UNIVERSITY OF VAASA
FACULTY OF BUSINESS STUDIES
DEPARTMENT OF ACCOUNTING AND FINANCE

Pekko Lonka

FORECASTING REALIZED VOLATILITY IN NORD POOL ELECTRICITY MARKET

Master's Thesis in
Finance

Master's Degree Programme in Finance

VAASA 2020

TABLE OF CONTENTS

page

LIST OF FIGURES

LIST OF TABLES

UNIVERSITY OF VAASA
Faculty of Business Studies
Author: Pekko Lonka
Topic of the Thesis Forecasting realized volatility in Nord Pool electricity market
Name of the Supervisor: Jussi Nikkinen
Degree: Master's Degree in Finance
Department: Department of Accounting and Finance
Master's Programme: Finance
Year of Entering the University: 2014
Year of Completing the Thesis: 2020 **Pages: 61**

ABSTRACT

Electricity markets, like other commodity markets, offer many opportunities for their participants, but their high volatility and the unstorable nature of electricity makes them quite different. Due to the high volatility, volatility forecasting would be even more useful in the electricity markets, but as they produce high frequency data, the traditional models for forecasting volatility often perform poorly. Realized volatility has emerged as one possible solution for this problem.

This study tests the possibility to use the realized volatility of daily spot prices in the Nord Pool electricity market to form forecasts about the next day's realized volatility and the behavior of the daily and hourly spot prices during the next day. The Nord Pool electricity market is chosen due to its uniqueness among the European electricity markets, and due to the lack of existing studies about this area. The Nord Pool markets also strongly experience the effects of seasonality and the weather, which could affect the effectiveness of volatility forecasting. The hourly electricity spot price data used in this study is collected directly from Nord Pool.

Realized volatility and the heterogeneous autoregressive model of realized volatility, the HAR-RV model, have proven to be successful forecasting tools, even when using high frequency data. The HAR-RV model has been shown to be far more effective and accurate in high-frequency markets than the previously traditional volatility forecasting models. Realized volatility by itself makes it easier to view intraday prices, and it can be used to view the historical data inside the high-frequency data.

To test the forecasting power of realized volatility in the Nord Pool electricity markets, the effectiveness of the HAR-RV model is tested with OLS regression. The results of this model are then compared to the actual data, which is inspected more closely to find out possible patterns in the behavior of realized volatility and the hourly electricity prices. The results show that the HAR-RV model is able to accurately forecast the next day's realized volatility, and these results can then be used to form predictions about the behavior of the next day's electricity prices. As the model can be used to forecast over longer time periods as well, this gives ground for further study to be made from this area.

KEYWORDS: Realized volatility, Electricity markets, Nord Pool, Forecasting, HAR-RV.

1. INTRODUCTION

Modern-day life is deeply dependent on electricity, which powers most aspects of our life. It is even considered as being one of the basic necessities. Different technologies, economics and the quality of life have improved alongside the improvements in energy production and delivery. Kirschen and Strbac (2004) state that currently the average consumer is deprived of electricity less than two minutes in a year and the delivered amount of electricity has doubled approximately every eight years for the last several decades. Currently in Nordic countries, electricity is bought by consumers from retailers operating in competitive markets. The energy markets were not always competitive though, as they were regulated by governments. Economists argued against this regulated model in the 1980s, as the prices would be lower and the efficiency higher in unregulated markets (Kirschen & Strbac 2004). The process of deregulation of the energy markets in Europe began in Norway in 1990 by the enactment of the new Energy Act, and Norway was also one of the first countries to liberate its energy markets (Bye & Hope 2005).

For the energy markets to be completely market-based, Bye and Hope (2005) set five requirements for included markets: 1) markets for trading energy, 2) markets and instruments for hedging risk, 3) short-term markets for balancing supply and demand and for production capacity, 4) markets for new capacity investments and 5) markets for trading environmental energy products. In Nordic countries, Nord Pool fulfills requirements 1-3, with the fourth one being handled by each country's transmission system operators (Bye & Hope 2005), and the fifth one is handled by each Nordic country individually, except for joint trading of green certificates between Sweden and Norway (Amundsen & Bergman 2012).

While competitive energy markets do provide the benefits of more efficiency and lower prices, they come with their consequences too. Kirschen and Strbac (2004) mention one of these being the separation of generation from the transmission of electricity. They consider this as a key factor in achieving unrestricted access to the energy market, and the pricing of transmission becomes the essence in achieving operation efficiency and the least-cost efficiency develops the whole system. As generation and transmission have become separate systems, the investments are coordinated by the efficiency of pricing mechanisms. This separation is also demanded by Jamasb and Pollitt (2005) as a requirement for restructuring the energy markets and in achieving proper competition in these markets. They also require establishing wholesale and retail markets in order to liberate the competition in the energy markets.

In Europe as a whole, the process of deregulation began in the early 1990s, as the ending of the cold war made it easier to import gas from Russia, and the added capacity of their newly built generation plants (Jamasb & Pollitt 2005) along with the pressure from economists to reform the markets more competitive (Kirschen & Strbac 2004). The European Union made energy directives with the idea of eventually forming one common energy market inside the union. These directives were among the incentives for countries to begin reforming their energy markets, Norway and the UK being the first countries to adopt these practices (Bye & Hope 2005). In the late 1990s, Germany drove the deregulation process in the continental countries, their market being the biggest among the continental countries and the fastest to open up to competition (Karan & Kazdağli 2011).

Energy markets differ from other commodity markets as electricity itself cannot be stored, and the markets are quite vulnerable to external risks. Keskikallio and Lindholm (2003) list seven external factors affecting the fluctuations in supply and demand, which are the defining factors for the market price of electricity in Nordic markets. These factors are the hydrological situation, temperature, time, fuel prices and exchange rates, transmission capacity and congestion, business cycles, and other weather-related factors (such as wind and sun). From these, they name the hydrological situation as the key factor, having effects on the spot price and derivatives for up to three years ahead. The reason for the importance of hydrological situation is easily explained, as half of the electricity produced in Nordic markets is generated in hydro powerplants, and Norway is almost entirely powered by it (Botterud, Kristiansen & Ilic 2010; Nord Pool 2019).

The energy markets are also classified as high frequency markets, as the volume of changes in the electricity prices and the financial contracts can change rapidly and often, and the prices of electricity are continuously evolving. This makes it even harder to predict the movements of prices. As the competitive wholesale energy markets developed after the deregulation process, the need for better tools to analyze the market increased as well. Where previous models failed to perform in high frequency markets, Corsi (2009) developed a heterogeneous autoregressive model utilizing realized volatility (the HAR-RV model) to help make predictions using high frequency data. The HAR-RV model has been used in energy markets successfully to predict future volatility in the studies of Chan, Gray and Van Campen (2008), and Qu, Duan and Niu (2018) among others.

This thesis examines the daily realized volatility in the Nord Pool electricity market by using the HAR-RV model along with the hourly spot prices of electricity. In the Nordic market area, it can already be expected that seasonality is going affect the electricity prices, that is the average prices being higher during winter than during summer, and large changes in the expected weather will affect the price as well. By studying the realized volatility in the Nord Pool's electricity markets, this study aims to identify possible ways how the realized volatility of the hourly spot prices can be used to assess future spot prices and realized volatility. To calculate the daily realized volatility, hourly spot prices collected from Nord Pool are used to compute the overall daily realized volatility for each day in the sample period.

1.1 Research methods and hypothesis

To study the predictive power of the spot price realized volatility, Corsi's (2009) HAR-RV model is formed from the hourly price data of Elspot day-ahead prices. The HAR-RV model forecasts realized volatility for the near future by using the current day's realized volatility and the average realized volatility of the recent past. The required daily realized volatilities for the model are calculated by using the logarithmic returns during each day from the hourly spot price data.

The realized volatility for the daily Elspot prices will be studied to find what information it holds about the Nord Pool's electricity market. Data will be reviewed for the whole sample, as well as dividing the data for winter and summer seasons according to Nord Pool's specifications. The effectiveness of the model is tested by including the overall market volatility and the hydrological levels of Norway's hydro reserves in the model.

Approximate predictions about the future prices can be made depending on the seasons and using future contracts, but the high frequency of the electricity markets makes it difficult to predict the prices from the actual price data. The main research problem of this study is then to find out whether the realized volatility of daily spot prices has any predictive power in Nord Pool energy markets, and if so, then what kinds of predictions can be drawn from it. It is expected, that by using the past hourly spot prices of electricity the HAR-RV model is able to predict the future realized volatility accurately.

Using the HAR-RV model built by Corsi (2009), realized volatility in the near future can be explained by using the current day's realized volatility and the average realized volatility of the recent past. Various studies have successfully utilized this model in forecasting volatility, especially in high frequency markets. Unlike the majority of previous literature, this study aims to find out the possible usefulness of realized volatility of hourly electricity spot prices in forecasting realized volatility, as they are more readily available in more specific areas than the future and forward contract prices. Following the work done by Chan, Gray and Van Campen (2008), and Qu, Duan and Niu (2018) where they state the possibility of forecasting volatility using the HAR-RV model made by Corsi (2009), the main hypothesis for this thesis is formed as:

H1: The predicted spot price realized volatility accurately predicts the actual future realized volatility.

This thesis also aims to examine the realized volatility in the Nordic electricity market further, to find possible relationships between the daily spot prices and the realized volatility to give a more accurate view of the possible ways these predictions from the realized volatility can be used.

1.2 Motivation and contribution of the thesis

The Nordic energy market differs greatly from other European energy markets. In Europe, it is the most harmonized market area and experiences clear seasonal shifts (Keskikallio & Lindholm 2003, Karan & Kazdağli 2011). The electricity prices also reflect the current season, as according to the study of Lucia and Schwartz (2002) the prices between cold and warm seasons are consistently different. Predicting volatility is a highly sought-after method, but though various models have been developed, there is still a need for more improvement. Applying the methods commonly used in studying volatility is even harder in high frequency markets, like the energy markets.

The uniqueness of the Nordic energy markets and the realized volatility in high frequency markets provide an interesting subject to study. Also, the interest in energy markets seems to be on the rise due to the increase in attention to global warming and environmental movements. There also does not seem to be a lot of studies about the realized volatility in the Nordic energy markets, even fewer using the daily spot price of electricity as the source for calculating the realized volatility.

This thesis aims to contribute to the existing literature by possibly widening the available methods to utilize realized volatility and applying previously researched methods for realized volatility to the specifically unique Nordic energy markets and the daily spot price of electricity. Previous literature utilizing the HAR-RV model to various electricity markets have mainly focused on using the spot prices of electricity futures and forward contracts. By using the hourly updated daily spot prices to predict the next day's realized volatility with the HAR-RV model, this thesis examines the results to find out if this method is accurate to be used in predicting realized volatility. Examining the possible relationship of the price data and the daily realized volatility and their behavior is done to show how the predicted realized volatilities could be used.

1.3 Structure of the study

The next chapter gives background to the workings of energy markets in Europe as a whole and provides a closer look at the Nordic electricity market area. The third chapter explains volatility in general and discusses further the theories and applications of realized volatility and the HAR-RV model. In the fourth chapter, the data and methodology used in the study are introduced and discussed, followed by the presentation and discussion of the empirical results in the fifth chapter. The sixth chapter gives the final remarks and conclusions of the study.

2. ENERGY MARKETS IN EUROPE

The current competitive energy markets are the result of the deregulation process that swept across Europe starting in the early 1990s. The restructuring of the energy sector was driven by the need to move from government ownership to more beneficial private ownership. This reform took hold inside the European Union quite quickly, increasing the productivity of electricity companies and lowering the prices for the end-users. The reform also had an additional benefit specific to the European Union, as it standardized the diverse national energy markets to a certain degree. (Jamasb & Pollitt 2005.) Kirschen and Strbac (2004) point out, that while the unmanaged open market can be used in transferring electrical energy more efficiently, it lacks the reliability a managed power system has. They place the importance of a managed spot market over the open energy market when the time of delivery is approaching. By doing this, the managed spot market will then work as a balancing mechanism between load and generation. They explain further that once the spot market is made to be efficient, fair, and organized, the trading for electricity can be traded like any other commodity.

For the energy markets to run safely, efficiently, and reliably, the markets must be designed with sufficient care. Since electricity cannot be stored, it must be generated as it is consumed. Therefore, part of the generation capacity of energy plants must be kept on standby to allow fast response to the increase in demand or the failure of another plant. These requirements shape the workings of energy markets. Traders usually buy even amounts of energy from a generator based on predictions of their customers' consumption. However, it is very likely that neither consumption nor generation of electricity to be the amount that was agreed upon. The energy markets must ensure that the price is paid according to the actual generation and consumption, which is done by various short-term balancing mechanisms. (Green 2001.)

Since unpredictable effects stemming from both generation and consumption drive these markets, the short-term prices are highly volatile. To manage this risk, hedging can be done with trades made in advance for physical delivery, or with financial contracts. The settling of physical deliveries happens by deducting the agreed amount from the generations actual output sold in the short-term markets. Financial contracts balance the price paid with a side payment, that is inversely related to the market price. When the generator sells their whole output in the short-term market, the side payment of the contract balances the price paid for the volume agreed in the contract. (Green 2001.)

In the European Union, the electricity market is the leading market of the energy sector. It can be divided into three regional groups: Continental Europe, the United Kingdom, and the Nordic Countries. These regions differ amongst themselves in both historical aspects and their regional characteristics. The UK markets can be described as the most competitive one, with the highest consumer participation in their energy supply markets in the world. The Continental European market is the largest one by generation capacity and the number of participants. Their markets also opened the fastest, giving customers immediately free choice without restructuring their industry. The Nordic energy market is the most harmonized cross-border energy market in the world. By integrating their energy markets, Norway, Sweden, Denmark, and Finland formed the Nord Pool energy market. (Karan & Kazdağli 2011.)

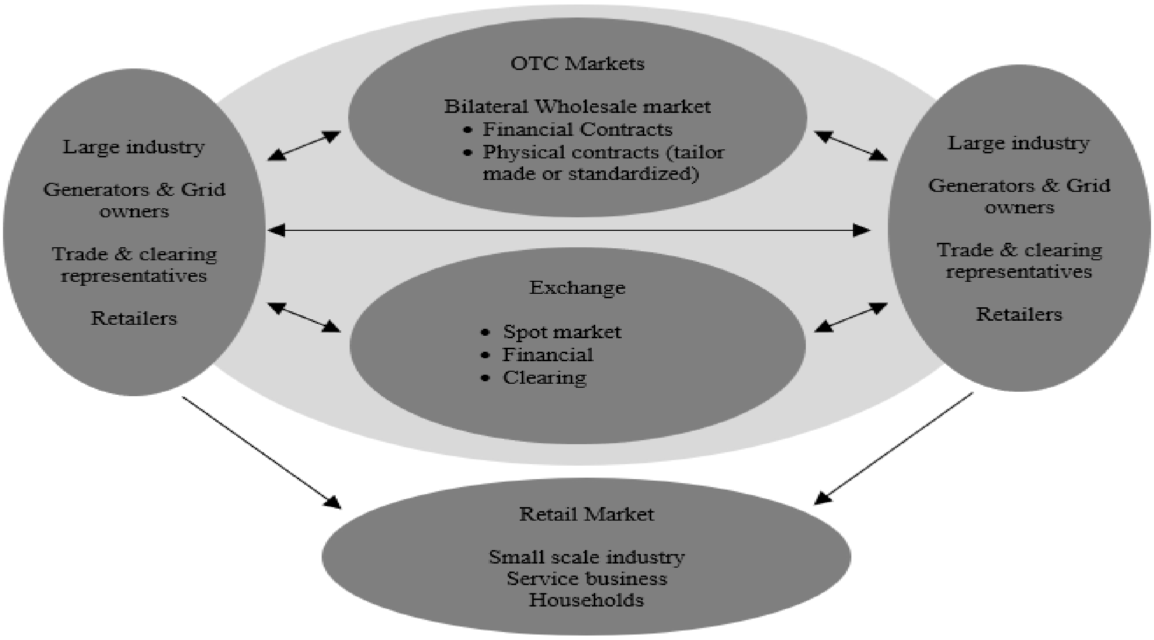

Figure 1. Nordic Electricity market overview (Flatabo et al. 2003).

The European wholesale energy market was the product of the deregulation process, which also caused the division between competitive and non-competitive aspects of the energy sector. Generation and supply represent the competitive side and grid operation the non-competitive side of the energy sector in Europe. In the Nordic region, competitive wholesale markets are built by Nord Pool exchange along with several brokers. The overview of the Nordic energy market can be seen in Figure 1. The main roles in this market are regulators, market operators, transmission system operators (TSO), network owners, market players, and retailers. *Regulators* are the separate controlling authorities. The only common *market operator* in the Nordic region is Nord Pool. *TSOs* are the national main grid owners functioning as coordinators between producers, consumers and other *network owners* that operate and maintain the network. *Market players* are producers, consumers or traders registered as members in the Nord Pool exchange or trading bilaterally. *Retailers* sell electricity to end-users. (Flatabo, Doorman, Grande, Randen & Wangensteen 2003.)

In an open electricity market, bilateral trading happens by forming *customized long-term contracts*, *over the counter trading* or *electronic trading*. Bilateral trading only involves the buyer and the seller, who enter the contract without the involvement of a third party. *Customized long-term contracts* face large transaction costs, so they are only formed when both the buyer and the seller are moving large amounts of energy, with flexible terms to meet the needs of both parties. Smaller amounts of energy are traded *over the counter*, with standardized delivery during different daily and weekly periods. This type of trading also has much lower transaction costs than long-term contracts. *Electronic trading* means the participants joining a computerized marketplace, where a computer matches the bids and offers anonymously. Electronic trading is the fastest and cheapest of these three types of trading. (Kirschen & Strbac 2004.)

The price of electricity in common use has only the single meaning of the current price of electricity, but in the electricity markets, it can mean either the spot price or the system price of electricity depending on the context. The spot price, as with other commodities, is the current price of electricity, and it can be used as the real-time price, or as a price for the day-ahead market. The equilibrium of the total supply and demand curves in the electricity market forms the system price, which is used as a reference price for most of the derivatives trading. (Vehviläinen & Pyykkönen 2005.)

The day-ahead markets allow trading energy for up to the next 24-hour period, where the spot price is formed for each hour. The intraday market is the near real-time balancing mechanism, where traders react to unforeseen events. While day-ahead markets handle the majority of the traded volume, intraday markets are gaining importance due to the increasing portion of renewable energy, like the increased production and usage of wind power. Wind power especially is unpredictable, so balancing mechanisms like the intraday market is needed to enable and encourage the usage of wind power in the energy mix. (Nord Pool 2019; Pape, Hagemann, and Weber 2016.)

Agents in the energy market hold their position in forms of either peak or baseload blocks, which they finetune near the physical delivery from day-ahead to as down as half-hourly, according to the requirements of the system operator. These changes are what forms the spot markets, as the traders are able to form transactions nearly in real-time. The accepted bids and offers form the two imbalance prices in electricity markets; the system buy price (energy deficiency) and the system sell price (the energy surplus). This spread between the two prices forms and unhedgeable element of risk in the electricity spot market. (Karakatsani & Bunn 2008.)

The energy markets differ from other commodity markets by a number of factors. Energy has greater economic and strategic importance, the environment has a greater impact on energy products, and its inherently non-storable feature makes the energy products to stand apart from other commodities (Karan & Kazdağli 2011). The risk factors are not the same in every region though. In Nord Pool markets, the main types of generated energy are hydro, thermal and nuclear power, with Norway being almost entirely powered by hydropower (Botterud, Kristiansen & Ilic 2010). So along with the typical risk factors of electricity products, in Nord Pool markets the hydro reservoir levels affect the price more than the other types of generation methods.

The differences separating the electricity markets from the other commodity markets are what make them more volatile than the others (Deng & Oren 2006). Spot markets for electricity, however, do not differ greatly from other types of spot markets, since the core nature of an electricity spot market is immediacy and the spot prices are quite volatile and fast to react to the news. Along with these, the reasons for high volatility include changes due to the weather and the forming of gaps between load and generation of energy. Due to the high volatility and unpredictability of the spot prices, like in other commodity markets, the energy markets rely on futures contracts to manage the risks of prices changing suddenly. (Kirschen & Strbac 2004.)

The effects of weather are even more dominant in regions experiencing all four seasons. Meyer-Brandis and Tankov (2008) find when estimating seasonality in their trend function, that among their data samples the Nord Pool area experiences the effects of seasonality the strongest, and the California-Oregon area the weakest. They explain Nord Pool’s strong effect as the result of their large share of hydropower depending greatly on the weather. Warmer or colder weather than usual causes abnormal returns/losses depending on the estimates made when deciding spot price for futures contracts.

Keskikallio and Lindholm (2003) describe the spot prices in the Finnish power market experiencing a clear seasonal pattern, prices increasing during winter and decreasing during summer, of course adding to this is the fact that the demand for electricity is higher during colder seasons. Lucia and Schwartz (2002) find that between warm and cold seasons, the volatility of the system price is consistently different. Of course, the demand for electricity changes depending on the weather as well. Cialani and Mortazavi (2018) find that during cold weather the demand for electricity is more sensitive than it is during hot weather.

2.1 Electricity derivatives

After the deregulation of government-controlled energy markets, the markets in Europe eventually developed into wholesale trading markets. These wholesale markets can be divided into Over the Counter (OTC) markets and energy exchanges, both of which in turn can be divided into spot and futures markets. Figure 2 gives an overview of the common structure of energy markets. The terms spot market and spot price differ slightly from the common concept when used in the electricity market. Spot price can mean both the current price of electricity or the price during the following day. In some situations, there is a distinction made between these two, and the prices for the following day is called the day-ahead spot. Similarly, the term spot market is used with both trading the electricity for the current day and trading electricity in advance for the next day. (Burger, Klar, Müller & Schindlmayr 2004; Rademaekers, Slingenberg, & Morsy 2008).

The various OTC markets and energy exchanges in European countries have emerged to answer the liberalization of the energy markets and the increased trading in gas and electricity. The OTC markets have the majority of trading in the wholesale markets. In Nordic countries, the trading of energy products is mainly done through Nord Pool. Nord Pool controls the spot markets in the Nordic region and the derivatives trading is handled through NASDAQ. (Karan & Kazdaǧli 2011.)

The energy derivatives markets can be divided like in any other financial market into forward markets, futures markets and option markets. These markets define the different types of contracts participants are able to make and define the types of delivery date, settlement, and conditions that are best suited for the different buyers and sellers. While the rest of the markets provide somewhat unique roles to the effectiveness of the energy markets, options markets do not have any unique aspect specific to the energy markets.

As in other markets, options in energy markets provide the alternative of conditional delivery, instead of unconditional delivery that is a part of the forward and the futures markets. (Kirschen & Strbac 2004.)

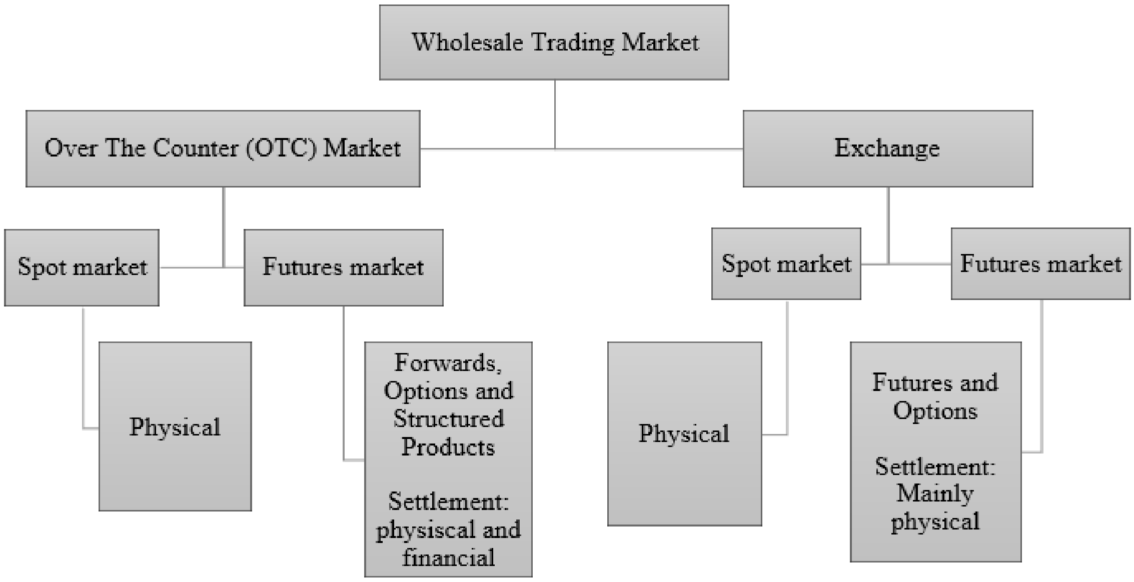

Figure 2. The structure of power trading in Europe (Rademaekers, Slingenberg, & Morsy 2008).

Energy trading with standardized products is done as an answer to the heightened volatility of the energy markets. (Karan & Kazdağli 2011). As mentioned by Keskikallio and Lindholm (2003), participants in these markets have an incentive in using futures to cover the risk of fluctuating spot prices, especially for the longer periods. Energy futures markets allow participants to trade electricity for longer periods in advance, basing the payments to specified spot prices (Green 2001). Without these futures contracts especially, it would be difficult for electricity retailer companies to exist. Futures contracts provide the important ability for electricity retailers to ensure the price for specific levels and the amount of electricity usually needed, it would require vast amounts of capital to ensure the company's survival if the price of the electricity or its demand changes suddenly. As last-minute changes are settled in the day-ahead spot market, forming contracts with their customers and providers the retail companies can protect themselves from the amount of these changes needed. The other parties benefit from fixed spot prices as well. The customers can expect the price of the electricity to not differ greatly from what was agreed upon and the production companies can expect the amount of demand in the future.

Forward markets for energy can be considered to consist almost entirely of bilateral trading between participants, and where the transactions are inherently financial. These contracts are handled privately, or through exchanges and brokers. Long-term contracts are made either through brokers or directly, and exchanges handle the short-term contracts. Some exchanges offer supplementary long-term markets as well, the prices from which can be used as a less volatile benchmark than spot prices. (Wilson 2002.) Deng and Oren (2006) divide electricity forward contracts by the delivery period into forwards on around the clock electricity, off-peak electricity and on-peak electricity. This categorizing is also applicable to almost all other electricity derivatives.

Tolling contracts and load-servicing full-requirement contracts are part of structured transactions. Tolling contracts are similar to a common contract between the buyer and the owner of a power plant. What differentiates this from a common electricity contract, is the amount of control they give to the buyer. By paying an upfront premium to the plant owner the scheduling of the plant can be controlled, or the outputted electricity can be taken during a specified time under specified constraints. The tolling contracts also specify the limits for the buyer on how to take the output electricity or operate the power plant. Load-servicing full-requirement contracts allow the buyer to have flexible consumption terms as well as being able to pay according to the actual consumption with a fixed rate. The suppliers who sign these full-requirement contracts need to hedge themselves against the volumetric uncertainty of their customers' consumption. (Deng & Oren 2006.)

Together these different derivative markets then form effective and productive wholesale energy markets and offer the necessary tools for participation and risk management. Risk management especially rises in a crucial role due to the high volatility of the energy markets. As was brought up before, the weather itself is a large factor in the heightened risk and uncertainty when estimating the future consumption of electricity. For pricing these electricity derivatives, Deng and Oren (2006) bring up two competing approaches in estimating the electricity price process: fundamental and technical. They favor the technical approach as it models the behavior of market prices directly using historical data. The fundamental approach uses a simulation of market and system operation to form the market prices, and while providing a more realistic system and transmission network, it requires a large number of scenarios to be considered. This kind of analysis Deng and Oren feel is more applicable to financial transmission rights than other electricity derivatives.

Pricing electricity derivatives differs from other commodities by the premiums paid in the derivatives markets. As electricity is an unstorable commodity, this characteristic causes price spikes and heteroscedasticity in electricity prices, which in turn makes the commonly used equilibrium models for commodities unusable in electricity markets. (Viehmann 2011). The unstorable nature of electricity makes the usual formulas pricing of forwards and futures unusable since convenience yield and cost-of-carry factors cannot be applied to them. (Fleten & Lemming 2003; Geman 2005). Pricing electricity derivatives, therefore, requires more complicated models or modifying the existing ones to suit the electricity markets exactly.

For example, the trading of electricity mostly happens through the day-ahead markets, which can be considered as one-day forward contracts. The pricing of forwards, however, requires the usage of net convenience yield or cost-of-carry relationships, which are not found in electricity markets, with the exception of hydroelectricity as water can be stored in reservoirs. (Fleten & Lemming 2003; Geman 2005.) The formula for pricing commodity forward contracts could be modified by replacing the cost-of-carry factor with the risk premium in electricity markets to make it applicable (Geman 2005).

The pricing of electricity commodities can then be thought to be about finding replacements for the convenience yield and cost-of-carry factors. But since hydro energy can be thought of as stored energy, the state of the derivatives markets is different in electricity markets where hydro energy is used in large amounts, like in the Nordic electricity market. The risk premiums in these kinds of markets behave differently for example. Risk premiums in both German and Nordic electricity markets present seasonal patterns, but it is more distinct in the German market (Botterud, Kristiansen & Ilic 2010; Viehmann 2011). In the Nord Pool market, a clearer seasonal pattern is found between the inverse relationship between the hydro reservoir levels and the net convenience yields in the market. The first half of the year having usually low reservoir levels and positive net convenience yields, and high reservoir levels and negative net convenience yields appearing usually in the second half of the year. (Botterud, Kristiansen & Ilic 2010.)

The net convenience yield is considered to be more relevant than the risk premium in the Nord Pool electricity market by Botterud, Kristiansen and Ilic (2010). They explain that due to the high share hydroelectricity in the market, the convenience yields are more relevant in the relationship between the spot and futures prices, rather than using the risk premium. They find that in the Nord Pool electricity market, this relationship is affected by the hydro reservoir levels, along with demand and changes in the electricity system.

The prices of futures are found to be usually higher than the spot prices, resulting in an average negative net convenience yield.

The modern electricity markets offer many opportunities for both investors and companies to manage their finances. Investors can trade financial contracts in energy markets like in any other commodity markets. The main difference to the other commodity markets is the larger volatility that is often part of the energy markets (Deng & Oren 2006). Companies can manage their costs and risks by using different possibilities available in the energy markets. Electricity consuming companies can form contracts with the electricity providers to buy electricity at a set price for a specific time period, or by monitoring the development of electricity prices to even halt the production at times when the spot price is too high. Electricity retailer companies can both ensure their ability to provide enough electricity to their customers and protect against the risk of price changes with the different financial contracts available in the energy markets. Electricity producing companies benefit from these contracts by knowing how much production is needed in the near future.

2.2 Nord Pool

Previously discussed workings of energy markets apply to the Nord Pool market area as well, even though its characteristics make it stand unique among the other European energy markets. This market area also covers different countries and regions, so this section discusses what this market consists of and how Nord Pool manages these markets to form a single, efficiently working electricity market.

Karan and Kazdağli (2011) described the Nordic markets as the most harmonized among the European energy markets, as none of the market participants hold a larger than 20% share of the market. What also makes the Nordic markets stand apart from the rest, is their larger consumption of electricity, which leads to more competitive markets as their customers have more incentive to be interested in the markets (Littlechild 2006). In this Nordic region, the trading of energy is mainly done through Nord Pool.

When the decision of deregulating the electricity market came to effect in Norway 1991, the Nordic electricity exchange was formed in Norway. This was later joined by Sweden in 1996, Finland in 1998 and Denmark in 2000. These countries formed the energy market known as Nord Pool. In 2010, Nord Pool ASA, Nord Pool’s market for exchanging commodity derivatives, was integrated into NASDAQ OMX Commodities. In the Nord Pool market area, there are currently 370 production companies, 500 distribution companies, and 380 suppliers. (Nord Pool 2019.) Approximately 50% of the electricity generated in the Nord Pool market area comes from hydropower. Due to the characteristics of hydropower pointed out before, and hydropower having such a large share of the energy generation, the Nord Pool markets stand quite unique among other markets. (Botterud, Kristiansen & Ilic 2010.)

Other types of generation used in the Nord Pool market area are thermal and nuclear power. In the Nordic markets, Norway is almost completely powered by hydropower, whereas Sweden and Finland use a mixture of thermal and nuclear power and Denmark is mainly powered by thermal power. (Nord Pool 2019.) The Nord Pool annual report of 2018 calculates the total volume traded in the Nord Pool markets as 524 TWh, of which 396 TWh had been traded in the Nordic and Baltic markets.

The main markets inside Nord Pool are the intraday and day-ahead markets. As with other electricity markets, also in the Nord Pool markets, the day-ahead market holds the majority of the traded volume. The intraday market is increasing in its importance, however, especially with the planned increase in wind power usage. Nord Pool's day-ahead market trades energy for over 500 TWh yearly, and it covers 13 countries and 19 bidding zones for over 300 daily traders. The day-ahead market is also known as the Elspot market. Nord Pool's intraday market covers the Nordic and Baltic regions, and the UK and the German markets. Its main purpose is to reinforce the day-ahead market by allowing the traders to react to the sudden changes in the generation of electricity. Having the ability to react nearly in real-time, the traders in the intraday market bring the market to back to its equilibrium. (Nord Pool 2019.)

Trading in the Nord Pool's day-ahead market is based on four different types of orders: single hourly orders, block orders, exclusive groups, and flexi orders. *Single hourly orders* are the largest type of day-ahead trading. The order is done by specifying the buy and/or sell volume for each hour of the day and choosing between price dependent and independent orders. *Block orders*, on the other hand, specify both volume and price for a specific number of consecutive hours of the same day. Block orders also provide the many different options to tailor the order according to the needs of the participant. The most used type of block order is the regular block order, which is an "all-or-nothing" type of order. These orders must be accepted completely, and the contracts cover all the hours and volumes specified. *Exclusive groups* and *flexi orders* are types of block orders.

Exclusive groups are formed from a cluster of buy and/or sell blocks, from which only one block can be active at a time. Flexi orders, on the other hand, are single block orders, that can have a maximum duration of 23 hours within a single day. (Nord Pool 2019.)

The official currency in the day-ahead markets is euro, but Nord Pool offers a currency service that the customers can choose from EUR, NOK, SEK or DKK to trade in. Price calculation is done by converting all orders to EUR according to the preliminary currency rates, which Nord Pool validates at 12:00 CET. After the trading system has determined the number of different currencies needed, two or three banks perform the official currency hedging, which sets the official exchange rates. (Nord Pool 2019.)

In the intraday market, trading can be done throughout the year for every hour of the day with 15-minute, 30-minute, hourly or block products. The trading is done with either limit or block orders. Block orders can be only accepted or rejected completely, and they consist of up to 24 consecutive hourly products. Limit orders can be partially executed, and they specify a price limit for either buy or sell order. The order can be executed either at this price limit or higher for sell orders and lower for buy orders. (Nord Pool 2019.)

Since the Nord Pool's day-ahead market covers a large area, with different countries and transmission systems, it is divided into bidding areas according to the local transmission system operators (TSOs). For example, Norway has currently five bidding areas, while Finland has one. Figure 3 shows all bidding areas that make up Nord Pool's market area. Different bidding areas ensure that the conditions of the regional market are reflected in the price and help to point out the constraints in the transmission systems. Bottlenecks in the transmission system make different areas have different prices, and the constraints in the transmission capacity in these areas make the power go from low price area towards the high, which is the desired result. (Nord Pool 2019.)

All consumers and producers buy and sell electricity according to their own area price. Nord Pool calculates their system price from all these different area prices. The market restrictions are excluded from these calculations and the capacities are added to infinity. This system price, or Elspot price, is formed for each hour of the following day according to the balance between the supply and demand of the traders. In the day-ahead markets, system price is used as the reference price in the Nordic region, and it is also the underlying price used in Nord Pool's standard financial contracts. (Nord Pool 2019.)

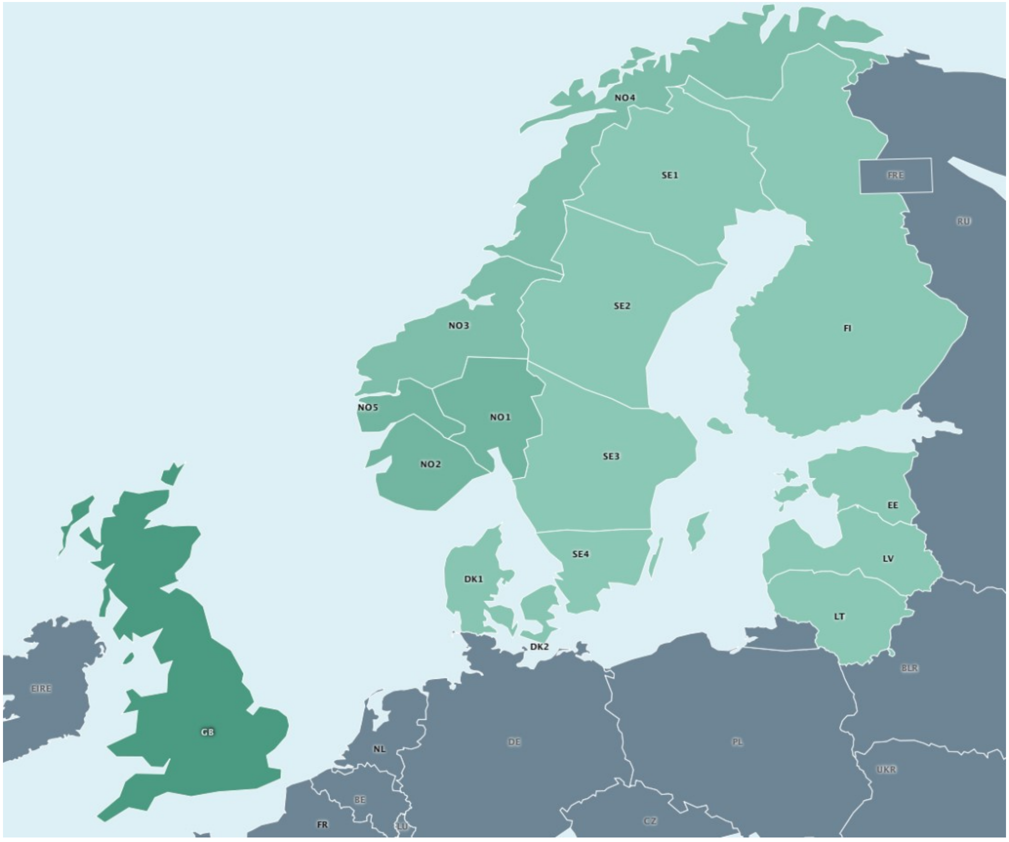

Figure 3. Nord Pool's bidding areas (Nord Pool 2019).

2.3 Nordic financial markets for electricity

Electricity markets can be divided into physical and financial markets. Currently, in the Nordic electricity markets, Nord Pool controls only the physical, the Elspot market. Before their incorporation to Nasdaq in 2010 (Nasdaq 2010), the financial markets in Nord Pool consisted of Eltermin and Eloption markets. The Eltermin and Eloption markets offered futures and forward contracts for up to five years, and the option of seasonal contracts and annual contracts. A year was divided into three seasons for both futures and forward contracts. (Lucia and Schwarz 2002; Botterud, Kristiansen & Ilic 2010)

Currently, the Nasdaq European Commodities, which is the trade name of Nasdaq Oslo ASA, has around 250 members across more than 20 countries, and it offers Europe's largest clearing house for power derivatives. Their multi-asset trading system is one of the fastest and most functionally complete in the world. The commodities exchange, Nasdaq Oslo ASA, trades power products that consist of Nordic, UK, German, French, Belgian, Spanish and Italian power derivatives.

Trading of financial derivatives is currently done through Nasdaq Oslo ASA with futures, deferred settlement (DS) futures, options, and EPAD contracts, without physical delivery. The DS futures accumulate value throughout the trading period and are settled financially only at the expiration date. EPADs, or Electricity Price Area Differentials, are DS futures contracts that reference the difference between the Nordic system price and the area price. The Nordic system price is used as the reference price in DS futures and futures contracts, but actual physical delivery costs are determined by the area prices (Figure 3). They allow hedging against the risk of area price differing from the system price. (Nasdaq Commodities 2019.)

3. VOLATILITY

Preparing for the unknown future is the motivation behind many financial models. For example, risk assessments are done to match pricing to the possible outcomes in the future and cash-flow forecasts help manage the company's finances. Forecasting volatility has been a crucial part of risk management in the financial markets. Especially, since volatility is the most important variable in the pricing of derivative securities. While volatility and risk are not the same thing, forecasting volatility effectively can give investors a good idea for the uncertainty associated with the possible investments for their holding period. This then gives proper grounds for assessing the risks of the investment. The overall volatility in financial markets has been observed to have widespread effects on the economy as a whole, so estimating and forecasting volatility are useful tools for policymakers as well to estimate the vulnerability of the economy. (Poon & Granger 2003.)

Often volatility and risk are used together and confused with each other. At its core, volatility represents the uncertainty in the financial markets. Andersen, Bollerslev, Christoffersen, and Diebold (2006) use volatility to define the variability of the random and unforeseen component of a time series, describe volatility more strictly in the terms of financial economics as *"the instantaneous standard deviation of the random Wiener-driven component in a continuous time-diffusion model."* They describe volatility as inherently unobservable and evolving stochastically through time. More simply put, volatility is the probability for deviation from the average, measured by the sample standard deviation, which is the square root of variance.

Previous literature has identified and confirmed a number of facts about volatility in financial asset prices. Engle and Patton (2007) list some of the most common characteristics of volatility as volatility clustering, mean reversion and asymmetry. While volatility by its nature is unobservable, it can still be predicted, as is shown by *volatility clustering*. This means, that the large changes in financial markets are likely followed by more large changes (in both directions). This then tells that after large changes, the volatility in financial markets must be predictably high. Traders often use this as a basic way to predict volatility, measuring the standard deviations over various periods and estimate the appropriate moving average to predict volatility. (Engle 1993.)

Where volatility clustering tells that volatility keeps fluctuating, *the mean reversion* in volatility is interpreted as volatility having a normal level, to which it will eventually return. While it is agreed, that long-run forecasts meet at the normal level of volatility, what this normal level is and if it stays constant might differ among practitioners. While many volatility models assume, that positive and negative shocks affect the asset's conditional volatility symmetrically, it is not always likely, especially for equity returns. This *asymmetry* of volatility is often also called the leverage effect or risk premium effect. (Engle & Patton 2007.)

Volatility forecasting models depend on different estimations of volatility. Three of the most used estimations can be defined as historical, implied and realized volatilities. *Historical volatility* is the measure of the standard deviation of past returns over a fixed interval (Poon & Granger 2003). *Implied volatility* is a forward-looking volatility measure, that is based on the forecasts of the market's future volatilities, which are estimated from the prices of options. *Realized volatility* describes the squared intraday returns and is able to exploit the information in high-frequency intraday data. (Andersen et al. 2006.)

The original tool for analyzing the volatility forecasts was the autoregressive conditional heteroscedastic (ARCH) process developed by Engle (1982), which has later on been built on to further statistical models, such as GARCH and EGARCH models. These three are all models of conditional variance, which is the variance of a random variable when some other variables are known. The ARCH process gives information about the one-period forecast variance by using the recent past. In the simplest specification of the conditional variance is estimated with the ARCH(p) model, which weighs the average of past squared forecast errors. Whereas before the focus in finance had been using the variance to measure volatility, the ARCH measures volatility using the conditional variance of returns instead. (Engle 1993.)

As data from increasingly shortening intervals has become available over time, so has the usefulness and accuracy of these volatility forecasting models increased. However, they have begun to struggle at the introduction of high frequency intraday data. Traditional volatility forecasting is mainly done through GARCH models, which struggle greatly to produce reliable predictions, especially when used for high-frequency data. As these models rely heavily on the weighted moving averages of past squared returns, they are slow to adapt to the movements of volatility. A newer direction in volatility forecasting has employed the use of realized volatility, which has the ability to react quickly to the changes in volatility. (Andersen, Bollerslev, Diebold & Labys 2003.)

3.1 Realized volatility

As many financial products are only traded on specific hours during the business day, the usual methods of forecasting and modeling volatility reflect this. The appearance of obtainable high frequency data made these models a poor fit in the situations where the financial product under observation produces continuous high frequency data. When such a product is traded only during specific hours, the volatility is able to develop outside these hours during the day. (Hansen & Lunde 2005.) As the traditional models are only able to take into account the data produced during the trading hours, the amount of volatility developed outside these hours remains undetected and distorts the accuracy of the results produced by these models.

Where standard volatility forecasting models fail to properly accommodate intraday data, realized volatility can be easily calculated from high frequency, intraday returns. The theory of realized volatility was first introduced by Andersen, Bollerslev, Diebold and Labys in 2001. The idea behind this theory boils simply down to summing squared intraday returns to calculate the realized volatility during the day. When the sampling is done frequently enough, the calculated realized volatility becomes close to the underlying integrated volatility. (Andersen et al. 2001, 2003.)

While the bottom line of realized volatility is simple enough, the theory behind it is much more extensive. Using the studies of Barndorff-Nielsen and Shephard (2002), and Hansen and Lunde (2005), a short overview of these underlying theories is now presented to give some understanding of how the realized volatility is built, and how they lead to the simple final formula of the realized volatility.

Realized volatility is the square root of the realized variance. Calculating the realized volatility for the whole day in question needs high frequency data of the entire 24 hours of the day (Hansen & Lunde 2005). Barndorff-Nielsen and Shephard (2002) show realized volatility as the result of using integrated volatility and a stochastic volatility model for log-prices. As the log-price $y^*(t)$ follows the stochastic differential equation:

$$\mathrm{d}y^*(t) = \{\mu + \beta\sigma^2(t)\}\mathrm{d}t + \sigma(t)\mathrm{d}w(t) \tag{1}$$

where $\sigma^2(t)$ is the spot volatility and μ and β are defined as drift and risk premium respectively. When the length of the time interval is Δ > 0, the returns are defined as:

(2) $$y_n = y^*(\Delta n) - y^*\{(n-1)\Delta\}$$

where n = 1,2,…, and which implies that for every model of σ^2, it follows

(3) $$y_n|\sigma_n^2 \sim (N(\mu\Delta + \beta\sigma_n^2, \sigma_n^2)$$

Then the process for integrated volatility (σ^{2*}) can be written as:

(4) $$\sigma_n^2 = \sigma^{2*}(\Delta n) - \sigma^{2*}\{(n-1)\Delta\}$$
$$\sigma^{2*}(t) = \int_0^t \sigma^2(u)\mathrm{d}u$$

From this, Barndorff-Nielsen and Shephard (2002) then explain that $\sigma^{2*}(t)$ is the quadratic variation of the stochastic volatility model, and it can be recovered using the entire path of $y^*(t)$. Then the following formula can be formed:

(5) $$[y^*](t) = \operatorname*{plim}_{q\to\infty}[\Sigma\{y^*(t_{i+1}^q) - y^*(t_i^q)\}^2] = \sigma^{2*}(t)$$

where the partitions $t_0^q = 0 < t_1^q < \ldots < t_{m_r}^q = t$, with $\sup_i(t_{i+1}^q - t_i^q) \to 0$ for $q \to 0$. In the equation, the plim describes the probability limit of the sum. They point out that the stochastic volatility model is not a good fit at a fine level for continuous data of prices, and the quadratic variation result presented above indicates that actual volatility for a day could be estimated with the squared sum of returns. If there is a fixed M amount of observations during each day, then the daily squared intraday changes are:

(6) $$\{y\}_n = \sum_{j=1}^{M}\left[y^*\left\{(n-1)\Delta + \frac{\Delta j}{M}\right\} - y^*\left\{(n-1)\Delta + \frac{\Delta(j-1)}{M}\right\}\right]^2$$

which is an estimate of the actual volatility. This $\{y\}_n$ is also known as realized volatility in economics.

Hansen and Lunde (2005) show a simpler approach through realized variance, following the definition of integrated volatility in equation 4 they define realized variance as an empirical estimate of the integrated volatility that is formed from intraday returns. When the price is observed from a to b, so that $a = t_0 < t_1 < \ldots < t_m = b$, then the equation for realized variance (RVar) can be formed as:

$$(7) \qquad \mathrm{RVar}_{[a,b]} = \sum_{i=1}^{m} \{p(t_i) - p(t_{i-1})\}^2$$

where p is the price at time t_i for $i = 1, \ldots, m$. Realized variance can then simply be calculated from the m number of squared intraday returns. Realized volatility would, therefore, be simply $RV_{[a,b]} = \sqrt{RVar_{[a,b]}}$, which is the form realized is commonly presented.

Andersen, Bollerslev, Diebold, and Labys (2003) find that instead of the popular approach of forecasting volatility using the GARCH model, the models built on realized volatility are far superior in forecasting volatility. They identify the reasons for this as the quadratic variation (equation 5) and its empirical representation, the realized volatility itself. The characteristics of realized volatility are what make it such a great tool to use in forecasting models. As seen from the studies by Hansen and Lunde (2005), and Andersen, et al. (2003), the ability to incorporate all the high-frequency intraday data of the present conditions produces far more accurate and more quickly adapting models than by using the traditional volatility forecasting models. There still remains the problem of obtaining proper high-frequency intraday data to be used with these models though.

However, as using realized volatility depends on high-frequency data, this opens up a risk of microstructure noise to affect the results of the predictions greatly. Meddahi (2002) and Bandi and Russel (2008) bring up this concern and point out that the risk lies in compounding the effect the noise term has on prices when summing the high-frequency intraday returns. This effect can be managed though, when it is suspected that the data is contaminated by noise. Meddahi (2002) suggests that adding a constant or other variables with the realized volatility reduces the noise, while Bandi and Russel (2008) suggest sampling the data at different frequencies.

Despite the possibility of prices being contaminated by noise, by using realized volatility it is possible to observe intraday prices more accurately. The applications of it are then not only limited to forecasting models. For example, Corsi, Fusari and La Vecchia (2013) developed a new method, a discrete-time stochastic volatility option pricing model that uses realized volatility to access the historical data within the high-frequency data. They point out, that the ability to utilize historical data makes the latent volatility observable, which in turn makes their model much easier to estimate than the other stochastic volatility models relying on much time-consuming filtering processes. Even though mainly used in forecasting, the ability to properly observe intraday data and the information it and historical data holds can be applied successfully elsewhere as well.

3.2 The HAR-RV model

The ability to incorporate the volatility outside trading hours was listed as one of the advantages of using realized volatility instead of the traditional volatility forecasting methods. A good real-life example of volatility evolving outside the trading hours is the electricity markets. In the electricity markets, active trading is usually done during specific hours, but the price of electricity (and along with it the volatility) continues to evolve throughout the day. The electricity market, therefore, produces ideal high frequency data to be used with the realized volatility models for forecasting volatility. Chan, Gray, and Van Campen (2008) were the first to approach the problem with forecasting electricity price volatility by utilizing the Heterogeneous Autoregressive model of Realized Volatility (HAR-RV) developed by Corsi (2009).

Corsi's (2009) HAR-RV model is based on the Heterogenous Market Hypothesis made by Müller, Dacorogna, Davé, Pictet, Olsen and Ward (1993). The hypothesis assumes, that in financial markets there exists different types of traders that have time horizons of fractal structure, which range from short- to long-term. These market dynamics also critically helps the fact that the trader work on different continents and different time zones.

Corsi (2009) names one of the possible reasons for heterogeneity emerging in financial markets, the heterogeneity stemming from the difference in time horizons, as the motivation behind the HAR-RV model. When the agents in financial markets have different time horizons, the volatility components they perceive and react to are different. Volatility components caused by these agents are different as well. When volatility is measured over different time horizons, their interrelations show the dynamics of these different market components.

Volatility over longer periods is observed influencing strongly on volatility over shorter periods, and the pattern emerging is a volatility cascade from low frequencies to high frequencies. A good example is to observe short- and long-term traders. The long-term volatility matters to short-term traders, as it sets the expected size of trends and risk in the future. So, the short-term traders then change their trading behavior according to the changes in the long-term volatility, and in doing so are causing short-term volatility. The trading behavior of the long-term traders, on the other hand, is unaffected by the short-term volatility. (Corsi 2009.)

The observation that the market structure generates volatility cascades is what led to the motivation behind the HAR-RV model. With three heterogenous volatility components, the model is able to consider volatilities that have been realized over different time intervals, and despite its simplicity, the model presents significant forecasting ability. This simplicity also allows easy variations of the model, as significant variables could be added as additional regressors as needed. (Corsi 2009.)

One example of these additional regressors is the inclusion of jump components in the study by Chan, Gray and Van Campen (2008), which was also suggested by Corsi (2009) as a further application of the model. They follow the addition to jump-diffusion models of separating the total variation into jump and non-jump components and study the changes in the ability to forecast volatility by modifying Corsi's HAR-RV model to include these components.

As explained, the HAR-RV model is a volatility cascade model, that has three heterogenous volatility components representing time horizons of daily *(d)*, weekly *(w)* and monthly *(m)*. It is assumed, that each component corresponds to a market component forming expectations for the volatility of the next period. These expectations are based on the current observed realized volatility and on the expectations on the longer horizon volatility. (Corsi 2009.) Corsi (2009) defines this volatility cascade model as:

$$\begin{aligned} (8) \qquad \tilde{\sigma}_{t+1m}^{(m)} &= + c^{(m)} + \phi^{(m)} RV_t^{(m)} + \tilde{\omega}_{t+1m}^{(m)}, \\ \tilde{\sigma}_{t+1w}^{(w)} &= + c^{(w)} + \phi^{(w)} RV_t^{(w)} + \gamma^{(w)} \boldsymbol{E}[\tilde{\sigma}_{t+1m}^{(m)}] + \tilde{\omega}_{t+1w}^{(w)}, \\ \tilde{\sigma}_{t+1d}^{(d)} &= + c^{(d)} + \phi^{(d)} RV_t^{(d)} + \gamma^{(d)} \boldsymbol{E}[\tilde{\sigma}_{t+1w}^{(w)}] + \tilde{\omega}_{t+1d}^{(d)}, \end{aligned}$$

where the daily integrated volatility $\tilde{\sigma}_t^{(d)} = \sigma_t^{(d)}$ determines the return process as the highest frequency component. The coefficients $\tilde{\omega}_{t+1m}^{(m)}$, $\tilde{\omega}_{t+1w}^{(w)}$ and $\tilde{\omega}_{t+1d}^{(d)}$ stand for volatility innovations, and are contemporaneously and serially independent zero-mean nuisance variates, and they have an appropriately truncated left tail to guarantee the positivity of partial volatilities. Corsi (2009) points out that this positivity could also be achieved by writing the model with the log of RV.

Corsi (2009) then writes this cascade model into a simpler form:

(9) $$\sigma_{t+1d}^{(d)} = c + \beta^{(d)} RV_t^{(d)} + \beta^{(w)} RV_t^{(w)} + \beta^{(m)} RV_t^{(m)} + \widetilde{\omega}_{t+1d}^{(d)}$$

When seen as a three-factor stochastic volatility model, this equation can then be derived to the functional form of $\sigma_{t+1d}^{(d)} = RV_{t+1d}^{(d)} + \omega_{t+1d}^{(d)}$, where $\omega_t^{(d)}$ includes both the latent daily volatility measurement and estimation errors. With these, Corsi (2009) writes the volatility cascade model as a simple time-series representation:

(10) $$RV_{t+1d}^{(d)} = c + \beta^{(d)} RV_t^{(d)} + \beta^{(w)} RV_t^{(w)} + \beta^{(m)} RV_t^{(m)} + \omega_{t+1d}$$

where $\omega_{t+1d} = \widetilde{\omega}_{t+1d}^{(d)} - \omega_{t+1d}^{(d)}$ and the daily realized volatility $RV_{t+1d}^{(d)}$ is continuously compounded over fixed intervals from intraday returns. The realized volatility over weekly and monthly time horizons is normalized to the daily level by taking the average of daily quantities, to allow comparisons between these three different horizons. The normalization is done to the daily level, as the daily frequency is the highest frequency volatility component in the cascade.

Equation 10 can be further modified to fit the situation in hand. Chan, Gray and Van Campen (2008) and Qu, Duan and Niu (2018) drop the monthly realized volatility and include jump components. Also, whereas Corsi (2009) uses only the business days to take the weekly realized volatility to the daily level, both of these studies use all seven days of the week as the electricity price continues to change even when electricity is not actively traded. The forecast is not limited to the next day either. When testing his model, Corsi (2009) also makes forecasts for 1-week and 2-week periods.

As previously stated, by using realized volatility, it opens up the possibility for microstructure noise affecting the results (Meddahi 2002, Bandi and Russel 2008). Corsi, Fusari and La Vecchia (2013) however state that, at least for option pricing purposes, the multi-component specification behind the HAR-RV model smooths the results that would otherwise be too noisy. They also bring up the fact that even though not formally a part of the class of long-memory processes, the model has the ability to provide the same persistence observed in financial data. Corsi, Fusari and La Vecchia (2013) list these attributes as the reasons for the HAR-RV model emerging as one of the standard models in forecasting and describing the realized volatility.

The simple form of the HAR-RV model and the benefits of realized volatility are the reasons this method was chosen to be used to test the possibility to form forecasts from the hourly spot price data in Nord Pool electricity markets. The simple form of the formula makes it adapt quickly to the changes in the market, and also allows further applications to be done more easily. As the weather has been shown to be a significant factor in the electricity prices in the Nordic region (Keskikallio and Lindholm 2003; Meyer-Brandis and Tankov 2008), this quickly adapting nature would be ideal when applying the HAR-RV model to Nord Pool's market area.

4. DATA AND METHODOLOGY

This section reviews in detail the data used in this study, as well as presents the methods of how the HAR-RV model is applied to study the realized volatility of the spot prices in Nord Pool's electricity market. While the previous chapter presented the theory behind realized volatility and the HAR-RV model, section 4.2 presents them briefly again to show thoroughly how these theories are applied and modified to fit this study according to previous similar studies. Nord Pool's electricity market is chosen as the subject of this study due to its unique standing among European markets, and the ideal type of high-frequency price data available to be used with the HAR-RV model. This study does not, however, utilize the available high frequency data directly with the HAR-RV model, but uses hourly updating daily spot prices calculated from the continuously evolving high frequency spot price data.

4.1 Description of the data

The data in this study is collected directly from Nord Pool in March of 2019, and it consists of daily Elspot prices taken at an hourly frequency for every day of the sample period. The daily price updates every hour and as the Nord Pool's system price, the Elspot represents the price of electricity for the whole Nord Pool market area. The hourly price data is collected from the period of 2008 to 2018. Nord Pool has made distinctions in the data for summer and winter prices, and this distinction will be followed in this study as well. Approximately, summertime is considered covering 30.3. – 30.10. of each year, and the rest of the year is considered as wintertime.

The daily price for the whole day (P_t) is updated on top of every hour in the collected set of data, and the overall price for the electricity for a day is calculated as an average of these hourly spot prices ($p_{t,j}$). These calculated overall daily prices are also provided in the Nord Pool's data and will be used directly to cover for any discrepancies in the hourly price data. The hourly frequency of sampling the electricity price data is not the only one available as the prices for electricity are continuously evolving, for example, Nord Pool's intraday market also offers prices updating every 15 and 30 minutes (Nord Pool 2019).

The hourly prices are used in the returns and volatility calculations. Further, as the price continues to change on each hour of the day for every, all 24 hours of the day and seven days of the week are taken into the calculations of this study, not just the trading hours as is commonly done. The following Table 1 presents the descriptive statistics of the data. Testing for autocorrelation shows that there is no autocorrelation in the coefficients listed in Table 1.

The data set is modified by removing the day where the Elspot price dropped to 0 for several hours, as this produced exceptionally high volatility outliers. Each year also had the price for the third hour of the day missing during one day at the end of March, so these missing prices were set to be the same as during the previous hour. This keeps the used models and equations uniform and removes the effect of the missing hour as the logarithmic return for this will be 0. Since the overall daily prices for each day are provided directly by Nord Pool, these remain unaffected as well. When calculating the returns for each day, the previous day's price for the 24th hour is also included to find the return between midnight and 01:00.

Table 1. Descriptive statistics.

Panel A: Daily prices (P_t)

	Mean	Median	Std. dev.	Kurtosis	Skewness	Minimum	Maximum	Observations
Total sample	36.37	34.33	13.28	2.24	0.94	3.88	134.80	4018
Winter	39.48	36.37	14.18	2.98	1.38	8.74	134.80	1667
Summer	34.17	32.78	12.14	0.04	0.34	3.88	71.80	2351

Panel B: Daily returns (r_t)

	Mean	Median	Std. dev.	Kurtosis	Skewness	Minimum	Maximum	Observations
Total sample	0.00	0.00	0.13	110.95	-1.10	-2.58	2.11	4018
Winter	0.00	0.00	0.09	81.08	-0.36	-1.22	1.11	1667
Summer	0.00	0.00	0.15	92.58	-1.11	-2.58	2.11	2351

Panel C: Daily realized volatility $(RV_t^{(d)})$

	Mean	Median	Std. dev.	Kurtosis	Skewness	Minimum	Maximum	Observations
Total sample	0.27	0.17	0.29	20.59	3.87	0.02	3.09	4018
Winter	0.23	0.15	0.23	14.63	3.25	0.02	2.00	1667
Summer	0.29	0.19	0.32	19.12	3.84	0.03	3.09	2351

Panel D: Hydro reservoir levels

	Mean	Median	Std. dev.	Kurtosis	Skewness	Minimum	Maximum	Observations
Total sample	73.66	78.78	23.29	-0.93	-0.47	19.94	111.00	574
Winter	70.98	73.75	20.81	-0.80	-0.32	19.94	105.33	238
Summer	75.58	83.71	25.16	-0.96	-0.59	20.64	109.61	238

Following closely the work done by Chan, Gray and Van Campen (2008), where the spot price process is assumed to be governed by a continuous-time stochastic-volatility model, the intraday returns for a day t are calculated from the hourly updated Elspot prices $p_{t,j}$. However, unlike Chan, Gray and Van Campen, this study omits the added jump-component, and following the examples of Corsi (2009) and Ullrich (2012), log-prices are used for the intraday returns. For the sampling period of M days, the spot prices of electricity are sampled at equally spaced intervals K times per day. The notations in equation 11 are used for the rest of the thesis as well. For the use of this thesis, the spot prices are taken at hourly intervals, so the daily returns will be formed from 24 hourly updated daily spot prices:

$$(11) \qquad r_{t,j} = log(p_{t,j}) - log(p_{t,j-1}) \quad j = 1, 2, \dots, K \quad t = 1, 2, \dots, M$$

Using these returns, and following the example presented in equation 7, the daily realized volatility for the Elspot prices at a day t is then calculated as:

$$(12) \qquad RV_t^{(d)} = \sqrt{\sum_{j=1}^{K} r_{t,j}^2}$$

Table 1 shows clearly that the data indicates differences during summer and winter seasons, during summertime both the average daily returns and daily realized volatility are on average slightly higher than they are during winter. Both volatility and returns also rise higher during summer than during winter. On the other hand, panel A in Table 1 and Figure 4 show that the daily prices of electricity are higher during winter, as well as the largest spikes in the daily Elspot price happening during winter.

So even though the prices are likely to be higher during winter, they seem to be more stable as well. This can also be seen from panels B and C, and figures 5 and 6, while the prices are quite volatile throughout the year, the spikes in volatility and the daily returns are more likely to happen during summer. The spikes occurring during summer appear also to be higher than those happening during winter.

The total hydro reservoir levels are included in the descriptive statistics, as it has been made clear in the previous literature that this provides an unusual effect in the Nord Pool electricity market when compared to others. The amount of stored hydro energy in TWh in the Nord Pool market is taken as a weekly frequency. The levels of hydro storage will also be regressed against the HAR-RV model to find out whether they have an effect on the predicted realized volatility.

Panel D in Table 1 shows that between the summer and winter seasons set by Nord Pool, there is not much difference in terms of hydro reservoir levels. Interestingly, as can be seen from Figure 7, the hydro energy storage levels usually reach their peak during autumn and are at their lowest point at the start of spring. Likely the usage of hydro storage during winter also plays a part in the prices being more stable in the winter. As pointed out by Meyer-Brandis and Tankov (2008), the large share of hydropower leaves Nord Pool markets more vulnerable to the changes in weather, and this seems to be especially true in regards to the daily returns and the realized volatility when the hydro reservoirs are at their highest.

Table 2. Unit root tests.

Panel A: Total sample

Returns		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-61.49	0.00
Test critical values:	1% level	-3.43	
	5% level	-2.86	
	10% level	-2.57	
$RV^{(d)}$		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-12.91	0.00
Test critical values:	1% level	-3.43	
	5% level	-2.86	
	10% level	-2.57	

Panel B: Winter

Returns		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-47.41	0.00
Test critical values:	1% level	-3.43	
	5% level	-2.86	
	10% level	-2.57	
$RV^{(d)}$		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-9.36	0.00
Test critical values:	1% level	-3.43	
	5% level	-2.86	
	10% level	-2.57	

Panel C: Summer

Returns		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-23.58	0.00
Test critical values:	1% level	3.43	
	5% level	-2.86	
	10% level	-2.57	
$RV^{(d)}$		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-8.88	0.00
Test critical values:	1% level	-3.43	
	5% level	-2.86	
	10% level	-2.57	

As the realized volatility stands upon the assumption of a stochastic volatility model, so the underlying series of daily returns and daily realized volatility of the Elspot prices will be tested for the possible presence of unit root. This will be tested with the Augmented Dickey-Fuller (ADF) unit root test, the results of which are presented in Table 2 for the total sample period, and for the winter and summer seasons. The null hypothesis for all

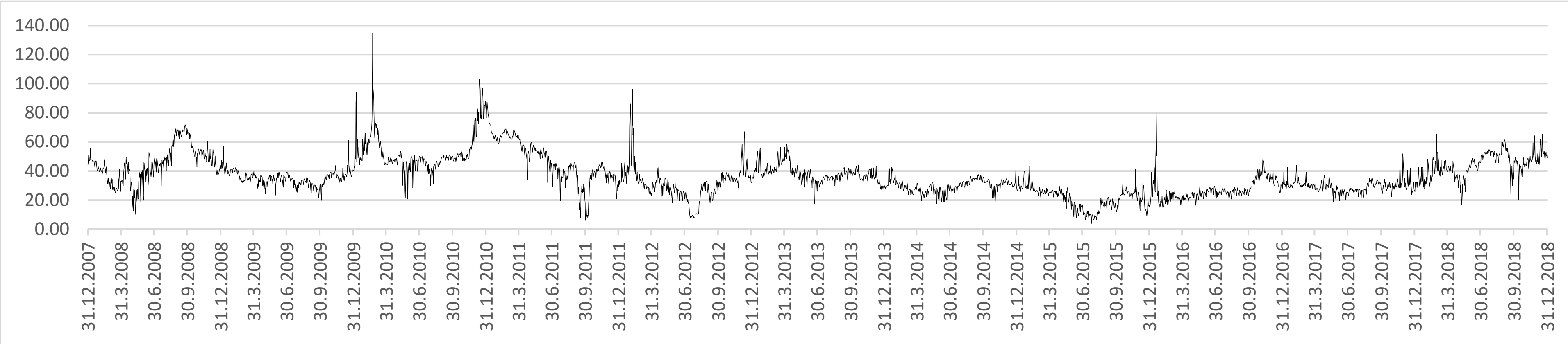

Figure 4. Elspot daily prices.

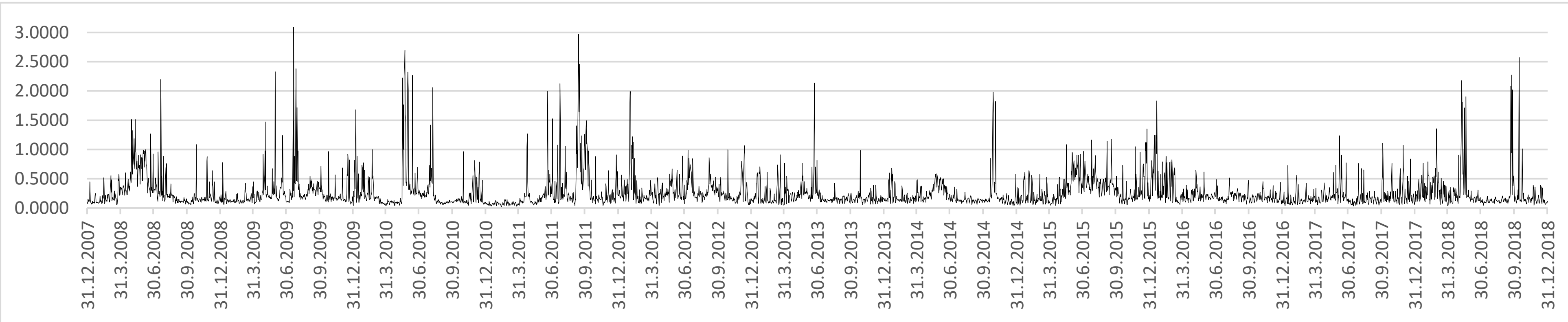

Figure 5. Realized volatility.

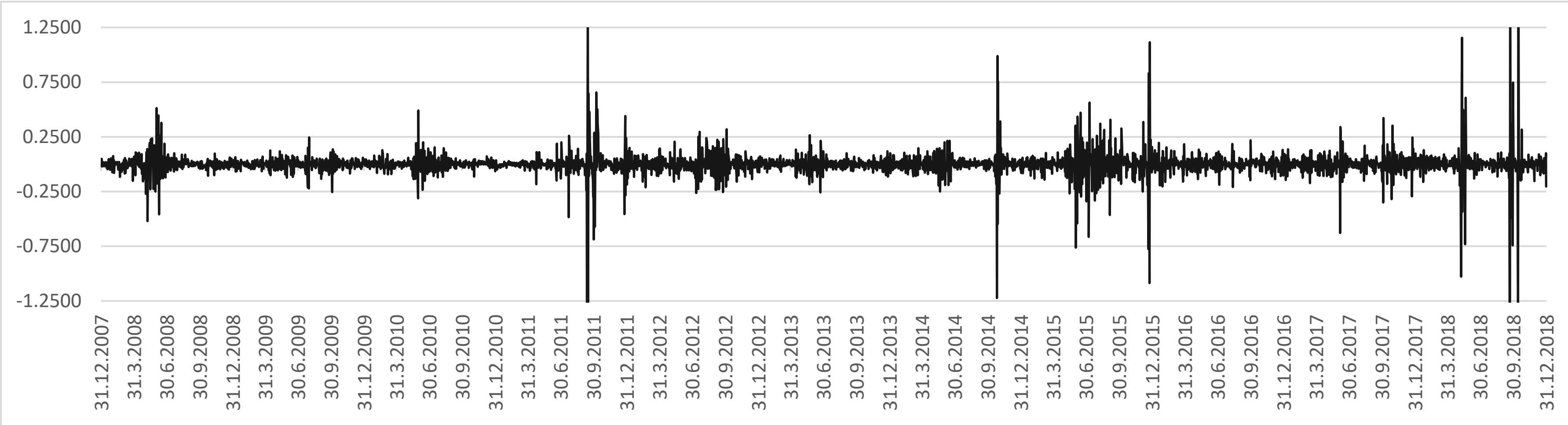

Figure 6. Daily returns.

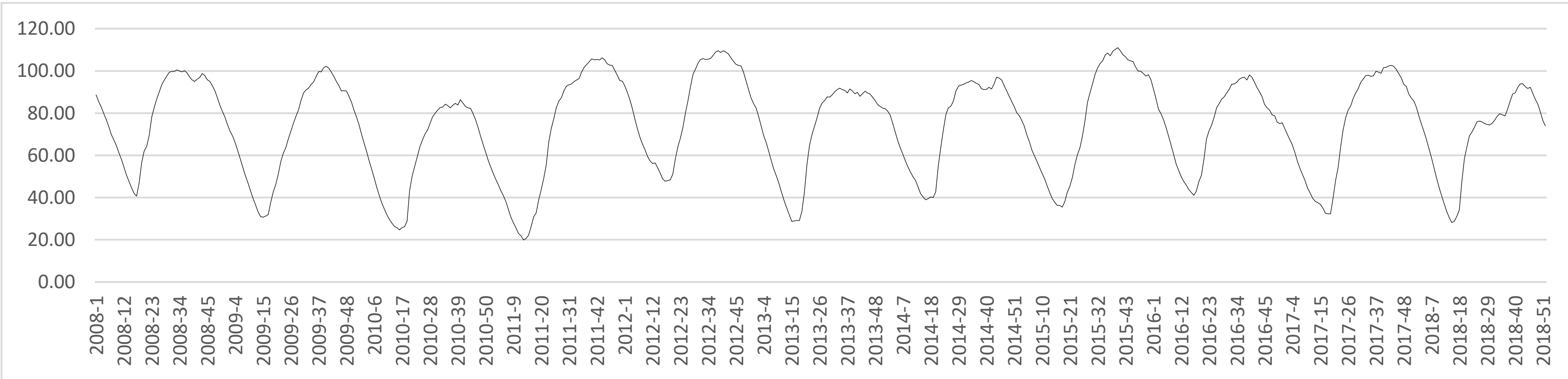

Figure 7. Hydro storage levels (TWh).

panels is that the series does have a unit root. For all series, the test statistic is significantly less than the 1% test critical value of -3.43, so the null hypothesis can be safely rejected for them all. This shows then, that both daily returns and daily realized volatility series are stochastic series, at least for the sample period of 2008 – 2018.

4.2 Explanation of the methodology

The purpose of this thesis was to study the realized volatility of the daily spot prices of Nord Pool electricity market, and test whether it can be used to make predictions about the future spot prices. This will be done by using the HAR-RV model developed by Corsi (2009), as it has been shown to produce superior and reliable forecasts from high frequency data. This thesis also follows closely the work of Corsi (2009) in forming the HAR-RV model and takes inspiration from Chan, Gray and Van Campen (2008) in forecasting electricity spot price volatility and applies it to the Nord Pool electricity markets.

Unlike Chan, Gray and Van Campen (2008), this thesis does not include the jumps in the spot prices to the HAR-RV model but focuses solely on the next day's realized volatility and its predictive power to the daily spot prices. Dividing the dataset to winter and summer seasons is done to see the effects during different seasons, since the seasons have a strong influence in the Nord Pool markets, as was seen by Meyer-Brandis and Tankov (2008).

To find out the possible uses of realized volatility in the Nord Pool markets, a closer inspection is done for the days where the realized volatility is high. The behavior of the realized volatility and the spot prices for these days is looked at as well, to see what conclusions can be drawn about the possible relationship between daily spot prices and realized volatility.

4.2.1 Modifying the HAR-RV model

One of the advantages of Corsi's (2009) HAR-RV model is its modifiability due to the simple nature of the model. This section shows the modifications made to the base model presented in equation 10 to make the model fit the circumstances of Nord Pool and the energy markets in general.

To calculate the realized volatility for longer periods, the average of the different daily realized volatilities generated during this period must be taken. Since the Elspot price continues to change outside the usual trading hours, all seven days of the week are taken into calculations. Corsi's (2009) study, for example, uses only five days to get the weekly average. Following the examples of the studies of Corsi (2009) and Chan, Gray and Van Campen (2008) the weekly realized volatility in this study is calculated as:

$$RV_t^{(w)} = \frac{1}{7}\left(RV_{t-1}^{(d)} + RV_{t-2}^{(d)} + \cdots + RV_{t-7}^{(d)}\right) \tag{13}$$

This form of the weekly realized volatility allows to account all hours of the sample period, as well as simplifying the collection of data as holidays need to be eliminated from the dataset.

Corsi's (2009) HAR-RV model explains the next day's realized volatility ($RV_{t+1}^{(d)}$) as the sum of the current daily realized volatility and the average daily realized volatility in the recent past. So, regarding to the specifications of this study and the Nord Pool electricity markets, the model for predicting next day's realized volatility can be written as:

$$RV_{t+1}^{(d)} = c + \beta_1 RV_t^{(d)} + \beta_2 RV_t^{(w)} + \epsilon \tag{14}$$

Corsi (2009) includes the monthly realized volatility in the model as well, but following the example of Chan, Gray and Van Campen (2008) this study omits the monthly variable as well. As the aim is to forecast one day ahead, this way the focus will only be at the recent past to provide quickly adapting models, without the longer historical trend in realized volatility restricting the results.

4.2.2 Applying the HAR-RV model

Equation 14 presents the mathematical representation of the model used to forecast realized volatility in this study. To find out how well the HAR-RV model forecasts the next day's realized volatility in the Nord Pool electricity market, the model will be estimated with OLS. To account for the possible variations between winter and summer seasons, the OLS estimation will be done with these divided sets of data as well. OLS regression will also be done with variables for overall European market volatility and the hydrological storage levels included in the model to find their effect on the predicted realized volatility. The overall market volatility is highly likely to affect the realized volatility of the daily spot prices in the electricity market as well, and the importance of the hydrological storage levels in the Nord Pool markets has been brought up in the existing literature.

5. EMPIRICAL RESULTS

This section will discuss the results of the HAR-RV model predicting realized volatility in Nord Pool's electricity market. The HAR-RV forecast model has been used successfully in other energy spot markets, but it has not been applied to the Nord Pool spot market. Chan, Gray and Van Campen, (2008) and Qu, Duan and Niu (2018) use HAR-RV forecast models successfully in Australian spot markets. Similarly, Haugom, Westgaard, Solibakke and Lien (2011) study the effectiveness of HAR-RV models in Nord Pool's electricity forward markets. In this study, however, the focus is on the Elspot market, and how the basic HAR-RV model performs in predicting the next days realized volatility.

Before performing the necessary regressions and tests to study the effectiveness of forecasting with realized volatility, a closer look is taken in the data of the Elspot realized volatility to show what information realized volatility holds about the Elspot prices, and what conclusions can be drawn from the levels and changes of realized volatility.

5.1 Data analysis

As volatility is defined as the frequency at which the underlying factor is expected to move, spot price volatility means the degree in which the spot prices are expected to move. Since the daily realized volatility is calculated from the hourly Elspot prices, high daily volatility means high fluctuation in the hourly changing daily spot prices during the day in question. When taking a closer look at days with the daily Elspot realized volatilities over 1, it can be seen that for the majority of these days this is indeed the case. Figure 8 shows that for many of these days, the daily price changes greatly as well. For over half of these days, the change in the daily price from the price of the previous day was over 5€. So predicted high realized volatility could be an indication that the spot prices will change so much during the day that the average daily price will be considerably different from the current day, as well as an indication of predicting the hourly Elspot price to fluctuate greatly during the day.

The change in the daily price seems to be significantly large, especially when compared to the price changes in the whole data set. For the days with realized volatility over 1, only during 16% of the days the daily price movements were within 2€. On the whole data set, on the other hand, the daily price was within 2€ from the previous day's price on 61% of the days.

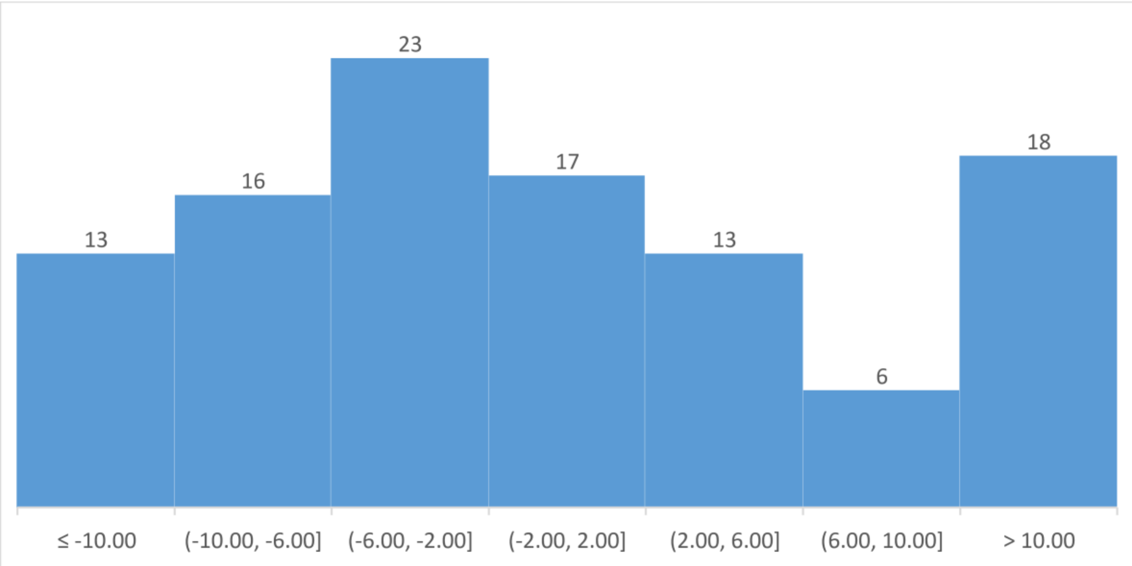

Figure 8. Change in daily Elspot price.

Figure 9 shows the hourly prices of each day with realized volatility over 1. To simplify the charts, the data is divided so that those days with hourly prices lower than 55€ belong to the "lower" group and those with hourly prices exceeding 55€ belonging to the "higher" group. The average results of each group are included as well. As can be expected, the days that experience high realized volatility show a great fluctuation in the hourly prices during the day. Interestingly, dividing the days into lower and higher price groups shows two different patterns in the development of hourly Elspot prices during the day. Lower price groups show the prices dropping often to their lowest between 4:00 and 5:00, before rising again. The higher price group, on the other hand, shows two spikes in the hourly Elspot price at 9:00 and 18:00.

Both of these patterns, however, seem to be in line with the usual behavior of the hourly Elspot prices, as can be seen from Figure 10 describing the behavior of the average hourly prices for the whole sample. The lower Elspot price days seem to be responsible for the price drop around 04:00 and the days of higher Elspot price causing the 09:00 and the 18:00 spikes. The behavior of hourly Elspot prices then seems to remain unaffected when the realized volatility rises. The difference to the average behavior lies in the extremes of these spikes during the days with high realized volatility.

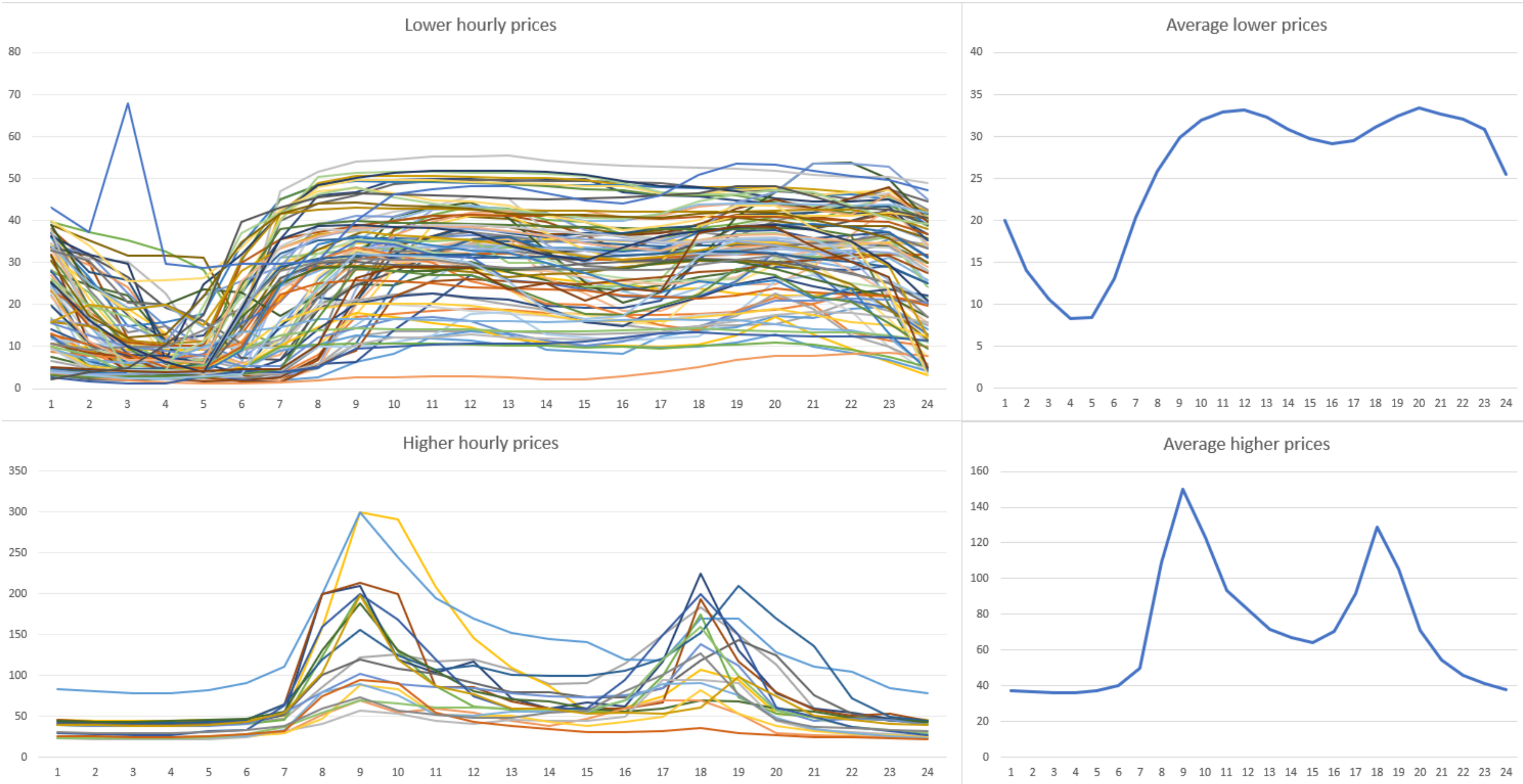

Figure 9. Hourly prices of the high realized volatility days.

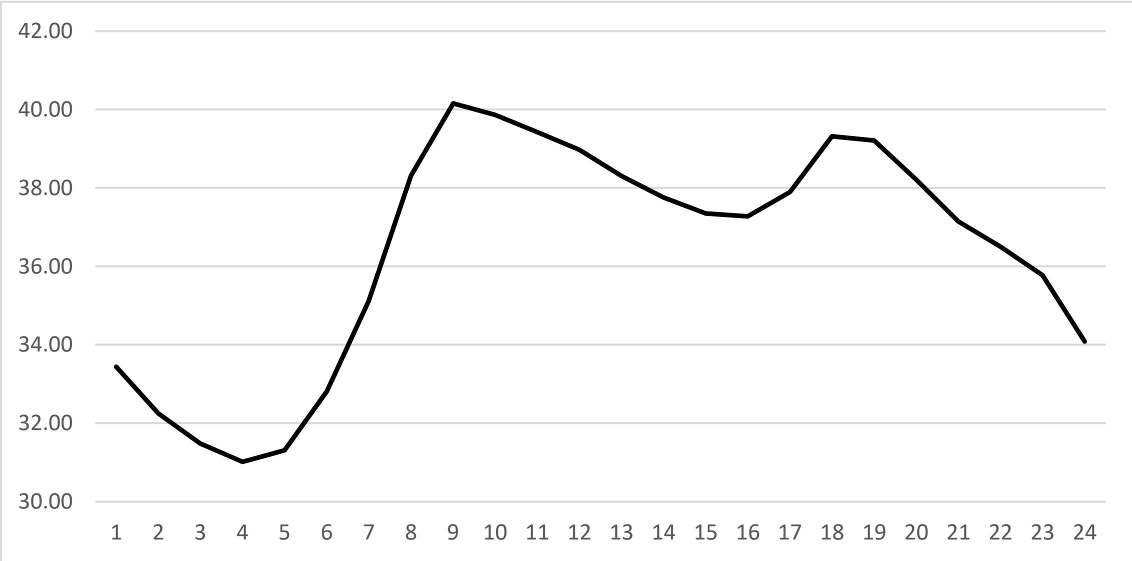

Figure 10. Average hourly prices.

So, in summary, the high realized volatility for the Elspot prices seems to be a good indicator of a significant change in the daily price. Of course, as is its nature, high realized volatility means higher fluctuation in the hourly prices during the day, but this seems to be somewhat in line with the normal behavior of the Elspot prices even during high volatility days. Predicting high realized volatility for the next day could then help to prepare in a high change in the overall daily Elspot price, in addition to the higher fluctuation of the hourly prices during the next day. And as can be seen from Figure 9, depending on the daily Elspot price along with high volatility, predictions could be made about the expected pattern of the changes in the hourly prices.

5.2 Regression results

Using the calculated daily and weekly realized volatilities for the Elspot prices, the series for the next day's realized volatilities are then estimated with OLS according to equation 14. The sample is adjusted to begin from 8.1.2008 so that the first weeks realized volatility can be calculated from the original sample data. The results of this regression are presented in Table 3. As can be seen from the results, the realized volatility of current day and recent past are statistically significant at 1% confidence level in predicting the realized volatility of the next day for the whole sample, and when dividing the data between summer and winter seasons. When comparing these two seasons, the HAR-RV model seems to be slightly better fit during summer. Corsi's (2009) HAR-RV model can, therefore, be effectively used in the Nord Pool electricity markets to forecast the spot price realized volatility. The OLS regression for the HAR-RV model presents both heteroskedasticity and very slight autocorrelation, so the standard errors of the regression are biased and underestimated. The estimated coefficients, however, remain unbiased.

Table 4 shows the results of the HAR-RV model with the added macroeconomic regressors, the European market volatility (VSTOXX) and the level of hydrological reservoirs in Nord Pool's market (Hydro levels). The difference in the daily observations is due to the fact that VSTOXX is not computed for every day of the year. For the whole sample, the original model remains significant on a 10% confidence level, as well as the VSTOXX. Hydrological reservoir levels appear to be statistically insignificant for the whole sample, and for both seasons as well. Winter seasons show the original model being statistically significant at a 5% confidence level, and both added regressors as insignificant. For the summer season though, the constant goes insignificant and the VSTOXX is significant at a 1% confidence level.

As expected, the overall market volatility has some statistically significant effect on predicting the future realized volatility with the HAR-RV model, but this effect shows to be quite minimal. The hydrological reservoir levels show no effect on the future realized volatility. Even though the large share of hydro energy makes Nord Pool markets more vulnerable to the effects of weather, this does not seem to reach the realized volatility. However, it is possible that these effects are reflected in the realized volatility through the spot prices, but the reservoir levels have no direct impact on the predicted realized volatility. When compared with the original results in Table 4, it can be seen that the HAR-RV model is able to produce accurate results without interference from these two macroeconomic regressors.

The results from both tables 3 and 4 show, that the HAR-RV model still works effectively when using spot price data. These regressions then show that it is possible to use the spot price of electricity directly in realized volatility forecasts. Currently existing studies use mainly the high frequency data from futures and forwards contract spot prices in the realized volatility calculations. Of course, by using the hourly updating daily spot prices, the data is no longer high frequency data, as the sampling period rises to one hour.

To further review the effectiveness of the relationship between the changes in realized volatility and the changes in the daily price, Table 5 presents a correlation analysis between these two, as well as the correlations between the coefficients in the HAR-RV

Table 3. HAR-RV estimation.

$$RV_{t+1}^{(d)} = c + \beta_1 RV_t^{(d)} + \beta_2 RV_t^{(w)} + \epsilon$$

Total sample				Winter				Summer			
	Coefficient	t-Statistic	Prob.		Coefficient	t-Statistic	Prob.		Coefficient	t-Statistic	Prob.
c	0.06	9.72	0.00	c	0.06	6.98	0.00	c	0.06	7.42	0.00
β_1	0.49	33.79	0.00	β_1	0.51	22.73	0.00	β_1	0.48	25.08	0.00
β_2	0.30	14.74	0.00	β_2	0.24	7.40	0.00	β_2	0.31	11.90	0.00
R-squared	0.41			R-squared	0.37			R-squared	0.41		
Adjusted R-squared	0.40			Adjusted R-squared	0.37			Adjusted R-squared	0.41		
Observations	4010			Observations	1659			Observations	2351		

Table 4. HAR-RV model with macroeconomic regressors.

Total sample				Winter				Summer			
	Coefficient	t-Statistic	Prob.		Coefficient	t-Statistic	Prob.		Coefficient	t-Statistic	Prob.
c	0.03	1.71	0.09	c	0.04	2.10	0.04	c	0.03	1.56	0.12
β_1	0.57	30.80	0.00	β_1	0.60	25.42	0.00	β_1	0.47	22.65	0.00
β_2	0.21	9.14	0.00	β_2	0.10	2.62	0.01	β_2	0.25	9.19	0.00
Hydro levels	0.00	0.11	0.91	Hydro levels	0.00	0.64	0.52	Hydro levels	0.00	-0.64	0.52
VSTOXX	0.00	1.85	0.06	VSTOXX	0.00	-0.43	0.67	VSTOXX	0.00	2.61	0.01
R-squared	0.42			R-squared	0.49			R-squared	0.45		
Adjusted R-squared	0.42			Adjusted R-squared	0.49			Adjusted R-squared	0.45		
Observations	2864			Observations	1184			Observations	1680		

model. The changes in both realized volatility and Elspot price are taken as a percentual change. The daily price is considered to change from the current day to the next, and the realized volatility from the current day to the forecasted the next day.

The results in Table 5 show that there exists a statistically significant, albeit weak correlation between the change in price and the predicted change in realized volatility. However, the change in the realized volatility and the daily Elspot prices are shown to be uncorrelated. It seems, that while the realized volatility does not offer great accuracy in predicting the Elspot prices, it can provide some clue on the direction it is expected to move.

Table 5. Correlation analysis.

Correlation t-Statistic Probability	Daily price	Daily price change	Change in $RV_t^{(d)}$	$RV_{t+1}^{(d)}$	$RV_t^{(d)}$	$RV_t^{(w)}$
Daily price (P_t)	1.00 ---- ----					
Change in P_t	-0.14 -9.01 0.00	1.00 ---- ----				
Change in $RV_t^{(d)}$	-0.02 -1.18 0.24	0.10 6.47 0.00	1.00 ---- ----			
$RV_{t+1}^{(d)}$	-0.16 -10.58 0.00	0.09 5.77 0.00	0.42 29.69 0.00	1.00 ---- ----		
$RV_t^{(d)}$	-0.16 -10.44 0.00	0.14 9.08 0.00	-0.19 -12.13 0.00	0.61 48.81 0.00	1.00 ---- ----	
$RV_t^{(w)}$	-0.21 -13.35 0.00	0.08 5.06 0.00	0.00 0.02 0.98	0.49 35.14 0.00	0.55 41.59 0.00	1.00 ---- ----

Paired with the results from Figure 8 and using the level of the predicted realized volatility and how much it changes from the current level, conclusions of the likelihood and the level of the change in daily price for the next day can be drawn. Higher expected realized volatility and the larger change to the current realized volatility indicates larger movements in the daily Elspot price. Forecasted higher realized volatility for the next day is indicating a drop in the price. This type of information could be highly useful for traders or factories highly invested in controlling their usage of electricity during high spot price hours.

In addition to the expected change in realized volatility, the other factors in the model are also positively (and significantly) correlated with the changes in Elspot prices. This is expected, as the higher realized volatility suggests higher price movements during the day, which is likely to lead to larger changes in the daily price. The significant negative correlation between these factors and the daily price explains the same thing. Interestingly, the weekly realized volatility is more highly correlated with the daily price than the daily realized volatility, while the correlation with the change in the daily price is the other way around.

The uncorrelation between the expected change in the daily realized volatility and the past week's average realized volatility is likely explained by the Corsi's (2009) formula giving larger weight for the current day's volatility, as the realized volatility in the recent past is taken as an average. It then stands to reason, that the current day's realized volatility is more significant to the change in the realized volatility for the day.

To further evaluate the forecasted series, the forecasted series for 2018 will be compared to the actual series of realized volatility in 2018. The distribution of both series will also be compared. The comparison with these two series for 2018 and their distributions for the whole sample can be seen in Figure 11. As can be seen from the two series, the forecasted realized volatility precedes accurately the actual realized volatility series. Similarly, the distributions of the two realized volatility series are very closely alike. It can be seen then that the HAR-RV model provides accurate results about the realized volatility of the next day.

With these previously discussed results, the hypothesis of this thesis can be confirmed: "*The predicted spot price realized volatility accurately predicts the actual future realized volatility*". The acceptance of this hypothesis leads to the conclusion, that the realized volatility has predictive powers for the future realized volatility of the Elspot prices of Nord Pool electricity markets. Further, by studying the past realized volatility and using the forecasted results, assumptions about the future spot price movements can be made. The HAR-RV model can, therefore, be used in the Nord Pool markets effectively to make forecasts about the realized volatility and the behavior of the Elspot prices in the near future.

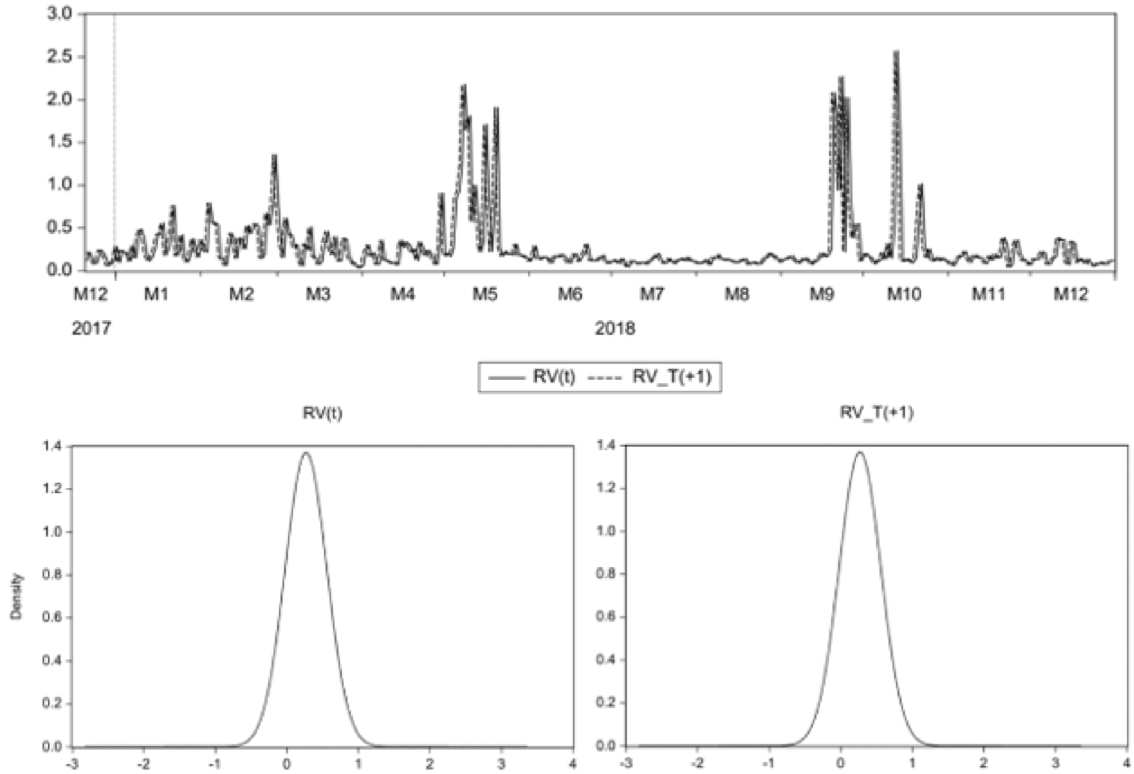

Figure 11. Forecast evaluation.

5.3 Analyzing the results

While the success of the HAR-RV model has been proven in various studies, there was still uncertainty of it working in the parameters of this study, as the previous studies mainly used the spot prices of futures and forward contracts. The results of this study then show that the HAR-RV model still works as intended when the direct spot price of electricity is used, at least in the Nord Pool electricity markets. As Corsi's (2009) study shows, the model can be used to predict even further into the future, so it would then seem possible that even longer predictions about the behavior of spot prices and their realized volatility could be computed using this model and the spot price data.

According to the data from 2008-2018, by forecasting the daily realized volatility for the next day with the HAR-RV model, more can be concluded from the results than just the expected level of change that the hourly prices will likely experience during the next day. By inspecting the past realized volatility, predicted changes can indicate both the magnitude and the direction the daily Elspot price will likely change, and even when the hourly prices will deviate from their normal behavior during the day. Predicting low and little changing realized volatility, on the other hand, indicates that the hourly prices are likely to behave in their usual way and the changes in the daily prices will likely stay minimal.

Of course, the usefulness of these results is limited, as they only apply to the Nord Pool market area as a whole. The simple form of the model, however, makes it easy to apply it to the level of a country or a bidding area. The mainly benefiting operators are those looking into managing their financial contracts with Nord Pool, or those interested prices during the day-ahead-market. The goal of this thesis was to study the effectiveness of HAR-RV model forecasts and realized volatility in Nord Pool markets, for which the results provide a proof of concept. As the model is shown to be working in the Nordic spot markets, modifying the model to a more local level will likely increase its usefulness to more electricity market participants.

The results also show an interesting fact about the seasonality of the Elspot prices. Even though the prices during winter can rise far above the prices during summer, the realized volatility of the prices during summer is still slightly larger than during winter. This is likely due to the fact that the electricity providing and producing companies are aware of the seasonal trend of electricity consumption, that is during winter the consumption of electricity is significantly larger than during summer and are then prepared for it accordingly. Even if the temperature during winter would differ from the usual, the effect on the profits/losses for these companies and on electricity prices would be minimal. However, since during summer the consumption of electricity is expected to be much lower than during winter, such preparations would be more difficult, not to mention more expensive, when they are made for the summer season. Therefore, the weather has more effect on electricity prices during summer, which increases the realized volatility.

Other interesting behavior found about the Elspot prices are the price spikes during different hours, or more specifically the missing of these spikes during the days of high realized volatility. The behavior of these spikes is expected, as larger factories starting and stopping their production at specific hours usually affects the overall prices of electricity as well. Higher realized volatility combined with high enough electricity prices seems to increase the variation of electricity prices between 09:00 and 18:00 and eliminate the 04:00 drop in price altogether. The reasons for this would need further study into this phenomenon. This also raises the question is this only unique behavior in Nord Pool markets or does this affect other electricity markets as well.

Overall, the realized volatility and the HAR-RV model have shown to be accurate in predicting the realized volatility using the daily spot prices of electricity, at least in the Nord Pool electricity market. Although the majority of previous studies use the spot prices of forward and futures contracts in their calculations, this type of information will often need to be obtained from other institutions. In Nord Pool's case, this data would need to be obtained from NASDAQ. The spot prices for electricity, however, are much easier to obtain, as they are often available from the electricity providers and producers directly. This also means that by using the spot prices to calculate the realized volatility, it could be applied to smaller areas than the spot prices of forward and futures contracts would allow. The usefulness of this method would, of course, depend on the market in question, and how the realized volatility and the electricity prices behave in the chosen area.

5.4 Criticism of the results

As this study uses the HAR-RV model at its simplest form to forecast realized volatility in the Nord Pool electricity markets, the results of the regressions are mainly relevant as a proof-of-concept of using direct spot prices for forecasting realized volatility. For more accurate results, the characteristics of electricity prices need to be taken into account when calculating the intraday returns. Ullrich (2012) for example demeans the collected high-frequency returns using half-hourly median return to fix the non-zero skew and large excess kurtosis of the return distributions. The returns are demeaned by a month of a year, a day of a week and half-hour of a day. The presence of autocorrelation and heteroskedasticity in the regression is also a point for further improvement, for example modifying the model to be used with the weighted least squares method (WLS) instead of OLS.

6. CONCLUSIONS

The purpose of this thesis was to study the realized volatility in the Nordic electricity market and examine if Corsi's (2009) HAR-RV model can be successfully used with the hourly updating daily spot prices. The data used in this study was collected directly from Nord Pool, and it consists of hourly updating daily spot prices for every hour of every day from 2008 to 2018. The daily realized volatilities were calculated from the hourly intraday returns, and the model predicts the next day's realized volatility from the current daily realized volatility and the average daily realized volatility of the previous seven days. This study uses the HAR-RV model to forecast the next day's realized volatility, as it has been shown to provide superior forecasts than the other traditional models, like the Black-Scholes model.

This study also follows the work of Chan, Gray and Van Campen (2008) to form the forecasting model, as they show the possibility for using the spot prices of electricity for forecasting the realized volatility of the next day. By using only the daily spot prices, the forecasts will include all the historical data up to the point of the forecasts. This also allows the model to be applied to more specific markets as the spot price data is available more easily than for example the price data of options and futures contracts. However, using intraday data from forward or futures contracts would increase the accuracy of the results, as the higher number of intraday returns would increase the precision of the estimator (Haugom et al. 2011). This kind of data can often be more difficult to gather than the daily spot prices used in this study.

The results from the OLS regression show that the HAR-RV model is stable when using daily spot prices, and the predictions about the next day's realized volatility seem to accurately predict the actual realized volatility. So, therefore, by using the results from this model, predictions about the next day's hourly prices and the overall daily price can be made. In the Nord Pool electricity market, the predicted level of next day's realized volatility shows the likelihood of how much the hourly spot prices are expected to move during the next day, while the change in the realized volatility indicates the direction where the price is likely to move.

For example, in the Nord Pool's market, predicting an increase in the current realized volatility would predict a drop in the daily price, while the level of the realized volatility would indicate the possible scale of this drop. Inspecting the relationships and behavior of the daily and hourly spot prices for the electricity market in question allows more effective forecasts to be made with the predicted results about the future realized volatility.

Since the intraday returns were taken in their “raw form” without demeaning them according to the behavior of the spot prices and the presence of heteroskedasticity and autocorrelation in the OLS regression, building a more detailed model is recommended to increase the accuracy and efficiency of the model. While the results of this thesis show the possibility of using the HAR-RV model with the daily spot prices, fixing these deficiencies will make the model more efficient for further applications.

When beginning this study, the significant effect of seasonality was thought to be one possible difficulty in producing accurate results, but the results show that the model performs well in both winter and summer seasons. As the Nordic electricity market experiences all four seasons, a more detailed inspection could be made. The data used in this thesis was divided into two seasons according to the specifications of Nord Pool.

As it has already been shown that the effectiveness of the HAR-RV model is likely to surpass the other volatility forecasting models, this study does not perform comparisons between these different models, but focuses only on the possibility to produce accurate and usable forecasts in the Nord Pool electricity market using the HAR-RV model. For this reason, this study also omits the inclusion of jump components in the model, as the model has been shown to provide accurate forecasts without them.

The HAR-RV model also makes it possible to forecast over longer distances than the next day, so the inclusions of jump components in the model and making forecasts for further periods are great points for further study. Another point for further research would be using the high frequency data available in the electricity market directly, as this study only uses this data for the hourly spot prices, and the model has been shown to effectively utilize high frequency data to produce accurate forecasts. The higher number of intra-day returns offered for example by forward and futures contracts would increase the reliability of this model, as was pointed out by Haugom et al. (2011).

As the majority of previous literature concerning realized volatility in the Nordic energy markets seems to focus mainly on the forward price data, the results of this study contribute to the existing literature by showing the possibility to use the HAR-RV model in these markets. These results also give grounds for further study in these markets by forming more elaborate realized volatility models to suit more specific needs. By showing the possibility to perform these forecasts by using hourly spot prices instead of forward prices, this method is more applicable to more specific markets, and it is easier to use as the spot price data is more readily available. Depending on the situation, these results give the possibility to choose between the prices of forward and futures contracts, and the hourly spot prices. For example, using the prices of forward and futures contracts could be more useful for investors or electricity companies hedging against their price risk. Using spot prices, on the other hand, could prove more useful for high consumption end-users, like large factories following the spot prices to control their production costs.

REFERENCES

Amundsen, E. S., & Bergman, L. (2012). Green certificates and market power on the Nordic power market. *The Energy Journal*, 101-117.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2001). The distribution of realized exchange rate volatility. *Journal of the American statistical association*, 96(453), 42-55.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2003). Modeling and forecasting realized volatility. *Econometrica,* 71(2), 579-625.

Andersen, T. G., Bollerslev, T., Christoffersen, P. F., & Diebold, F. X. (2006). Volatility and correlation forecasting. *Handbook of economic forecasting*, 1, 777-878.

Bandi, F. M., & Russell, J. R. (2008). Microstructure noise, realized variance, and optimal sampling. *The Review of Economic Studies*, 75(2), 339-369.

Barndorff-Nielsen, O. E., & Shephard, N. (2002). Econometric analysis of realized volatility and its use in estimating stochastic volatility models. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 64(2), 253-280.

Botterud, A., Kristiansen, T., & Ilic, M. D. (2010). The relationship between spot and futures prices in the Nord Pool electricity market. *Energy Economics*, 32(5), 967-978.

Burger, M., Klar, B., Müller, A., & Schindlmayr, G. (2004). A spot market model for pricing derivatives in electricity markets. *Quantitative finance*, 4(1), 109-122.

Bye, T., & Hope, E. (2005). Deregulation of electricity markets: the Norwegian experience. *Economic and Political Weekly*, 5269-5278.

Chan, K. F., Gray, P., & van Campen, B. (2008). A new approach to characterizing and forecasting electricity price volatility. *International Journal of Forecasting*, 24(4), 728-743.

Cialani, C., & Mortazavi, R. (2018). Household and industrial electricity demand in Europe. *Energy policy*, 122, 592-600.

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics*, 7(2), 174-196.

Corsi, F., Fusari, N., & La Vecchia, D. (2013). Realizing smiles: Options pricing with realized volatility. *Journal of Financial Economics*, 107(2), 284-304.

Deng, S. J., & Oren, S. S. (2006). Electricity derivatives and risk management. *Energy*, 31(6-7), 940-953.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, 987-1007.

Engle, R. F. (1993). Statistical models for financial volatility. *Financial Analysts Journal*, 49(1), 72-78.

Engle, R. F., & Patton, A. J. (2007). What good is a volatility model?. *Forecasting volatility in the financial markets (pp. 47-63). Butterworth-Heinemann*.

Flatabo, N., Doorman, G., Grande, O. S., Randen, H., & Wangensteen, I. (2003). Experience with the Nord Pool design and implementation. *IEEE Transactions on power systems*, 18(2), 541-547.

Fleten, S. E., & Lemming, J. (2003). Constructing forward price curves in electricity markets. *Energy Economics*, 25(5), 409-424.

Geman, H. (2005). *Commodities and commodity derivatives: modeling and pricing for agriculturals, metals and energy*. Chichester: John Wiley & Sons. 416 p. ISBN 0-470-01218-8.

Green, R. (2001). Markets for electricity in Europe. *Oxford Review of Economic Policy*, 17(3), 329-345.

Hansen, P. R., & Lunde, A. (2005). A realized variance for the whole day based on intermittent high-frequency data. *Journal of Financial Econometrics*, 3(4), 525-554.

Haugom, E., Westgaard, S., Solibakke, P. B., & Lien, G. (2011). Realized volatility and the influence of market measures on predictability: Analysis of Nord Pool forward electricity data. *Energy Economics*, 33(6), 1206-1215.

Jamasb, T., & Pollitt, M. (2005). Electricity market reform in the European Union: review of progress toward liberalization & integration. *The Energy Journal*, 11-41.

Karakatsani, N. V., & Bunn, D. W. (2008). Intra-day and regime-switching dynamics in electricity price formation. *Energy Economics*, 30(4), 1776-1797.

Karan, M. B., & Kazdağli, H. (2011). The development of energy markets in Europe. *Financial Aspects in Energy* (pp. 11-32).

Keskikallio, J. & Lindholm, J. (2003). *The Nordic electric power market: A study of the market characteristics, price factors and the competitive environment of the Nordic power market*. 11/2003 Helsinki: Ministry of Trade and Industry, Energy Department: Edita. 79 p. ISBN 951-739-733-X

Kirschen, D. S. & Strbac, G. (2004). *Fundamentals of power system economics*. Chichester: Wiley. ISBN: 978-1-119-21325-3

Littlechild, S. (2006). Competition and contracts in the Nordic residential electricity markets. *Utilities policy*, 14(3), 135-147.

Lucia, J. J., & Schwartz, E. S. (2002). Electricity prices and power derivatives: Evidence from the nordic power exchange. *Review of derivatives research*, 5(1), 5-50.

Meddahi, N. (2002). A theoretical comparison between integrated and realized volatility. *Journal of Applied Econometrics*, 17(5), 479-508.

Meyer-Brandis, T., & Tankov, P. (2008). Multi-factor jump-diffusion models of electricity prices. *International Journal of Theoretical and Applied Finance*, 11(05), 503-528.

Müller, U. A., Dacorogna, M. M., Davé, R. D., Pictet, O. V., Olsen, R. B., & Ward, J. R. (1993). Fractals and intrinsic time: A challenge to econometricians. 39th *International AEA Conference on Real Time Econometrics*, 14–15 October 1993, Luxembourg.

Nasdaq (2010). *Press release May 31, 2010* [online] [cited on 1.7.2019]. Available from World Wide Web: <URL:https://www.nasdaq.com/about/press-center/ nasdaq-omx-completes-nord-pool-asa-acquisition>.

Nasdaq Commodities (2019). *Power Derivatives* [online] Nasdaq [cited on 1.7.2017]. Available from World Wide Web: <URL:https://www.nasdaq.com/solutions/ power-derivatives-european-commodities>.

Nord Pool (2018) *Annual report* [online]. Nord Pool [cited on 13.6.2019]. Available from World Wide Web: <URL:https://www.nordpoolgroup.com/globalassets/ download-center/annual-report/annual-report_2018.pdf>.

Nord Pool (2019) *Company homepage* [online] [cited on 18.12.2019]. Available from World Wide Web: <URL:https://www.nordpoolgroup.com>.

Pape, C., Hagemann, S., & Weber, C. (2016). Are fundamentals enough? Explaining price variations in the German day-ahead and intraday power market. *Energy Economics*, 54, 376-387.

Poon, S. H., & Granger, C. W. (2003). Forecasting volatility in financial markets: A review. *Journal of economic literature*, 41(2), 478-539.

Qu, H., Duan, Q., & Niu, M. (2018). Modeling the volatility of realized volatility to improve volatility forecasts in electricity markets. *Energy Economics*, 74, 767–776.

Rademaekers, K., Slingenberg, A., & Morsy, S. (2008). *Review and analysis of EU wholesale energy markets* [online]. ECORYS Netherlands, EU DG TREN Final Report [cited on 4.6.2019]. Available from World Wide Web: <URL:https://ec.europa.eu/energy/sites/ener/files/documents/ 2008_eu_wholesale_energy_market_historical.pdf>.

Ullrich, C. J. (2012). Realized volatility and price spikes in electricity markets: The importance of observation frequency. *Energy Economics*, 34(6), 1809-1818.

Vehviläinen, I., & Pyykkönen, T. (2005). Stochastic factor model for electricity spot price – the case of the Nordic market. *Energy Economics*, 27(2), 351-367.

Viehmann, J. (2011). Risk premiums in the German day-ahead Electricity Market. *Energy Policy*, 39(1), 386-394.

Wilson, R. (2002). Architecture of power markets. *Econometrica*, 70(4), 1299-1340.