carbon prices are included in calculations these spreads are referred as *clean* dark and *clean* spark spreads. Cost of mitigating emissions via fuel switch increase while gas prices climb and decrease as coal prices rise. Moreover, as the rising fuel switching costs increase the demand for coal the price of EUAs also increases simultaneously. (Rickels et al., 2015).

In addition, also weather conditions have an impact on the demand and thus the price of emission allowances. Extreme temperatures affect prices positively as demand for heating or cooling increases. The relationship between EUA prices and precipitation, changes in wind speed and amount of sunlight is based on the increasing amount of renewable energy production. As this study partly focuses on Nordic markets it is important to be conscious of the impact of hydropower as it is the main energy production method in the Nordic region. Especially in this geographical region dry environment substantially increases the demand for fossil fuels in energy production and thus EUA price rises. (Hinterman, 2010; Mansanet-Bateller et al., 2007).

5 Volatility estimation

Volatility as a concept has been widely researched in the financial literature. The interest towards researching volatility modelling and forecasting is driven by the importance of understanding the fundamentals of the phenomena in for example risk management and option valuation. Also, as volatility and uncertainty are closely related to financial risks, understanding volatility is important for investors and corporate managers (Poon & Granger, 2002). As the main focus of this study is in understanding the volatility dynamics between electricity and emission markets it is important to have an understanding regarding the basics of volatility estimation. This chapter briefly describes volatility as a concept and the basic methodology of volatility measurement.

Scholars have identified important properties of financial time series volatility that recur regularly in research samples. These characteristics are fat-tailed distributions, volatility clustering, mean reversion and volatility co-movements between different financial markets. Unlike financial returns, volatility is guided by a stochastic process and is thus difficult to be observed during a beforehand defined period. According to Hull (2015, p.521), due to the stochastic movement, the intraday changes in volatility are large and the impact grows following bad news and market turmoil. However, with a short enough observation frequency and a large number of observations researchers have been able to estimate volatility. (Poon & Granger, 2002).

5.1.1 ARCH models

Among the first propositions to measure the volatility is the autoregressive conditional heteroskedastic (ARCH) process which was originally proposed by Engle (1982). The ARCH process is designed to capture the return distribution over a certain time period that has a constant mean μ and a time-varying conditional variance σ^2. In the ARCH-framework return process is considered to be described with the following properties

$$r_t = \mu + \varepsilon_t, \qquad (1)$$

$$\varepsilon_t = \sigma_t z_t \qquad z_t \sim i.i.d\ (0,1), \tag{2}$$

in the equations above, r_t is the conditional mean constructed from a set of regressors μ and a shock parameter ε_t. The shock parameter is assumed to include a normally distributed innovation z_t which is then scaled by a stochastic parameter σ_t. According to the ARCH process, conditional volatility is estimated based on the squared residual returns with the following equation.

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-i}^2, \tag{3}$$

in which σ_t^2 is the conditional variance at time t, ω is the constant describing the long-term volatility rate that is restricted to be positive. α_i is the parameter that measures the magnitude of the effect of past observations to conditional volatility with the restriction of $\alpha_i \geq 0$ and q is the number of autoregressive terms or in other words lagged parameters. The ARCH(q)-model described by the equation 3 is able to illustrate the conditional volatility, by utilizing the lagged values of past returns and errors. In more detail, the ARCH(q)-model is able to distinguish the difference between the long-term average volatility and the effect behind a defined number of lags.

5.1.2 GARCH models

Furthermore, Bollerslev (1986) has derived a widely used generalization of the autoregressive conditional heteroskedasticity modelling. This model is commonly referred as the GARCH(p,q)-model which allows one to investigate also the effects of past conditional volatility in addition to sole past sample variances. The return regressions are similar in both ARCH(q) and GARCH(p,q) while the latter is further defined with the following equation

$$\sigma_t^2 = \omega + \sum_{t=1}^{q} \alpha_j \varepsilon_{t-1}^2 + \sum_{t=1}^{p} \beta_j\, \sigma_{t-1}^2, \tag{4}$$

where $\omega > 0$, $\alpha_j \geq 0$, $\beta_j \geq 0$ and $\alpha_j + \beta_j \leq 1$. The number of lagged sample variances is denoted by q while p describes the number of lags in unconditional variances. Thus, for p = 0 the process is simply reduced to the ARCH(q) process. Finally, β_j measures the impact of past conditional variances on future volatility.

Volatility modelling with the GARCH-family has received a great amount of interest from researchers and institutions because of its capability of measuring characteristics of financial data. This interest towards the methodology has led to an increasing amount of advanced models that are based on regular GARCH(p,q) modelling. For example, the sign and magnitude of effects from positive and negative shocks may differ significantly. However, the regular GARCH-model is unable to capture these asymmetric effects of positive and negative innovations as it only considers the magnitude of the effect instead of its sign (Brooks, 2014). Due to this lack of ability researchers have derived a wide range of extended GARCH models. Some extensions to the GARCH framework have been constructed in order to tackle the incompleteness of the original model. To name a few, the exponential GARCH-model is constructed to enable the modelling of the logarithm of variance for appropriate response for asymmetric shock effects (Nelson, 1991). The quadratic GARCH-model first discovered by Engle and Ng (1993) is designed to account for both an asymmetric effect of conditional variance and higher kurtosis which beneficial in analysing financial time series. The QGARCH-model is also implementable to univariate and multivariate scenarios. Threshold heteroskedastic models or simply TGARCH-models introduced by Zakoian (1994) is used most frequently to identify the leveraged effects of positive or negative news on financial volatility.

Moreover, a special volatility characteristic of financial time series is the co-movement of variance between different markets. In more detail, this indicates that news and shocks create volatility not only in their target markets but also in other markets as well. The family of GARCH-models includes model specifications that are capable to measure the significance and magnitude of volatility transmission effects. For example, this study utilizes the dynamic conditional correlation GARCH-model. DCC-GARCH allows investigation of return and volatility spillovers and time-varying correlation. Also models such as VAR-GARCH and BEKK-GARCH are used to determine how the volatility flows between markets.

6 Data & empirical methodology

6.1 Data description

The data included in the empirical part of this study consists of daily prices for European emission allowances trading in the European energy exchange and a series of Nordic electricity exchange daily average prices. The sample period begins on 28th January 2009 and ends on 16th March 2020 thus yielding a total of 2904 daily observations from EUA trading phases II and III. Following the methodology of Dutta (2019) the whole first trading phase and the first days from the second phase are left out from the scope of the study as the price of European emission allowances was practically zero due to inter-phase banking restrictions of allowances. Figure 5 illustrates the price developments of European emission price and Nordic electricity price over the observation period.

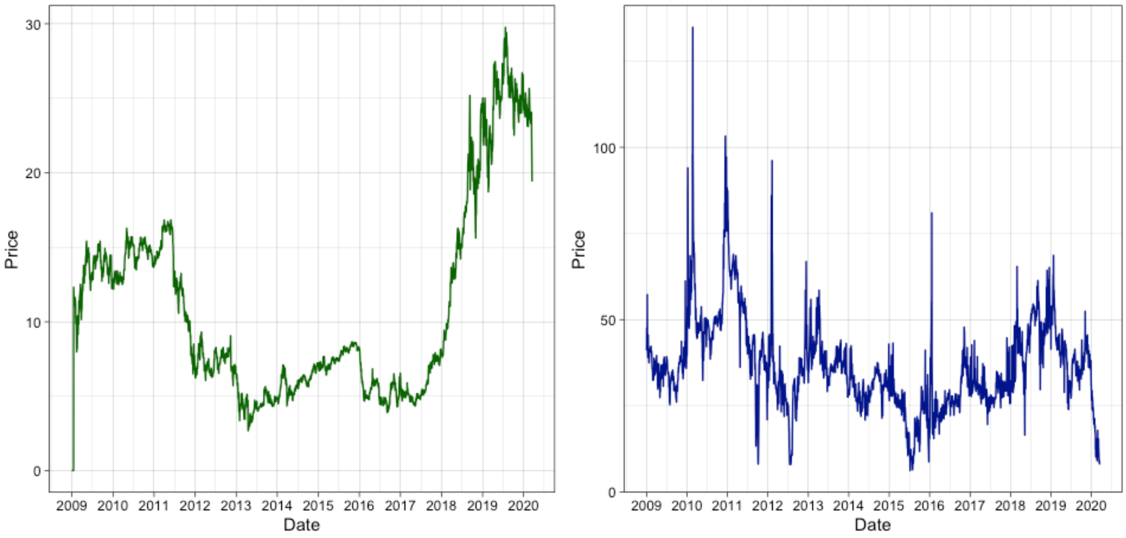

Figure 6. Price development of EUAs and Nordic electricity.

As can be observed from figure 5 above, during recent years the price of European emission allowances, presented in the leftmost part of the figure, has been on a rising trend due to tightening cap and implementation of new operationalities such as market stability reserve. Since the beginning of the year 2017, the price of carbon permits has surged to almost 30 €/tCO_2 before declining back to the price level around 20 €/tCO_2. The price series of Nordic electricity which is illustrated on the right-hand side of the figure above, exhibits strong volatility, seasonality and extreme prices. Volatile behaviour is due to the special characteristics of electricity such as high seasonality and non-storability.

The summary statistics for both price series are included in the table 1. Comparison of values of corresponding standard deviations implies that electricity markets are more volatile than carbon emission markets. Both price series are positively skewed indicating long right-hand tails for both distributions. Moreover, values of kurtosis for each price series are found to be over three. This suggests that the price data follows leptokurtic distributions instead of being normally distributed. In order to further test the normality of distributions Jarque-Bera tests are conducted. Results from these tests report high values which are evidence that supports rejection of the null hypothesis of normally distributed prices in both markets.

Table 1. Summary statistics for price series.

Price	EUA	Nord Pool
Min	Feb.68	Jun.23
Max	29.76	134.80
Mean	10.950	36.476
Median	8.045	34.850
Standard deviation	6.446	13.020
Skewness	1.028	1.058
Kurtosis	3.066	6.249
Jarque-Bera	511.82 *(0.00)****	1819.49 *(0.00)****

*Notes: This table includes the main descriptive statistics for the daily price series. The values in parentheses denote the p-values. *** indicates statistical significance at 1% level.*

Furthermore, studying volatility connections between electricity- and emission prices with a model that is included in GARCH-family demands derivation of logarithmic returns from the price series. The logarithmic returns are calculated with the following equation:

$$R_{i,t} = \ln\left(\frac{P_t}{P_{t-1}}\right), \tag{5}$$

in which $R_{i,t}$ is the logarithmic return of variable i at time t, P_t represents the price of a variable at time t and P_{t-1} is the variable price lagged with on period. Figure 6 illustrates the corresponding logarithmic returns for both Nordic electricity and European emission allowances over the research period. As can be recognized from the images, both logarithmic return series exhibit extreme values and volatility clustering. In other words, periods of high volatility are likely to be followed by another period of high volatility and periods of low volatility are probable to be followed by low volatility in both markets.

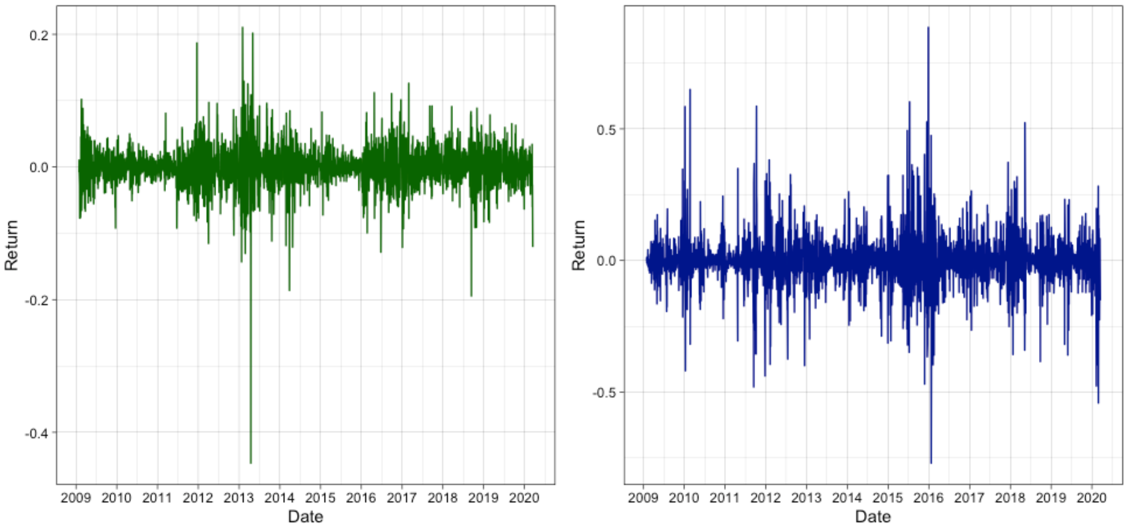

Figure 7. Logarithmic returns of EUA and Nordic electricity.

In the table 2 summary statistics for both logarithmic return series are presented. As can be observed from the table logarithmic returns derived from Nordic electricity prices exhibit more extreme values as minimum and maximum values are further apart from each other. The means of both series are close to zero. However, the signs are different as the mean of emission allowance returns is positive while the corresponding value derived from Nord Pool electricity returns is negative. Comparison of standard deviations reveals that electricity returns are distinctly more volatile than emission returns.

Moreover, summary statistics regarding the distribution shape measures, that is skewness and kurtosis, reveals that the distribution of EUAs is highly negatively skewed while skewness of Nordic electricity returns indicates that the distribution would be symmetric. High values of kurtosis reveal that both series can be considered to have leptokurtic distribution. Again, the non-normality of both distributions is verified with Jarque-Bera tests.

Table 2. Summary statistics for logarithmic return series.

Returns	EUA	Nord Pool
Min	-0.4466	-0.7699
Max	0.2106	0.8856
Mean	0.0002	-0.0007
Median	0.0000	-0.0010
Standard deviation	0.0309	0.0952
Skewness	-1.0001	0.3673
Kurtosis	22.0996	13.3891
Jarque-Bera	44470.7410 *(0.00)****	13080.1292 *(0.00)****

*Notes: This table includes the main descriptive statistics for the daily return series. The values in parentheses denote the p-values. *** indicates statistical significance at 1% level.*

Finally, augmented Dickey-Fuller and Philips-Perron stationarity tests are conducted in order to solve if unit root exists or in other words, whether the time series fulfil the stationarity condition. Both tests report similar results which are presented in table 3. These results suggest that both price series do not fulfil the stationarity demand. Thus, in order to successfully utilize an empirical model included in the GARCH-family time series of logarithmic returns are ought to be utilized as they are found to be stationary.

Table 3. Augmented Dickey-Fuller and Philips-Perron stationarity test results.

	Price		**Returns**	
	EUA	Nord Pool	EUA	Nord Pool
Dickey-Fuller	-1.1448 *(0.92)*	-3.8774 *(0.015)***	-15.028 *(0.00)****	-16.447 *(0.00)****
Philips-Perron	-3.637 *(0.91)*	-83.156 *(0.00)****	-2644.5 *(0.00)****	-2634.7 *(0.00)****

*Notes: This table shows the results for the ADF and PP tests. The values in parentheses are the p-values. *** and ** indicate the statistical significance at 1% and 5% respectively.*

6.2 Empirical methodology

To capture the possible volatility spillovers, return dynamics and time-varying nature of the correlation between assets this thesis follows the methodology of Dutta (2019). In the study, the author utilizes a bivariate DCC-GARCH model in order to study the relationships between EU ETS and biodiesel feedstock markets. The DCC-GARCH model was originally proposed by Engel (2002). In general, the model is a generalization of Bollerslev's (1990) constant conditional correlation model. While the CCC-GARCH model assumes that conditional correlations between assets remain constant over time the DCC specification allows one to study the time-varying nature of the correlation between assets. Moreover, the DCC framework is suitable for modelling volatility of financial time series as it enables a simple method for estimating models with a large set of variables. The superiority of DCC-GARCH in multivariate volatility modelling has been addressed by different researchers in the recent past. For example, Chevallier (2012) finds evidence that the DCC framework is the most satisfactory in modelling dependencies between oil, gas and carbon prices. Further, Tian et al. (2016) suggest that the empirical framework is suitable for studying the relationship between EU ETS and stock prices of electricity companies.

The two equations that form the main building parts of the DCC-GARCH model utilized in this thesis are mean and volatility. The mean equation of the bivariate framework of this study is illustrated by equations 7 and 8:

$$R_t = L + \tau R_{t-1} + \varepsilon_t, \tag{6}$$

$$\varepsilon_t = H_t^{1/2} \xi_t. \tag{7}$$

In the mean equation, R_t is a matrix including returns for EUA and Nordic electricity prices, L is a matrix of fixed parameters, τ is a matrix including coefficients representing the effects from own and cross mean values and ε_t represents the error term. Furthermore, $H_t^{1/2}$ is a matrix including conditional volatilities of electricity- and emission prices and ξ_t is a matrix of independent and identically distributed innovations.

Moreover, the matrix $H_t^{1/2}$ that includes volatilities of assets under study is decomposed out of the following equations:

$$H_t = D_t R_t D_t, \tag{8}$$

$$D_t = diag(\sqrt{h_t^c}, \sqrt{h_t^e}), \tag{9}$$

$$R_t = diag(Q_t)^{-1} Q_t diag(Q_t)^{-1}, \tag{10}$$

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha \varepsilon_{t-1} \varepsilon'_{t-1} + \beta Q_{t-1}. \tag{11}$$

Equation 9 describes the conditional covariance matrix. In the DCC framework the correlation matrix, denoted as R_t, is allowed to vary over time. Furthermore, Equation 12 illustrates the construction of time-varying covariance matrix denoted as Q_t. In the equation, α and β are non-negative scalar parameters that are demanded to fulfil the condition $\alpha + \beta < 1$. Here, the condition represents the mean-reverting process that is correlation returning to long-term average after a shock affecting the returns. In a case where $\alpha + \beta = 0$ the model is simply reduced to the constant conditional correlation model. Furthermore, parameters α and β are measuring the impacts from past shocks and past dynamic conditional correlations on current conditional correlations between emission- and electricity prices.

In the equations the conditional volatilities of carbon emission and electricity prices are denoted with h_t^c and h_t^e. In order to measure the own and cross-volatility transmission the conditional volatility equations are decomposed as follows:

$$h_t^c = d_c^2 + \beta_{11}^2 h_{t-1}^c + \beta_{21}^2 h_{t-1}^e + \alpha_{11}^2 \varepsilon_{c,t-1}^2 + \alpha_{21}^2 \varepsilon_{e,t-1}^2, \tag{12}$$

$$h_t^e = d_e^2 + \beta_{12}^2 h_{t-1}^c + \beta_{22}^2 h_{t-1}^e + \alpha_{12}^2 \varepsilon_{c,t-1}^2 + \alpha_{22}^2 \varepsilon_{e,t-1}^2. \tag{13}$$

In above-mentioned equations β measures the own and cross-market effect of conditional variance on current carbon and electricity volatility respectively. Furthermore, α parameters capture the corresponding own and cross-market impacts of past shocks and news on emission and electricity volatility.

7 Empirical results

The estimated results from empirical modelling are presented in this chapter. In more detail, it describes the significancy, sign and magnitude of possible volatility spillovers between the EU ETS and Nordic electricity markets. Moreover, as DCC-GARCH modelling allows for observation of time-varying correlation structure and mean equations results regarding these functionalities will also be included.

7.1 DCC-GARCH estimation

7.1.1 Mean and variance equations

Table 4 illustrates the estimation results from the DCC-GARCH model. In the table, r^{e}_{t-1} measures the return of a particular electricity market at time t-1 and r^{c}_{t-1} includes effects of returns from the European emission trading scheme. The squared error terms ε^{e}_{t-1} and ε^{c}_{t-1} measure the effect from shocks and surprising news on in electricity and emission markets, respectively. Finally, h^{e}_{t-1} measure the effect of conditional variance of electricity returns while h^{c}_{t-1} includes the conditional variance of the corresponding sample from emission markets

Table 4. Results from DCC-GARCH model.

Ind. Var.	Nord Pool	EUA
Mean equation		
r^e_{t-1}	-0.0948 *(0.00)****	0.00569 *(0.00)****
r^c_{t-1}	-0.00977 *(0.72)*	0.0119 *(0.53)*
Variance equation		
ε^e_{t-1}	0.4494 *(0.00)****	-0.00024 *(0.00)****
ε^c_{t-1}	0.0128 *(0.30)*	0.1607 *(0.00)****
h^e_{t-1}	*0.6455* *(0.00)****	0.00023 *(0.00)****
h^c_{t-1}	-0.00675 *(0.65)*	0.8407 *(0.00)****
θ_a	-0.0046 *(0.00)****	
θ_b	0.7796 *(0.00)****	

*Notes: This table includes the results for the DCC-GARCH model. The first section reports the findings related to mean equations, while the second section includes results from variance equations. Values in parentheses are p-values. *** indicates statistical significance at 1% level.* r^e_{t-1} *measures the return of the electricity market at time t-1 and* r^c_{t-1} *includes effects of returns from EU ETS.* ε^e_{t-1} *and* ε^c_{t-1} *measure the effect from shocks and surprising news on electricity and emission markets, respectively.* h^e_{t-1} *measures the effect of conditional variance of electricity returns while* h^c_{t-1} *includes the conditional variance of the corresponding sample from emission markets.*

Further examination of the mean equation of Nordic electricity reveals that past emission allowance returns do not have any significant impact on current electricity returns. However, past own returns in Nordic electricity markets are found to have significant impact on current values. Moving on to the mean equation of European emission allowance returns suggests that the impact from electricity market returns is significant while own past returns do not affect current EUA returns. Therefore, electricity returns can be used to predict both current emission and electricity returns.

The variance equation section in the table 4 presents the own and cross-asset volatility effects between emission allowances and Nordic electricity. Results indicate that own past volatility and shocks have a positive and significant effect on Nordic electricity prices. Yet, past values of emission allowance variance and news do not have statistically significant impact on the current volatility of Nordic electricity. Thus, according to estimations there exists no volatility spillovers from the European emission allowance market to the Nordic electricity market. This is contrary to the evidence of Castagneto-Gissey (2014) who identifies significant volatility transmission from carbon prices to continental Europe's and especially Nordic electricity prices. This difference could be due to different observation periods and the evolution of markets during recent years. Castagneto-Gissey's (2014) sample covers only the second emission trading phase whilst this thesis is able to include data from the second and third phase. Moreover, the volatility of primary fuels used in electricity production is found to have an impact on the volatility of electricity. Further, the volatility of coal is seen as the main driver behind electricity's volatility. (See e.g. Castagneto-Gissy, 2014; Paraschiv et al., 2014). During recent years countries operating in the Nord Pool's market region have decreased the carbon intensity of their energy production. This increase in sustainable energy production could have mitigated the impact of European emission trading on the Nordic electricity markets.

Moreover, for the current volatility of European emission allowances own past variance and shocks are found to have a significant impact similarly as with electricity price volatility. Contrary to the results regarding electricity's variance equation a significant volatility flow from Nordic electricity markets to emission markets exists according to the estimation results. Past shocks in electricity markets are found to have a negative impact on carbon market volatility while the effect of electricity's past volatility is positive. As mentioned earlier electricity markets are highly volatile and the magnitude of rapid price swings is large. Electricity market volatility might affect the demand of EUAs as producers move towards right in the Merit order curve. In other words, as demand for electricity and heating increases utilities may have to ramp up more emission intensive production facilities. This could be the driver behind volatility spillovers from electricity markets to EU ETS. Finally, DCC-parameters θ_a and θ_b are found out to be significant while the sum of the two parameters is below one which indicates that the correlation between assets is dynamic and time-varying by nature.

7.1.2 Time-varying correlation

In addition to the investigation of return and risk transmission, the DCC-GARCH model enables inspection of how correlations between assets evolve through time. Table 5 includes the summary statistics for the time-varying correlations between Nordic electricity returns and European emission allowances over the research period. Taking a look at the coefficients presented in the table one can observe that the mean correlation between the commodities is positive. Therefore, on average an increase in emission prices leads to an increase in Nordic electricity price. This result is in line with prior findings (See e.g., Castagneto-Gissey 2014; Huisman & Kilic, 2015) which suggest that carbon prices pass through to electricity price thus increasing it. However, power production mix and carbon intensity of production are proven to impact the magnitude with which EUA prices pass through to electricity price (Tian et al., 2016). As Hydropower and renewable production are dominant in Nordic countries the magnitude of the correlation is close to zero. Even though the mean correlation is positive the near-zero correlation could suggest possible hedging benefits in certain market circumstances. Furthermore, the negative correlation swings are found out to be larger in magnitude than corresponding positive values. Thus, the correlation can be considered to be asymmetric as negative swings are larger than positive.

Table 5. Summary statistics of time-varying correlation.

Min	Max	Mean	Standard deviation
0.21525	-0.34327	0.00688	0.02862

Notes: This table reports the main summary statistics for the time-varying correlation between assets.

Figure 7 illustrates how the correlation has evolved through the observation period. From the figure, it is clearly observable that the DCC correlation varies over time. The correlation is found to demonstrate both positive and negative values which can be extreme from time to time. However, the amount and magnitude of negative spikes are found to be higher which could indicate asymmetric correlation traits. That is the impact of negative news is greater than the corresponding effect from positive news. The EU ETS trading period changed at the beginning of 2013 which, according to the estimation, caused extreme spikes in the DCC correlation. Some key changes made in the EU ETS at the beginning of phase III were the end of broad free allocation of allowances and reserving 30 million emission permits to the New Entrants Reserve (European Commission, 2021). Thus, the changes made in the emission trading scheme while the trading phase changed could have caused the correlations to have extreme swings. Notably, both negative and positive spikes demonstrated values that are amongst the largest in magnitude in the observation period around the beginning of the year 2013. Moreover, acknowledging the time-varying nature of the correlation between emission allowances and Nordic electricity is important for policymakers and managers responsible for risk management and forecasting. Thus, the importance of this dynamic nature has to be addressed when considering volatility modelling of electricity and carbon prices (Lu et al., 2017).

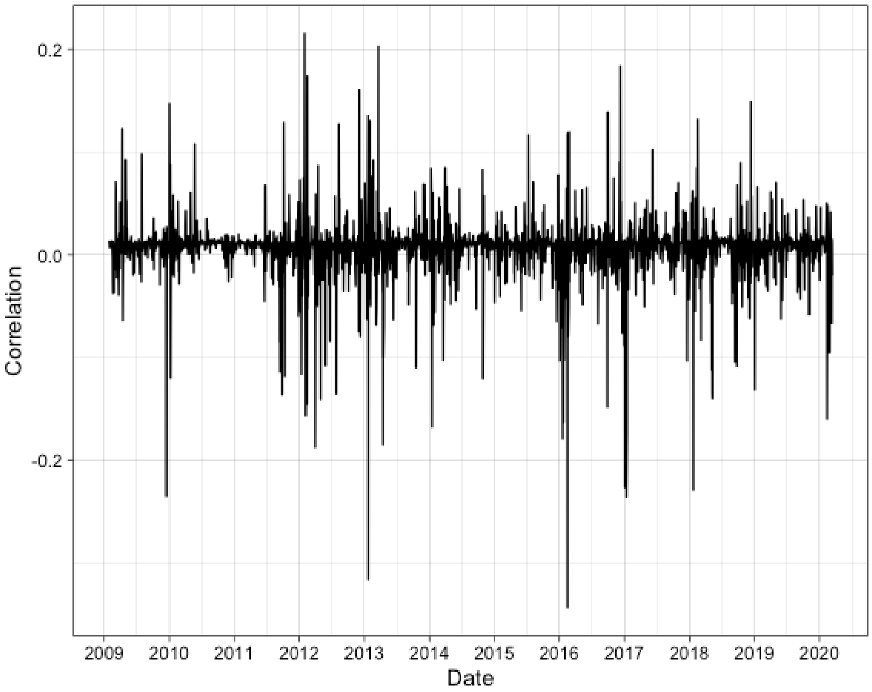

Figure 8. Time-varying conditional correlation.

7.2 Hedging effectiveness

Results regarding the time-varying correlation suggest that possible hedging benefits between assets could exist. To further investigate whether including carbon assets in a portfolio with Nordic electricity reduces the risk in the combination portfolio a hedging effectiveness (HE) analysis is conducted. Notably, a higher value of hedging effectiveness indicates more efficient risk reduction. In line with Ku et al. (2007) HE is estimated with the following formula:

$$HE = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}}, \tag{14}$$

in which $Var_{unhedged}$ includes the variance of the unhedged portfolio including only Nordic electricity. Var_{hedged} defines the corresponding variation in the combined portfolio including both Nordic electricity and EUA. Var_{hedged} is given as:

$$Var_{hedged} = (\omega_t^{ce})^2 h_t^c + (1 - (\omega_t^{ce})^2) h_t^e + 2\omega_t^{ce}(1 - \omega_t^{ce}) h_t^{ce}, \quad (15)$$

where h_t^c and h_t^e are the conditional volatilities of EUA and Nordic electricity defined in equations (13) and (14). h_t^{ce} represents the conditional covariance between assets understudy and ω_t^{ce} is the optimal weight of emission allowances in a portfolio combining carbon and electricity. ω_t^{ce} is further decomposed as follows:

$$\omega_t^{ce} = \frac{h_t^c - h_t^{ce}}{h_t^c - 2h_t^{ce} + h_t^e}. \quad (16)$$

Results from the analysis suggest that the hedging effectiveness amounts to 18.48%. This indicates that investors holding assets in the Nordic electricity sector can reduce the risk in their portfolio by also including a carbon asset. Overall, the results confirm that the emission market is an effective instrument for decreasing the downside risk of the Nordic electricity prices.

7.3 Robustness check

Robust estimators, by definition, are not sensitive to atypical observations. With more robust estimators one is able to draw more accurate conclusions and forecasts based on the empirical results (Brooks, 2008). Following Dutta et al. (2020) the robustness of DCC-GARCH estimation results is tested with an asymmetric DCC-GARCH-model. ADCC-GARCH was originally proposed by Cappiello et al. (2006) to generalize the symmetric DCC-GARCH model. The asymmetric model is able, for instance, to take into account the magnitudes from effects with different signs. Due to these capabilities, it is well suited for financial time series which are often non-linear by nature.

In the asymmetric framework the mean equation is formulated similarly as in the symmetric DCC-GARCH model. Also, the conditional volatility formula remains the same. However, the time-varying conditional dependence formula Q_t is different when compared with the symmetric model. In asymmetric modelling time-varying dependence is formulated as:

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_3 \bar{Z} + \theta_1 \xi_{t-1}\xi'_{t-1} + \theta_2\, Q_{t-1} + \theta_3\, z_{t-1} z'_{t-1}, \quad (17)$$

where θ_3 captures the different correlations from positive and negative shocks. Furthermore, in an asymmetric framework also conditional volatilities h_t^c and h_t^e are further decomposed similarly as in the symmetric model presented in an earlier chapter.

Table 6 presents the estimation results from the ADCC-GARCH model. First, focusing on the mean equation the asymmetric framework confirms the results acquired from the symmetric model. That is, significant effects from past electricity returns to both present electricity- and emission prices. The effect of past carbon returns is found to be insignificant in both empirical frameworks. Similarly, results from variance equations from both models reflect each other relatively accurately. Notably, the sole difference is the impact from past electricity variance on the current volatility of electricity, which is found to be significant in the asymmetric framework but not in the symmetric model. Moreover, the positive effects from past variance and news of electricity on the current electricity variance are verified. Considering emission allowances, impacts of past information from both carbon and electricity markets are significant in both frameworks. Moreover, coefficient θ_3 is found to be significant. This indicates that the correlation between assets understudy is asymmetric and thus reacts differently to positive and negative news.

Table 6. Results from ADCC-GARCH model.

Ind. Var.	NORDPOOL	EUA
Mean equation		
r^e_{t-1}	-0.0846 *(0.00)****	0.0073 *(0.04)***
r^c_{t-1}	0.0077 *(0.79)*	0.00404 *(0.83)*
Variance equation		
ε^e_{t-1}	0.3464 *(0.00)****	-0.000114 *(0.02)***
ε^c_{t-1}	-0.00173 *(0.86)*	0.1169 *(0.00)****
h^e_{t-1}	0.6991 *(0.00)****	0.0000898 *(0.02)***
h^c_{t-1}	0.0565 *(0.00)****	0.8838 *(0.00)****
θ_1	0.0407 *(0.00)****	
θ_2	-0.0500 *(0.90)*	
θ_3	-0.0447 *(0.00)****	

*Notes: This table includes results from the ADCC-GARCH model. The first section reports the findings related to mean equations, while the second section includes results from variance equations. Values in parentheses are p-values. *** and **indicate statistical significance at 1% and % level respectively. re*$_{t-1}$ *measures the return of the electricity market at time t-1 and* r^c_{t-1} *includes effects of returns from EU ETS.* ε^e_{t-1} *and* ε^c_{t-1} *measure the effect from shocks and surprising news on electricity and emission markets, respectively.* h^e_{t-1} *measures the effect of conditional variance of electricity returns while* h^c_{t-1} *includes the conditional variance of the corresponding sample from emission markets.*

In overall, a comparison of coefficients related to mean and variance equations from both empirical frameworks prove that the original results regarding return and volatility spillovers acquired from the symmetric DCC-GARCH model can be considered to be fairly robust.

8 Conclusions and discussion

The rising threat of climate change has forced governments and corporations to take action in mitigating their greenhouse gas emissions. Among these actions is the EU ETS which aims to set a price on carbon emissions in Europe following the framework of the Kyoto Protocol. Since the initial establishment of the carbon trading scheme, it has received a lot of attention from scholars. Looking at the industry level participation to the EU ETS the electricity sector is among the largest individual participants in the scheme. Moreover, actions from utilities have a significant effect on the carbon price. Due to this, it is important to study the connection between emission and electricity markets.

Most of the existing literature focuses on the price and return connections between different assets and EU ETS. However, the volatility connection between electricity and carbon markets is scarcely studied. The main purpose of this thesis is to shed light on this issue and to provide the groundwork for possible future research on the matter. Understanding the volatility structure of the constantly evolving carbon market is a key factor in risk and investment management in related industries. To analyse volatility connections between markets the thesis utilises the DCC-GARCH model following the work of Dutta (2019). The model allows the investigation of both variance and return spillovers between markets. In addition, the dynamic conditional correlation modelling enables one to illustrate how the correlation has evolved through the observation period. This is especially interesting with EU ETS as the European emission markets develop constantly due to governments trying to find the most efficient ways to mitigate their emissions.

The main results of this study suggest that there exists a significant relationship between the European emission trading scheme and the Nordic electricity markets. Surprisingly, the connection is found to be one-directional as returns and volatility flow only from Nordic electricity to European emission markets. No return or volatility streams from EU ETS to Nordic electricity are found according to the empirical results. In detail, the results suggest that on a mean level past returns of European emission allowances have forecasting power on neither own market nor in electricity markets. Controversially, past returns of electricity influence both current own and EUA returns. Thus, European electricity prices can be used to predict the evolution of carbon price. Further observation of variance equations provides information on the effects from past news as well as past conditional variance. Looking at the results, past news and volatility from the emission market cannot be used to predict current electricity volatility. However, both past shocks and volatility of electricity returns are found to have a significant impact on the volatility of carbon returns. This finding is not in line with the earlier work of Castagneto-Gissey (2014) who was able to identify a significant volatility flow from emission markets to Nordic electricity markets. However, the difference in results could be due to this study being able to use more recent data. During recent years Nordic countries have been transforming to more sustainable energy production which could lower the exposure to the swings in the carbon price. Moreover, in both markets, values of own past volatility factors are found to have significant impacts on the current variability.

Inspection of time-varying correlation between emission and electricity markets suggest that the correlation is truly time-varying and, in more detail, positive and near-zero on the mean level. Looking at the results the correlation is found to present seasonality and extreme values depending on observation time. Variability in correlation seems to cluster during periods including changes in the European union’s environmental policies. For instance, as the third trading phase including new operationalities to the trading scheme begun in early 2013 extreme values and variability was observed in the correlation between the markets. Also, one of the lowest correlation values is observed after the change of trading phase which indicates that changing environmental policy could divert the price movements. Overall, the magnitude of negative values is higher on average. As the correlation values are found to be near zero a hedging effectiveness analysis is also conducted. The results from such a model suggest that operators in the Nordic electricity market are able to reduce their downside risk by including also a carbon asset into their portfolio.

Overall, this study is able to contribute the existing literature regarding the volatility dynamics in both electricity and emission markets. The inclusion of the third emission trading phase provides recent market information of a continuously developing market. Moreover, the volatility connection between electricity and emissions has not been widely studied in the literature. As this study is able to identify a significant volatility flow from Nordic electricity to EU ETS the thesis could provide incentives for additional research regarding volatility relations. In the future, researchers could further investigate the connection between carbon and electricity markets by including additional geographical regions in samples. For example, in the continental Europe electricity production mix differs significantly with the generation methods in Nordic region. Thus, the carbon intensity of production is different which might imply that also the relationship with carbon trading is different. Other ideas for future studies could focus on the asymmetric effects between the markets that were identified in the robustness check of this study. Moreover, studies could also focus on the impact of a crisis, and especially the recent COVID-19 pandemic, on the volatility connection between markets.

References

Aatola, P., Ollikainen, M., & Toppinen, A. (2013). Price determination in the EU ETS market: Theory and econometric analysis with market fundamentals. *Energy economics*. 36, 380-395. DOI: https://doi.org/10.1016/j.eneco.2012.09.009

Alberola, E., Chevallier, J., & Chèze, B. (2008). Price drivers and structural breaks in European carbon prices 2005-2007. *Energy Policy*. 36, 787-797. DOI: https://doi.org/10.1016/j.enpol.2007.10.029

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics,* 31(3), 307-327. DOI: https://doi.org/10.1016/0304-4076(86)90063-1

Bollerslev, T. (1990). Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized Arch Model. *The Review of Economics and Statistics.* 72(3), 498-505. DOI: https://doi.org/10.2307/2109358

Brooks, C. (2014). *Introductory Econometrics for Finance.* (3rd edition). Cambridge University Press.

Cappiello, L., Engle, R. F., & Sheppard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial econometrics*. 4(4), 537-572. DOI: https://doi.org/10.1093/jjfinec/nbl005

Castagneto-Gissey, G. (2014). How competitive are EU electricity markets? An assessment of ETS Phase II. *Energy Policy*. 73, 278-297. DOI: https://doi.org/10.1016/j.enpol.2014.06.015

Chan, H.S., Li, S., & Zhang, F. (2013). Firm competitiveness and the European Union emissions trading scheme. *Energy Policy*. 63, 1056-1064. DOI: https://doi.org/10.1016/j.enpol.2013.09.032

Chevallier, J. (2010). A Note on Cointegration and Vector Autoregressive Relationships between CO2 allowances spot and future prices. *Economics Bulletin*. 30(2), 1-20. Retrieved from: https://core.ac.uk/reader/6279330

Chevallier, J. (2012). Time-varying correlations in oil, gas and CO_2 prices: an application using BEKK, CCC and DCC-MGARCH models. *Applied Economics*. 44(32), 4257-4274. DOI: https://doi.org/10.1080/00036846.2011.589809

Chung, Y.C., Jeong, M., & Young, J. (2018). The Price Determinants of the EU Allowance in the EU Emissions Trading Scheme. *Sustainability,* 10(11), 4009. DOI: https://doi.org/10.3390/su10114009

Cramton, P. (2017). Electricity market design. *Oxford Review of Economic Policy*. 33:4, 589-612. DOI: https://doi.org/10.1093/oxrep/grx041

Creti, A., Jouvet, P., & Mignon, V. (2012). Carbon price drivers: Phase I versus Phase II equilibrium? *Energy Economics*. 34, 327-334. DOI: https://doi.org/10.1016/j.eneco.2011.11.001

Daslakis, G., & Markellos R. (2008). Are the European Carbon Markets Efficient? *Review of Futures Markets.* 17(2), 103-128. Retrieved from: https://www.researchgate.net/profile/Raphael-Markellos/publication/228203774_Are_the_European_Carbon_Markets_Efficient/links/00b49534548e070327000000/Are-the-European-Carbon-Markets-Efficient.pdf

Daslakis, G., & Markellos, R. N. (2009). Are electricity risk premia affected by emission allowance prices? Evidence from the EEX, Nord Pool and Powernext. *Energy Policy*. 37, 2594-2604. https://doi.org/10.1016/j.enpol.2009.02.010

Demailly, D., & Quirion, P. (2008). European Emission Trading Scheme and competitiveness: A case study on the iron and steel industry. *Energy Economics*. 30, 2009-2027. DOI: https://doi.org/ 10.1016/j.eneco.2007.01.020

Deng, S.J., & Oren, S.S. (2006). Electricity derivatives and risk management. *Energy*. 31(6-7), 940-953. DOI: https://doi.org/ 10.1016/j.energy.2005.02.015

Dhamija, A. K., Yadav, S. S., & Jain, PK. (2018). Volatility spillover of energy markets into EUA markets under EU ETS: a multi-phase study. *Environ Econ Policy Stud*. 20, 561-591. DOI: https://doi.org/10.1007/s10018-017-0206-5

Dutta, A. (2017). Oil price uncertainty and clean energy stock returns: New evidence from crude oil volatility index. *Journal of Cleaner Production*. 164, 1157-1166. DOI: https://doi.org/10.1016/j.jclepro.2017.07.050

Dutta, A. (2019). Impact of carbon emission trading on the European Union biodiesel feedstock market. *Biomass and Bioenergy.* 128. DOI: https://doi.org/10.1016/j.biombioe.2019.105328

Dutta, A., Bouri, E., & Noord M. H. (2018). Return and volatility linkages between CO_2 emission and clean energy stock prices. *Energy*. 164, 803-810. DOI: https://doi.org/ 10.1016/j.energy.2018.09.055

Dutta, A., Bouri, E., Das, D., & Roubaud, D. (2020). Assessment and optimization of clean energy equity riss and commodity price volatility indexes: Implications for sustainability. *Journal of Cleaner Production*. 243. DOI: https://doi.org/ 10.1016/j.jclepro.2019.118669

Engle, R. F. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica,* 50(49), 987. DOI: https://doi.org/10.2307/1912773

Engle, R. F. (2002). Dynamic Conditional Correlation. A simple Class of Multivariate Autoregressive Conditional Heteroskedasticity Models. *Journal of Business & Economics Statistics,* 20(3), 339-350. DOI: https://doi.org/ 10.1198/073500102288618487

Engle, R.F., & Ng, V. (1993). Measuring and testing the impact of news of volatility. *Journal of Finance,* 48, 1749-1478. DOI: https://doi.org/10.1111/j.1540-6261.1993.tb05127

Ernsten, R., Boomsma, T., Tegnér, M., & Skajaa, A. (2017). Hedging local volume risk using forwards markets: Nordic case. *Energy Economics*. 68, 490-514. DOI: https://doi.org/ 10.1016/j.eneco.2017.10.017

European Commission. (2015). *EU ETS Handbook* [Brochure]. https://ec.europa.eu/clima/sites/default/files/docs/ets_handbook_en.pdf

European Commission. (2021). *EU Emissions Trading System (EU ETS).* https://ec.europa.eu/clima/policies/ets_en

Eydeland, A., & Krzysztof, W. (2003). *Energy and power risk management: new developments in modeling, pricing and hedging.* (1st ed.). John Wiley & Sons Ltd.

Hammoudeh, S., Nguen, D. K., & Sousa, R. M. (2014). Energy prices and CO2 emission allowance prices: A quantile regression approach. *Energy Policy*. 8, 201-206. DOI: https://doi.org/10.1016/j.enpol.2014.03.026

Hinterman, B. (2010). Allowance price drivers in the first phase of EU ETS, *Journal of Environmental Economics and Management,* 59(1), 43-56. DOI: https://doi.org/ 10.1016/j.jeem.2009.07.002

Huisman, R., & Kiliç, M. (2015) Time variation in European carbon-pass-through rates in electricity futures prices. *Energy Policy*. 86, 239-249. DOI: https://doi.org/10.1016/j.enpol.2015.07.005

Hull, J. (2015). *Options, Futures and Other Derivatives*. (9th ed.). Pearson Eduaction, Inc. International Energy Agency. (2021). *Countries and Regions*. https://www.iea.org/countries

Junttila, J., Myllymäki, V., & Raatikainen, J. (2018). Pricing of electricity futures based on the locational price differences: The case of Finland. *Energy Economics*. 71, 222-237. DOI: https://doi.org/10.1016/j.eneco.2018.02.018

Kara, M., Syri, S., Lehtilä, A., Helynen, S., Kekkonen, V., Ruska, M., & Forsström, J. (2008). The impacts of EU CO^2 emission trading on electricity markets and electricity consumers in Finland. *Energy Economics,* 30(2), 193-211. DOI: https://doi.org/10.1016/j.eneco.2006.04.001

Keppler, J., H., & Mansanet-Bataller, M. (2010). Causalities between CO_2, electricity, and other energy variables during phase I and phase II of the EU ETS. *Energy Policy*. 38, 3329-3341. DOI: https://doi.org/ 10.1016/j.enpol.2010.02.004

Kim, W., Chattopadhyay, D., & Park, J. (2010). Impact of carbon cost on wholesale electricity price: A note on price pass-through issues. *Energy*. 35, 3441-3448. DOI: https://doi.org/10.1016/j.energy.2010.04.037

Kirschen, D., & Strbac, G. (2004). *Fundamentals of Power System Economics.* (1st ed.). John Wiley & Sons Ltd.

Ku, Y.H.H., Chen, H.C., & Chen, K. H. (2007). On the application of the dynamic conditional correlation model in estimating optimal time-varying hedge ratios. *Applied Economics Letters.* 14, 503-509. DOI: http://doi.wiley.com/10.1080/13504850500447331

Kumar, S., Managi, S., & Matsuda, A. (2012). Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. *Energy Economics*. (2012). 34, 215-226. DOI: https://doi.org/10.1016/j.eneco.2011.03.002

Luo, C., & Wu, D. (2016). Environment and economic risk: An analysis of Carbon emission market and portfolio management. *Environmental Research*. 149, 297-301. DOI: https://doi.org/10.1016/j.envres.2016.02.007

Mansanet-Bataller, M., Pardo, A., & Valor, E. (2007). CO2 Prices, Energy and Weather. *The Energy Journal,*28(3), 73-92. DOI: https://doi.org/10.5547/ISSN0195-6574-EJ-Vol28-No3-5

Meleo, L. (2014). On the determinants of industrial competitiveness: The European Union emission trading scheme and the Italian paper industry. *Energy Policy*. 74, 535-546. DOI: https://doi.org/10.1016/j.enpol.2014.06.030

Moreno, B., & da Silva, P. (2015) How do Spanish polluting sectors’ stock market returns react to European Union allowances prices? A panel data approach. *Energy*. 103, 240-250. DOI: https://doi.org/10.1016/j.energy.2016.02.094

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica,* 59, 347-370. DOI: https://doi.org/10.2307/2938260

Nord Pool. (2021). *About us – History.* https://www.nordpoolgroup.com/About-us/History/

Oberndorfer, U. (2009). EU Emission Allowances and the stock market: Evidence from the electricity industry. *Ecological Economics*. 68, 1116-1126. DOI: https://doi.org/10.1016/j.ecolecon.2008.07.026

Oestreich, A.M., & Tsiakas, I. (2015). Carbon emissions and stock returns: Evidence from the EU Emissions Trading Scheme. *Journal of Banking & Finance*. 58, 294-308. DOI: https://doi.org/10.1016/j.jbankfin.2015.05.005

Paraschiv, F., Erni, D., & Pietsch, R. (2014). The impact of renewable energies on EEX day-ahead electricity prices. *Energy Policy,* 73, 196-210. DOI: https://doi.org/10.1016/j.enpol.2014.05.004

Paraschiv, F., Fleten, S., & Schürle, M. (2015). A spot-forward model for electricity prices with regime shifts. *Energy economics*. 47, 142-153. DOI: https://doi.org/10.1016/j.eneco.2014.11.003

Perthuis C. & Trotignon, R. (2014). Governance of CO_2 markets: Lessons from the EU ETS. *Energy Policy,* 75, 100-106. DOI: https://doi.org/10.1016/j.enpol.2014.05.033

Poon, S.H., & Granger, C. W. J. (2002). Forecasting volatility in financial markets: A Review. *Journal of Econometric Literature,* 41(2), 679-682. DOI: https://doi.org/10.1257/002205103765762743

Reboredo, J. C. (2014). Volatility spillovers between the oil market and the European Union carbon emission market. *Economic Modelling*. 36, 229-234. DOI: https://doi.org/10.1016/j.econmod.2013.09.039

Rickels, W., Görlich, D., & Peterson, S. (2015). Explaining European Emission Allowance Price Dynamics: Evidence from Phase II. *German Economic Review,* 16(2), 181-202. DOI: https://doi.org/10.1111/geer.12045

Rittler, D. (2012). Price discovery and volatility spillovers in the European Union emissions trading scheme: A high-frequency analysis. *Journal of Banking & Finance*. 36, 774-785. DOI: https://doi.org/10.1016/j.jbankfin.2011.09.009

Sijm, J., Neuhoff, K., & Chen, Y. (2006). CO_2 cost past-through and windfall profits in the power sector. *Climate Policy.* 6(1), 49-72. DOI: https://doi.org/10.1080/14693062.2006.9685588

Tian, Y., Akimov, A., Roca, E., & Wong, V. (2016). Does the carbon market help or hurt the stock price of electricity companies? Further evidence from the European context. *Journal of Cleaner Production*. 112, 1619-1626. DOI: https://doi.org/10.1016/j.jclepro.2015.07.028

Uhrig-Homburg, M., & Wagner, M. (2009). Future Price Dynamics of CO_2 Emission Allowances: An Empirical Analysis of the Trial Period. *Journal of Derivatives*, 17, 73-88. DOI: https://doi.org/10.3905/JOD.2009.17.2.073

UNFCCC. (2003). *Caring for climate. A guide to the Climate Change Convention and the Kyoto Protocol* [Brochure]. https://unfccc.int/resource/docs/publications/caring_en.pdf

Veith, S., &Werner, J. R. & Zimmerman, J. (2009). Capital market response to emission rights returns: Evidence from the European power sector. *Energy Economics*. 31, 605-613. DOI: https://doi.org/10.1016/j.eneco.2009.01.004

Watanabe R., & Robinson G. (2005). The European Union Emissions Trading Scheme (EU ETS). *Climate Policy,* 5(1), 10-14. DOI: https://doi.org/ 10.3763/cpol.2005.0504

Wolff, G., & Feuerriegel, S. (2017). Short-term dynamics of day-ahead and intraday electricity prices. *International Journal of Energy Sector Management*. 11(4), 557-573. DOI: https://doi.org/10.1108/IJESM-05-2016-0009

World Bank. (2012). *State and Trend of the Carbon Market 2012*. https://openknowledge.worldbank.org/handle/10986/13336

World Bank. (2020). *State and Trends of Carbon Pricing 2020.* https://openknowledge.worldbank.org/bitstream/handle/10986/33809/9781464815867.pdf?sequence=4&isAllowed=y

Zakoian, J. M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and Control,* 18, 931-944. DOI: http://doi.wiley.com/10.1111/1468-0297.13911