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# Master Thesis

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## THE IMPACT OF WIND POWER PRODUCTION ON SPOT PRICE LEVEL AND VOLATILITY IN NORD POOL

- AN EMPIRICAL STUDY

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## Abstract

In recent decades the Nordic countries have launched massive investments in wind energy, due to an increased focus on climate change. This increasing wind production has caused a change in price determination of electricity. This thesis seeks to study whether increased wind power production in Nord Pool has led to a merit order effect, and whether it has affected volatility in electricity prices. We perform an empirical study using time series data over the period 2010-2017. The merit order effect is estimated by an autoregressive distributed lag (ADL) model. Our analysis finds evidence of an effect consistent with theory and previous literature studying the electricity market in Germany, Italy, and Spain.
Furthermore, a range of econometric models are built in order to study the effect of increased wind production on both estimated conditional variance of the electricity price and realized volatility. Our analysis does not support theory and previous literature, as we find that increased wind production lowers price volatility. As both the price level and volatility decreases with wind production, the analysis suggests that the Nordic countries, with the current installed capacity, can exploit the benefits of wind power.

# Foreword

First of all we would like to thank our supervisor, Heino Bohn Nielsen, for very constructive guidance and sparring throughout the project. Not only with regards to theoretical econometrics questions, but also assistance with OxMetrics and general guidance of how to structure the work. Furthermore, we would like to thank Danish Energy and Nord Pool Spot for providing data and making the project possible. Especially we thank Morten Stryg from Danish Energy for assisting with data, and discussions about the topic.

This thesis is written in collaboration and we have both contributed our thoughts and knowledge to form the contents of the entire work. However, to meet university requirements, we try to assign responsibility for each section. Sections 3.1, 3.2, 4.1 ,4.3.1, 4.3.3, 4.3.5, 4.3.7, 5.3, 5.4, 6.2, 7.2, 8, 9.1, 9.2.1, 9.2.4 are assigned to Dina Mønsted, while Sections 3.3, 3.4, 4.2, 4.3.2, 4.3.4, 4.3.6, 5.1, 5.2, 6.1, 7.1, 8.1, 8.2, 9.1.1, 9.2.2, 9.2.3 are assigned to Mathilde Astrid Schilling. Sections 1, 2, 9.2.5, and 10, as well as introductions and summaries to sections, are written in collaboration.

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# 1 Introduction

In recent decades, increased focus on climate change has launched a political interest in green and renewable energy sources and, in this regard, the Nordic countries can be seen as pioneers. In 2010, the total power supply from renewable wind production in the Nordic countries was only 3.2% [1]. Since then, Denmark and Sweden have both launched massive investments in wind energy, causing the total wind production to cover 43% and 10% of their total power production in 2016, respectively. Together, this covers more than 8% of total power production in the Nordic area [1].
Another feature of the Nordic power market is that it is characterized as a well-functioning and liberalized market, where producers and consumers meet and trade on the same terms. Furthermore, the whole market is connected by a grid, linking all areas of the countries in the region, which enables electricity to flow from areas with huge and cheap production to highly populated areas with large demand.

The large increase in wind power has caused a change in the price determination of power. Producers with more expensive power generation are pushed out of the market, because they are replaced by cheaper production such as wind power. This movement is expected to result in lower power prices, and is called the merit order effect. The sizeable investments, particularly in wind energy, have been driven by different kinds of support schemes such as subsidies. Examining the merit order effect therefore contributes to the analysis of whether, subsidies paid by consumers can be outweighed by monetary savings.
Apart from the merit order effect, another consequence of larger wind penetration could be an increase in the volatility of power prices. Wind power is solely determined by weather conditions, that cannot be controlled, and the installed capacity, that cannot be changed in the short run. Therefore, it could be expected that the large share and volatility of wind have resulted in more volatile power prices.
The aim of this thesis is to study whether increased wind power production has lead to a merit order effect, and whether it has affected volatility in electricity prices. We perform an empirical study of the Nordic area using time-series data for the period from 2010 to 2017.

In this thesis we examine the effect of wind power on the system price. To fully study the importance and cost-benefit of more renewable energy sources, many other factors such as construction and maintenance costs, capacity constraints, and different prices have to be taken into account. One example of this is consumer prices, which contribute to fund the subsidies [2]. Moreover, different prices are available for different

areas, containing information about each area and limitations in transmission capacities. This thesis focuses on the system price, that captures the pricing mechanisms of the whole Nordic area.
Overall, we are not able to include all factors relevant to study the effect of more wind, thus we can not make any conclusions about the total welfare consequences. However, analysing the effects on the system price contributes to the bigger analysis.

The thesis is structured as follows. A selection of existing literature is reviewed in Section 2. Section 3 introduces the Nordic power market and its different actors. Section 4 presents theory of price formation on electricity markets. In Section 5 we describe the dataset used in the empirical analysis, and in Section 6 we introduce econometric methods to model the level of the system price. In Sections 7.1 and 8 we build the models examining the merit order effect, and go through the results. In Section 9 the volatility of the system price is analysed. Finally, Section 10 presents conclusions and possible policy implications.

# 2 Literature review

Several empirical studies have investigated the merit order effect, including Gelabert et al. [3], Cludius et al. [4] and Clò et al. [5]. Clò et al. [5] examine the merit order effect in Italy, using OLS regression on daily averages of national wholesale electricity prices. They find an estimate of the merit order effect from wind power to be −4.2, based on the period from 2005 to 2013; i.e. the study indicates that the Italian wholesale electricity price decreases with 4.2 EUR/MWh when wind power generation increases with 1 GWh.

Cludius et al. [4] make a similar study for Germany over the period from 2008 to 2012, using hourly spot market prices. They estimate merit order effects from −0.97 to −2.27 EUR/MWh for an increase in wind power generation of 1 GWh. Additionally, they estimate a total average merit order effect by multiplying the coefficient estimate of wind power with a load-weighted average of wind. They find a total average merit order effect of wind power between -5.06 EUR/MWh and -10.80 EUR/MWh. They compare their results with other studies of the average total merit order effect and conclude that their results are in the same range.

In a similar vein, Gelabert et al. [3] examine the merit order effect of daily averages of Spanish electricity prices from 2005 to 2010. They estimate the merit order effect using first differences in their regression and find that an increase in production of renewables of 1 GWh decreases, on average, the electricity price by 1.86 EUR/MWh. According to Gelabert et al. [3], this merit order effect reflects a price reduction of around 3.7%, given an average electricity price of approximately 50 EUR/MWh. They perform the same analysis on weekly averages, which produces largely similar results.

Several studies have also examined the effect of wind power on price volatility. Rintamäki et. al [6] investigates how renewable energy affects the electricity price in Denmark and Germany for the time periods 2010-2014 and 2012-2014, respectively. They run a SARMA model using daily price volatility as the dependent variable and wind power as explanatory variable. They find that a 1% increase in wind production decreases the intraday price volatility by 0.06%-0,09% in Denmark. The results are opposite for Germany, where a 1% increase in wind power lead to an increase in intraday volatility of 0,03%. However, when estimating weekly volatility, an increase of wind power increases volatility for both Denmark and Germany. The contrasting impact of wind power on price volatility in Denmark is suggested to be due to Denmark's access to large hydro reservoirs in the Nordic countries. The results are also consistent with Mauritzen et. al [7], who also models wind power's effect on electricity price volatility in Denmark using a similar approach.

Another method is used by Ketterer [8], who analyses how wind power affects volatility of electricity prices in Germany for the period 2012-2016. Unlike Rintamäki et. al and Mauritzen et. al, she models daily volatility using an ARX-GARCHX model, with wind power as explanatory variable. She finds that an increase in German wind power production increases price volatility. The effect is larger when including the ratio of wind power penetration to the total production in Germany ($\beta = 0,045$), compared to including the natural logarithm of wind power ($\beta = 0,002$).

Our contribution to this line of research is to study the merit order effect and the volatility of electricity prices in the whole Nord Pool area as a result of a larger penetration of wind power.

# 3 The Nord Pool Power Exchange

Nord Pool is the leading power market in Europe and the world's first multinational energy exchange. The main role of Nord Pool is to provide power markets for producers and consumers, enabling them to trade electricity. There are several markets on the Nord Pool power exchange, and the power market with most traded volume is the day-ahead market. The Nord Pool power market acts as a power exchange, where producers and consumers submit their offers and bids for supply and demand for each hour of every day. Thus, the power exchange balances the Nordic power supply and demand by finding an equilibrium price for every hour. An energy exchange secures price transparency as all players can keep track of the prices and volumes, which are updated and published on the Nord Pool Spot website [9].

There are 380 companies from 20 countries trading on the Nord Pool exchange, and more than 80 percent of the total power consumption in the Nordic countries is traded via Nord Pool [10].

The Nord Pool power market is divided into bidding areas, that indicate constraints in transmission capacities. It is up to the local transmission system operator (TSO) to decide the amount of bidding areas in each country, and where to place them. The Nordic and Baltic countries consist of 15 bidding areas. Denmark has two bidding areas - East and West. Sweden was one area until November 1st 2011, when it was divided into four areas [9]. Norway is divided into five areas. Finland represents one area, and each of the Baltic countries represent one area. The different bidding areas are shown in Figure 1. Nord Pool operates the UK day-ahead power market separately by the exchange N2EX, which is also shown in Figure 1.
If power could flow freely in the whole Nordic and Baltic area there would be one common price, which is reflected in the so-called system price, which we will from now on refer to as the spot price. However, as the transmission capacities between bidding areas are constrained, power can occasionally not flow freely from one bidding area to another. In that case, different prices appear in different areas [11].


**Figure 1:** Nord Pool bidding areas. Source: Nord Pool website [9]

## 3.1 History

Nord Pool has its origin in Norway, where the Norwegian parliament decided to deregulate the power market in 1991. Being a deregulated power market means it has free competition and is independent of the state. In 1995, the first thoughts about making a common Nordic power exchange were presented to the Norwegian government, together with a license that would make cross-border trade of electricity possible. The idea behind a deregulated common Nordic power market was to increase efficiency of the market and secure power supply by using the available capacity from the whole Nordic region. In 1996, Sweden joined the power exchange. Finland joined in 1998, and the common Nordic power market that was pitched for the Norwegian parliament in 1995 became complete when Denmark joined in 2000 [9].

In 2010 Nord Pool opened a bidding area in Estonia, followed by a bidding area in Lithuania in 2012 and Latvia in 2013; this forms the current Nord Pool power exchange for the Nordic and Baltic countries. Today there are transmission capacities between the Nordic and Baltic countries and central Europe, which ensures an even more liquid market and a more secure power supply [9]. The larger a region that is able to share available capacity, the more security of supply is ensured [2].

Today, Nord Pool has a market share of above 80 percent of the total power consumption traded in the Nordic and Baltic area [10]. Apart from trading at Nord Pool, it is also possible to trade electricity outside a power exchange. This form of trading is called over-the-counter (OTC) trading, where a supplier and a consumer agree on a price and amount in a bilateral trade. As this trade does not go through a power exchange, the traded amount and price are not made public [11]. Most other power markets, for instance the German power market, are characterized by a large proportion of the trades being OTC and therefore non-published, which is one feature where the Nordic power market differs from other power markets [8].

## 3.2 Actors on the Nord Pool power market

In the following we will go through the relevant actors on the Nordic and Baltic power market, responsible for the process of electricity from production to consumption.

### 3.2.1 Producers

Producers provide power to the electricity system. Every day, producers submit their bids on a market, with their expected production for a given hour [12]. The Nordic power production consists of hydro, nuclear, and thermal power such as coal, gas, oil, and biomass, and in recent years wind production has played an increasing role, especially in Denmark [1]. However, hydro production is still by far the largest player on the Nordic power market, accounting for almost half of the total Nordic power production (given normal snow and rainfall) [1]. The total yearly power production in the Nordic and Baltic countries is on average 420 TWh [9].

### 3.2.2 Consumers and Retailers

The electricity consumers, or so called end-users, are everything from small households to large industrial companies. Most consumers do not trade on the Nord Pool markets themselves; only few large industrial consumers have that possibility. Most electricity demand is managed through retailers, that work as a link between the power markets and end-users. Therefore, households buy their electricity from a retailer, who is responsible for aggregating the demand from all their end-users, buying the required electricity on the power market, and reselling it to the consumers [9]. An example of a retailer is the company Ørsted (formerly DONG Energy) [12].

### 3.2.3 Transmission system operators (TSO)

The main role of the TSOs is to keep their areas electrically stable, maintain overall security of supply, and ensure equal market access to the grids. They do this by making market rules and trading on the regulating power market, which will be explained in detail in Section 3.4.3. The TSOs must be neutral and independent of other players in the market, meaning they cannot be producers or consumers themselves, nor have any interests in the market other than balancing the power volume between the different players on the market [13]. In Denmark the TSO is Energinet, which is an independent public company under the Ministry of Energy, Utilities and Climate.

The Nord Pool power exchange is owned by the Nordic Transmission System Operators (TSOs), i.e. Energinet (Denmark), Statnett SF (Norway), Svenska Krafnät (Sweden), Fingrid Oy (Finland), Elering (Estonia), Litgrid (Lithuania) og Augstprieguma tikls (Latvia) [9].

### 3.2.4 Distribution system operators (DSO)

Whereas the TSOs are responsible for stability in their areas and the overall security of supply, the distribution system operators (DSO) are local grid companies responsible for installing electricity meters in households and ensuring that electricity reaches the end users in their local grid. The local grid companies are monopolies closely regulated by authorities; in Denmark Energitilsynet (Danish Energy Regulatory Authority) [12].

## 3.3 Market Coupling and Cross Border Transmission

The Nord Pool power areas are coupled to other European countries by market coupling, implying that Nord Pool and other European power exchanges join and integrate their power markets. The advantage of one big market is that the supply and demand bids are not limited to the bidding areas of one exchange, such as Nord Pool, but bids from sellers and buyers from different exchanges can meet on the coupled marked on the common exchange [14]. This exploits the total energy in Europe in a more optimal way, as the transmission options are extended. Market coupling increases the liquidity of the market, which reduces price volatility in the different market areas [14]. Furthermore, by allowing transmission and trade between different power exchanges, prices will converge as the power in low-price areas will flow to high-price areas due to arbitrage, which results in increased social welfare [15]. Market coupling regulations, that make it possible to trade freely cross-borders, are an important step towards this goal. Market coupling is possible due to political initiatives for cross-border trading, but also due to the cross border grid. The more the European grid is expanded, the more energy can flow freely, less bottlenecks will occur, and Europe can converge towards a completed and integrated energy market [16].

Each power exchange in Europe submits their bids and offers for cross-border trading to the common single price coupling algorithm, EUPHEMIA, which is used to allocate power across Europe. Its goal is to match all bids optimally across borders and to maximize the overall European welfare. Moreover, EUPHEMIA is used as a tool to increase the transparency of calculation of the power prices and flows across countries and bidding areas in Europe, as Nord Pool does for the Nordic and Baltic countries [14].

## 3.4 Power Markets

The Nord Pool power exchange for the Nordic and Baltic countries consists of two markets, namely the day-ahead spot market and the Nord Pool intraday market (Elbas) [9]. Power can also be traded on a financial market and on a balancing market. The next sections will explain the different markets in more detail, in the chronological order shown in Figure 2: from the bidding time of the respective markets to operating hour, where power is delivered and utilized. We will, however, start with the day-ahead market and come back to financial markets later.

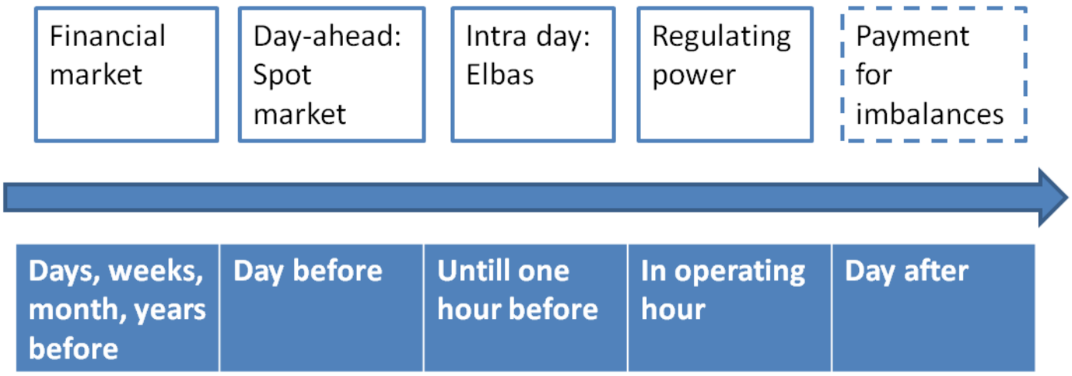



**Figure 2:** The different markets on the Nordic power market on different times before delivery of power. Source: Ea Energy Analyses[12]

### 3.4.1 The Day-Ahead Market

On the day-ahead market prices are set 12 to 36 hours in advance, based on production and consumption bids for the coming day. The day-ahead market is the most liquid market at Nord Pool, meaning that it is the market with the most traded volume. In 2015, the traded volume on the Nordic and Baltic day-ahead market was 374 TWh, corresponding to 76% of the total power traded on the Nord Pool power exchange. For comparison, the total trade on the Nordic, Baltic, and German intraday market was 5 TWh, or only 1% [9]. This is reassuring for the TSOs, who are responsible for keeping their areas electrically stable, and it gives time for the producers to prepare their production for the coming day. The day-ahead market can be seen as a first forecast for the producers on how much they will produce the next day, and for the retailers on how much their costumers will consume the next day. This is based on weather forecasts, capacity of power plants, seasonality, holidays etc.

The day-ahead market is open every day until noon, for deliveries from the following midnight and 24 hours ahead. When the market is open, producers and consumers submit their supply offers and demand bids for every hour the next day. When all offers and bids are submitted, the Nord Pool power exchange determines an equilibrium price for every hour from midnight and 24 hours ahead, on the basis of the aggregated supply and demand. The price is then published and production plans are sent to the TSOs. The equilibrium price for all of the Nordic and Baltic countries, disregarding the different bidding areas, is called the system price. The system price is the price that would clear the markets if no constraints in the transmission system were taken into account, or if flow between areas is less than the transmission capacities.

As mentioned above, constraints in the transmission capacities mean it is possible that bidding areas will have different prices. Thus, the system price is a common price in the Nordic area if there were no bottlenecks in the grid and power could flow freely through the transmission system. The price differences between the bidding areas therefore reflects bottlenecks in the transmission system. The design of the market ensures that power will flow from the low price areas to high price areas due to arbitrage. Thus, the power flows to the bidding areas where the demand is highest, which ensures the highest social welfare. Even though it is often the case that different equilibrium prices are determined in different bidding areas, the day-ahead system price is of great importance as it reflects the total power supply and demand in a given hour, and is used as the underlying price for other Nord Pool markets.

Due to the high liquidity of the day-ahead market, and the influence of the system price on other power markets, it is the best reflection of the development in the combined supply and demand for the Nordic and Baltic countries. We will therefore focus on the day ahead market in this thesis [8]. In Section 4 we will explain the price formation on the day-ahead market in detail, and how the supply and demand curves are formed.

### 3.4.2 The Intraday Market

The Nord Pool intraday market is offered in the Nordic and Baltic countries, the UK, and Germany. The intraday market opens every day at 2pm and closes one hour before delivery. It is a continuous market where buyers and sellers can trade closer to delivery time to make the markets balance. Hence, the intraday market is meant to counteract potential imbalances on the power market between the closure of the day-ahead market and the opening of the regulating power market, which comes into play in operation hour (described in Section 3.4.3) [17]. Producers and retailers can trade on the intraday market to secure balance between supply and demand [9]. The imbalances that appear after the closing of bidding time on the day-ahead market can be due to a power plant that breaks down, incomplete weather prognoses for wind production, or sudden changes in demand [12].

The intraday market plays an increasingly important role as the share of renewable energy, especially wind, contributes more to production. Wind production is much more unpredictable than regular thermal power plants. This gives rise to a larger gap between the predicted produced volume on the day-ahead market and the actual production ready for delivery. As a consequence, a larger volume is traded on the intraday market to secure balance on the power market [9]. Furthermore, the volume traded has great variation [12]. The existence of a market like the intraday market makes it possible to introduce more renewable energy in the total production [9].

### 3.4.3 The Balancing Market

There are 12-36 hours from the bidding hour on the day-ahead market to operation hour, and many imbalances can occur in the meantime. The intraday market can counteract some of these imbalances, but as the intraday market closes 1 hour before operation, a market that secures balance between production and consumption in the operating hour is necessary. This market is called the balancing market, and consists of the regulating power market and the balancing power market.

**The regulating power market** is a real-time market where electricity is physically traded. The function of the regulating power market is to provide power regulation to counteract imbalances from the day-ahead and intraday markets occurring in operating hour [17]. As explained in Section 3, the TSOs are responsible for ensuring balance in the power transmission grid, i.e. to ensure a stable frequency of 50Hz. In order to do this, the TSOs buy or sell power on the regulating power market. As on the day-ahead market, bids are submitted in a merit order structure and a market price (regulating power price or RP price) is found for every hour. Similar to the day-ahead price, that will be elaborated in Section 4.1, the RP price is a uniform price determined according to a marginal price principle; namely where the highest bid activated in an hour becomes the common RP price for that hour, and all activated bids receive that price [12]. The RP price will be the same across all bidding areas, if no bottlenecks occur [18]. All bids are submitted to a common Nordic regulating power market. The bids are sorted with increasing prices for up-regulation and decreasing prices for down-regulation [12].

If the power consumption exceeds the production, i.e. there is not enough electricity in the system, the system is in need of up-regulation. In that case the TSOs buy up-regulating power from producers with excess power production capacity. Bids are activated until the demand from the TSOs is met and a PR price is determined [12]. Conversely, if the power production exceeds the consumption, i.e. there is excessive electricity in the system, the TSOs must pay some producers to reduce their production, or some consumers to increase their demand. This is a case of down-regulation. Again, a PR price is determined for every hour according to the bids [12].

**The balancing power market** settles imbalances from the previous 24 hours, and the value of excess or required energy is exchanged with the TSOs. The RP price is crucial for the settlement of imbalances on the balancing power market, because it is used as the price for imbalance. Hence, there is a clear link between the overall imbalance the actors contribute to by having imbalances, and the cost associated with having other actors deliver the power instead.

Furthermore, there is a link between the spot price and the RP price. If the spot price is high, the producers need a high reservation price to save capacity for the regulating power market. As the RP price is set according to the demand from the TSOs and bids from suppliers of regulating power, the RP price is high if the spot price, and thereby the reservation price for regulating power, is high. The opposite scenario appears for low spot prices, where the suppliers require a lower reservation price to save capacity [12]. The RP price therefore moves in the same direction as the spot price.

### 3.4.4 Financial Market

In addition to the different markets listed above, it is also possible to trade power on a financial market. For the Nordic countries, the financial market is not controlled by the Nord Pool exchange, but is on the Nasdaq OMX Commodities exchange, which was separated from Nord Pool in 2011 [9]. On Nasdaq it is possible to trade future contracts and other derivatives on a financial market, i.e. there is no physical delivery of the traded power, it is only money that is exchanged between the two parties of a financial contract.

The financial market is used for hedging and risk management. Financial contracts often use the system price as an underlying reference, hence the system price must be reliable as the true market price, in order for the financial markets to function [13]. Many participants on the power markets trade on the financial markets to hedge against price changes in the day-ahead system price. The financial power market is a large market itself, but we will not go into more detail as we will concentrate our focus on Nord Pool's day-ahead market and the system price.

# 4 Price formation on Nord Pool's day-ahead spot market

In the following we will focus on the price formation on the day-ahead market. As explained in Section 3.4.1, an auction takes place every day at noon where producers and retailers submit their offers and bids for supply and demand for every hour of the following day, collectively making up an aggregated supply and demand curve. The intersection between the curves is the market-clearing equilibrium price for a given hour: the system price. Hence, Nord Pool calculates the system price and the equilibrium prices for the different bidding areas for every hour. The day-ahead prices, volumes and flows between areas are published on Nord Pool's website 42 minutes after the market is closed [9], i.e. at 12:42 pm every day. The specifics regarding the auction structure and how the supply and demand curve is formed will be described in the following sections.

## 4.1 Auction structure

The price on the Nord Pool day-ahead market is found on the basis of a so-called double-sided blind auction. Double-sided implies that both buyers and sellers submit orders, in contrast to a one-sided auction where it is typically the buyers that submit their orders. A blind auction implies that the participants do not know who they end up trading with, nor do they know the bids of the other participants [19]. All bids are anonymously submitted to Nord Pool for every hour of the following day.

One notable feature of the power market is that the auctions are repeated daily, as the day-ahead spot price of all hours of the day is determined every day at noon one day prior. The repetitions imply that participants in the auction can learn from previous auctions and find out which bidding strategies work. They are therefore able to exploit the rules of the auction, opportunities in the transmission system, and the price inelastic demand, as they can learn from the outcome of previous repetitions [19]. This can result in the same effect as if participants had agreed on a fixed price; participants can evaluate the various bidding strategies and rules of the game, such that they will know how to explore what is optimal for them. For instance, because security of supply is such an essential part of the power market, some buyers demand electricity regardless of the price, placing bids at the maximum price level (3000 EUR/MWh [9]). As the producers are aware of this, they have bidding strategies that exploit this inelastic demand by submitting bids at the maximum price level themselves (two real life examples of this strategy can be seen in Figure 16a and 16b in Appendix), which in rare circumstances can lead to spikes in the power price [20]. We will describe spikes in more detail in Section 5.1. Given that the Nord Pool day-ahead market is a repeated auction, the negative effects outlined above are minimized by using a blind auction, where an aggregation of the actual bids of the participants are not published before the market is cleared.

The equilibrium price on the Nord Pool spot market is a uniform price that all buyers pay and all sellers receive, regardless of the bids that they have submitted. This is in contrast to the pay-as-bid or discriminatory price, where buyers pay the price of their bids and sellers receive the price of their bids [20]. One advantage of a uniform price is that it increases transparency, because there would not be one equilibrium price to publish if all producers were paid their individual bids. Another advantage is that all producers have an incentive to bid their marginal costs, because they will at least receive a price that is equal to their bid.
The disadvantage of a uniform price is that some producers with low marginal costs will receive a mark-up additional to their marginal costs, i.e. gain profit without any risk. This can lead to high prices in the short run, because players with market power have an incentive to keep prices high [21]. However, according to Son et al. [21], pay-as-bid auctions can result in entry barriers for small participants, because marginal costs do not cover fixed or start-up costs. This can be harmful in the long run, as it favours existing and large participants.

## 4.2 The demand curve

The demand side of the power market consists mainly of retail companies that resell power to end-users [12]. The retailers submit the amount of power they anticipate their customers will demand, and at which price. The demand for power is very inelastic, resulting in a very steep, almost vertical demand curve. Hence, small changes in supply can therefore create large changes in the price. Power is seen as a good of necessity, i.e. an essential good which is difficult to substitute. Most consumers will therefore require the same amount of energy to keep their company or household going, almost regardless of the price. Additionally, power demand is characterized by inflexibility, because the opportunity for storage is limited and power must be used almost in the instant that it is produced. Because power is a good of necessity, the non-storing nature also contributes to making power consumers unable to respond to the price. Thus, the slope of the demand curve remains close to vertical in every given hour of the day, although the curve shifts horizontally according to seasonality and peak and off-peak hours.

## 4.3 The supply curve

### 4.3.1 Power sources

The supply side of the power market consists of different types of power generators. Figure 3 shows the power generation in the Nordic area by power sources in 2010 and 2016[1]. More than half of the total production in the Nordic countries comes from hydro plants. The large share of power production implies that hydro producers have great market power, and therefore play a very important role in Nord Pool, thus making the Nordic and Baltic power market different from other large power markets. The hydro plants are mainly located in Norway, and more than 96 percent of Norwegian electricity production is accounted for by hydro power [22]. Apart from the Norwegian hydro power plants, Sweden and Finland also contribute to the overall hydro power production in Nord Pool [9].

In 2016 wind power represented 8.3% of total power production in the Nord Pool area, an increase of 5 percentage points from 2010 [1]. The two countries with the most wind power are Denmark and Sweden, where the proportion of wind power is 43% and 10%, respectively, in 2016 [1]. These shares have been growing over the last decades, due to growing environmental awareness around the world [23].

Nuclear power makes up 21% of the power generation in the Nordic area, both in 2010 and 2016. All nuclear power is generated in Finland and Sweden, which both have several nuclear power plants [1]. Following the Fukushima nuclear plant accident in Japan in 2011 [24], the political discussion about the use of nuclear power has increased. A number of countries, including Sweden, have since decided to phase out nuclear power plants. Finland, however, is constructing more nuclear power plants. Overall, it is expected that the share of nuclear power production in the Nordic countries will be reduced in the coming years [25].

[1]Figure 3 does not contain production from the Baltic countries, even though they are a part of the Nord Pool area, because we do not have production data split on production plants available.

Thermal power, such as coal, natural gas, biomass, and oil, corresponded to 13% of total power production in 2016 [9]. The power production from thermal sources has decreased by 6,6 percentage points since 2010.
Finally, other power production includes geothermal, solar, etc. Generation from those power generators represents only a small fraction of the total power production in the Nordic countries; we will therefore neglect this power source and not go into detail with it.

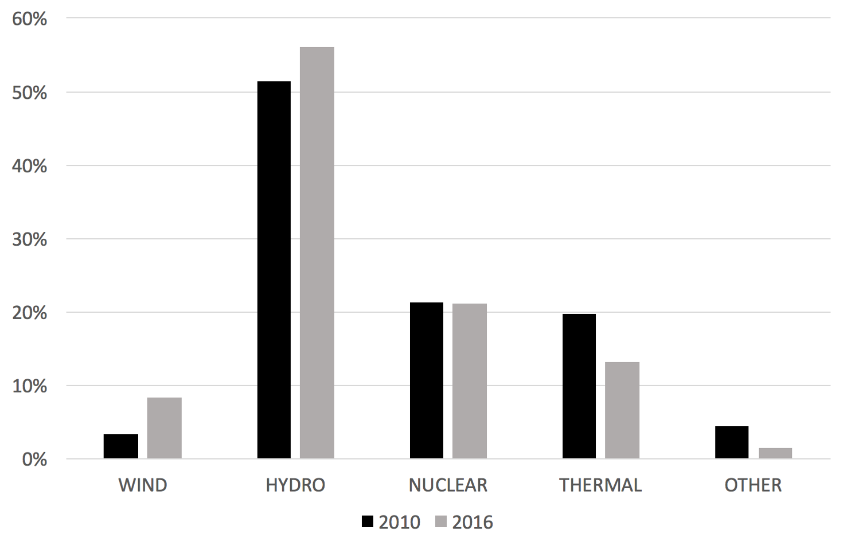



**Figure 3:** Power generation by power source in the Nordic area. Source: Syspower data [1]

### 4.3.2 Merit order principle

Apart from different demand levels in peak and off-peak times, the supply curve is the dominant factor determining the price, due to the inelastic demand curve. The supply curve on the day-ahead market is called the merit order curve, as it is formed by the so-called merit order principle. According to the merit order principle, all bids submitted to the Nord Pool power exchange are arranged according to the reservation price of the producers. Theoretically, this reservation price is the power producers' short-term marginal cost. The merit order curve is formed by all bids listed from lowest to highest. The least expensive power generators are present to the far left of the merit order curve, and these typically consist of renewable energy sources such as wind, hydro and solar power, as they have marginal costs close to zero.
In ascending order of bids comes nuclear, coal, gas, and oil. The hourly system price is then determined from the reservation price of the marginal plant needed to meet the demand of that particular hour [4]. As illustrated in Figure 4, the intersection of the

supply and demand curve is at a point where coal producers have submitted their bids, thus making coal plants the marginal plant determining the price in this example. It is generally the case that coal production is price-setting [24] on the power market. This is mainly due to the wide use of coal-fired production plants in the world [26]. Another reason for coal-fired plants to be price setting in the Nord Pool area is that the hydro producers are able to place bids strategically; this will be explained in Section 4.3.5.
As mentioned in Section 4.1, when the equilibrium price is found all retailers pay and all producers receive the same uniform equilibrium price. All producers with lower average costs than the equilibrium price will therefore have a positive producer surplus, corresponding to the gap between the equilibrium price and their marginal costs. Figure 4 shows an example of a merit order curve for the Nordic power market.

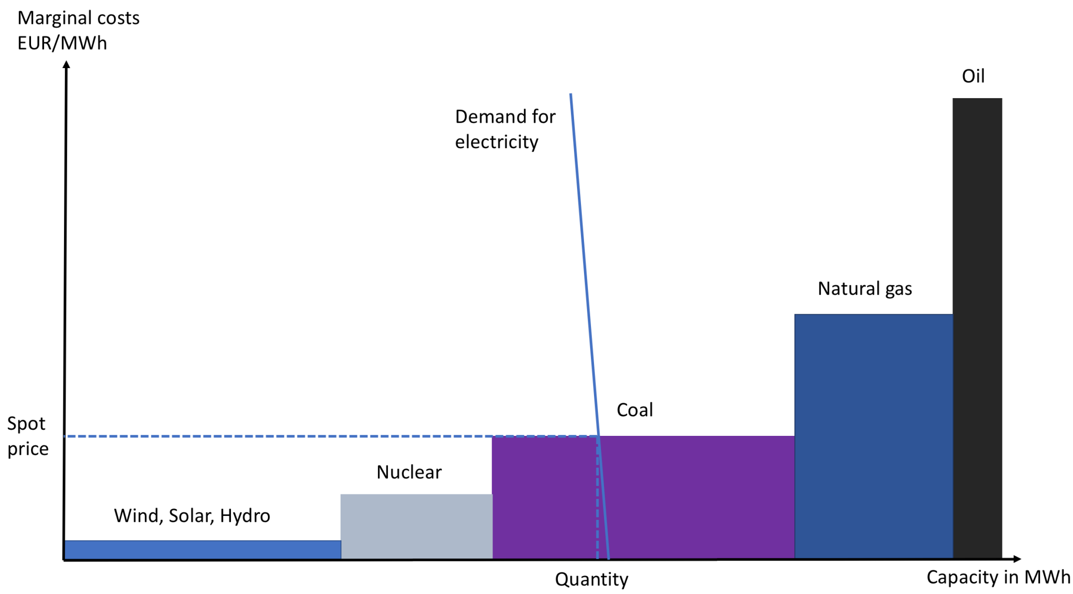



**Figure 4:** Example of a simplified merit order curve

Before power producers submit their bids they have to decide which market they want to sell their production on, when they want to produce, how much to produce, and at which price. The price is reflected by their marginal costs, which consist of operational costs, fuel costs, subsidies and carbon emission taxes. Additionally, some power producers engage in strategic bidding, i.e. they do not bid their true marginal costs. The quantity that the power producers offer is mostly determined by their capacity, although some plants would prefer to accept short term negative prices for their offer, as it is more expensive for them to close down and restart. Other power plants can change their production very quickly without any additional cost. Finally, due to the ordering structure of the merit order curve, producers need to take producers in other countries and bidding areas into account when they submit their bids. For example: if weather forecasts predict strong wind the following day, thermal power plants prepare themselves for lower production as there will be more wind energy generated to a lower price than the thermal power plants' marginal costs.

The various factors determining the marginal costs will be elaborated in the following.

### 4.3.3 Fuel costs

Renewable energy sources are located at the very beginning of the merit order curve as fuel costs are non-existing, resulting in marginal costs close to zero [4]. This implies that the suppliers of wind power can submit bids that are very low. Therefore, the bids from wind power generators are placed to the far left of the merit order curve, as other production plants have higher marginal costs.

As with other renewable energy sources, hydro plants have a marginal cost close to zero in terms of power generation, are CO2 neutral, and can therefore submit bids at a very low price. Hydro plants do not, however, always follow their true marginal costs when they submit bids; this will be elaborated in Section 4.3.5.

Next in the merit order structure comes nuclear power plants. The relatively low marginal costs of nuclear power reflect low fuel costs, as nuclear power plants are not subject to the volatile prices of fossil fuels. Hence nuclear plants are able to produce a large amount of relatively inexpensive power. The bids from nuclear plants are therefore often placed just to the right of the bids from renewable energy generators on the merit order curve. However, construction of a nuclear plant is very capital intensive and can take up to several years to build [27]. This implies that there is a substantial risk associated with the capital investment required to build a nuclear plant. The volatile development of energy prices makes it hard to predict future energy prices and ensure return on investors' capital, making investments in nuclear power very risky [27].

For the most part, the bids from thermal power plants are situated to the far right of the merit order curve, because these production forms have the highest marginal costs on the market, as they are very dependent on fuel. These fuels can either be renewable, such as biomass, or the traditional fossil fuels: coal, gas, and oil.

Despite being expensive to transport, compared to oil and gas, coal is a very cost-effective fuel, which is one of the reasons why coal plants are widely used throughout the world [26]. Transportation costs, together with the price of coal, are the dominant factor when coal plants submit bids. In 2016, coal power production corresponded to around 32% of the total thermal production in the Nordic countries [22]. Bids from natural gas-fired plants are found to the right of the bids from the coal plants on the merit order curve due to different fuel costs; the gas price is usually higher than the coal price. In the Nordic countries, around 20% of the total power production came from gas-fired plants in 2016 [22].

The most expensive power production comes from oil power plants, as oil is a more expensive fuel compared to coal and gas [4]. Bids from oil plants are usually located to the far right of the merit order curve, as illustrated in Figure 4. Furthermore, the price of oil is very volatile, thus future costs of a oil-fired power plant are hard to predict [20]. Because of the high marginal costs, oil-fired plants are typically one of the last power sources that come into operation, often only in a peak hour when demand is high, or if for some reason other power plants have shut down. In 2016 only 1% of the total thermal power production in the Nordic countries came from oil, and the major part of this was used during the winter months [22].

Because of the increasing interest in green energy in recent years, power generation from biomass has become more and more widespread. In 2016, biomass and biogas, which we will not distinguish between here, corresponded to 46% of the total thermal production in the Nord Pool area [22]. Biomass consists of materials from plants and animals, for instance wood, agricultural and animal waste, and some urban and industrial waste. An advantage of biomass is that it is not a fossil fuel that the globe will run out of. Biomass combustion does result in carbon emission, but proponents argue that when biomass is regrown, it will absorb the carbon that was released during combustion. Some coal-fired power plants also use biomass as a fuel, which is possible because the plants are technically similar [26]. This is done because it reduces the net carbon emission of the coal-fired power plants. The cost of biomass is similar to the cost of traditional fossil fuel as coal, but biomass combustion is typically less efficient in generating power, thus marginal costs are higher [26].

Besides the fact that fossil fuels are finite products that are not renewed and will therefore run out at some point, the disadvantage of thermal power plants is their dependence on these fuels. They have high operation and maintenance costs, because they rely on fossil fuels or biomass to operate. Prices of oil, gas and coal are generally very volatile and unpredictable [28]. This makes investments in thermal power plants risky, because future return on capital is uncertain. Another disadvantage of thermal power plants is that the energy efficiency is relatively low, because a lot of energy is lost as heat in the generating process. This can be improved by using the heat as a by-product to heat households, a process called combined heat and power or CHP. In the rest of this thesis we will not distinguish between different thermal production types, but instead look at thermal power production as a whole.

Ideally, the merit order curve would be based solely on fuel and operational costs. However, the marginal costs of the power generators are also affected by subsidies and carbon emission taxes.

### 4.3.4 Subsidies and carbon emission taxes

There is a common attitude that carbon emission has an undesirable impact on the environment, mainly through its impact on global warming. Due to the political position of reducing carbon emission, renewable and CO2 neutral energy sources such as wind power are growing fast. The benefit of renewable energy production is that it has a positive impact on the overall society, called a positive externality. The amount of wind energy produced is too little compared to the benefits for society as a whole [28], as the positive impact is not contained in the bids from the suppliers of wind power. The true external effects are not reflected by the bids forming the merit order curve. Figure 5 shows how the benefits for society are greater than the benefits for the producers alone, hence shifting the supply curve to the right and creating a welfare gain [15].

To overcome the problem of the positive externalities of wind power, policy makers have adopted different policy measures for regulation of the power market with the purpose of encouraging non-polluting energy sources such as wind, and thus shifting the supply curve to the right as shown in Figure 5. These policy measures include subsidies, which are widely used in the Nordic countries. Denmark has a large proportion of wind power production, which is motivated by intensive support schemes for windmills, including a market premium for both onshore and offshore wind. According to The European Wind Energy Association [28], wind power producers in Denmark receive a premium in addition to the market price per MWh produced. This premium is paid by the Danish end-users, who are charged with the so called PSO-tariff that covers the support for renewable energies [2].

One consequence of support schemes such as the premium received by wind power producers is that the producers can profit from generating power even when the electricity price is negative. This implies that the producers are willing to submit bids to

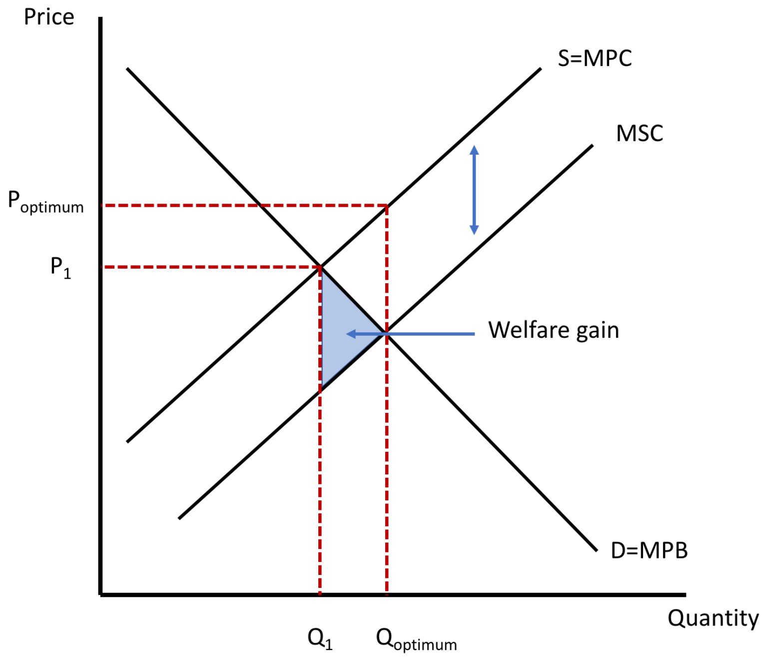



**Figure 5:** Positive Production Externality. MPC=Marginal Private Cost, MSC=Marginal Social Cost, MPB=Marginal Private Benefit [15]

Nord Pool with a required price below zero. In periods with a lot of expected wind, this can result in a negative equilibrium spot price [4]. Even though negative prices can theoretically appear in the system price, it is very rarely seen. It is, however, more common to see negative prices in the equilibrium prices for the different bidding areas. These negative prices appear as a consequence of transmission constraints between the bidding areas. If, for instance, strong wind is expected in the bidding area DK1 (see Figure 1) in a low demand hour, the transmission capacities between DK1 and its connected areas are expected to be fully utilized. In this case, the excess power in DK1 cannot flow to connected areas, as the capacities are full, and the spot price in DK1 will deviate from the other areas. If power could flow freely between all areas, the major supply in DK1 would flow to the rest of the areas, thus negative prices would not occur to the same extent [29]. Transmission capacities therefore play an important role in price formation of the different areas.

Until 2009 the price floor on Nord Pools day-ahead spot market was zero; after 2009, negative prices were allowed [9]. The reason for lowering the price floor was a demand from participants for the spot price to reflect the true price signals of the market. Besides subsidies for renewable energy sources, negative prices are an indication of the inelasticity and inflexibility of demand, as mentioned in Section 4.2. Furthermore, there is limited storage capacity for electricity, i.e. power must essentially be used in the instant it is produced. A sudden excess supply stemming from strong winds will result in a downward change in the power price, due to a lack of energy-storing possibilities [26]. Hydro reservoirs can, however, act as a form of energy storage that can dampen the price effect of sudden excess supply. This will be elaborated in Section 4.3.5.

Just as subsidies affect the bidding behaviour of wind producers, carbon emission taxes affect the marginal costs and thereby the bidding behaviour of thermal power plants. What is common for all thermal power plants, regardless of the type of fuel, is that they emit carbon into the atmosphere. Carbon emission is a negative externality on society, as it creates a welfare loss [15]. If this externality was not contained in the bids of the producers, and hence the supply curve, the equilibrium price would be too low and the produced amount too high compared to what is socially optimal. Therefore, the European Union has introduced a CO2 allowance system, where polluting companies such as thermal power plants must buy CO2 allowances in order for them to emit carbon into the atmosphere [16]. The aim of the CO2 allowances is to reduce overall carbon emission. In this way, the European Union is able to control the amount of pollution and increase the price of the polluting companies' products to offset the negative externalities. Coal-fired power plants are the most polluting way to produce power, resulting in high expenses for CO2 allowances. Oil power plants also have high expenses for CO2 allowances, hence increasing the marginal cost of oil plants even more [30]. Compared to coal and oil, combustion of gas produces considerably less carbon emission [26].

Finally, nuclear power has no carbon emission tax as they do not release carbon. However, they are subject a range of other environmental requirements due to uranium emission [26].

### 4.3.5 Storing possibility and strategic bidding

Even when fuel costs, operational costs, subsidies and taxes are taken into account, not all power plants submit bids reflecting their true marginal costs. The unique nature of hydro reservoirs plays an important role in shaping the generation mix in Nord Pool, and gives some producers the possibility of placing strategic bids.

There are two forms of hydro production, with markedly different characteristics. These are reservoir plants and run-of-river schemes. Reservoir plants account for 92% of the total hydro power production in the Nord Pool area [22]. Run-of-river schemes

are much cheaper to establish than hydro reservoirs, but the latter makes it possible to store energy. Storing energy also serves to make the electricity generation agile, as hydro producers can open and close the sluices when needed. As with most other renewable energy sources, run-of-river schemes cannot store energy, and they generate electricity continuously as the water flows down-river through the turbines.
The possibility of storing energy in hydro reservoirs is a key difference from other renewable energy sources, and this is what gives the Nord Pool area significantly different opportunities compared to other power exchanges. This phenomenon is called the battery effect, as the reservoirs act as enormous batteries for all the Nordic and Baltic countries [29].

In general, the inability to efficiently store energy is one of the biggest challenges when more renewable energy sources are added to the generation mix. More than one third of energy generation in Denmark stems from renewable power sources [2], and it has been suggested that the only reason the large share of wind is possible in Denmark is the connection to hydro power in neighbouring countries, especially Norway [29]. The storage capability of hydro reservoirs makes it possible for hydro plants to adjust their production capacity by opening and closing the sluices. Hence, Denmark can export excessive wind power to hydro-dominant countries, who decrease the hydro power production and store the power by filling up their reservoirs: the battery effect. The local consumption is then met with cheap wind power imported from Denmark. Thus, when it is windy in Denmark and the local demand is lower than the power generation, hydro production in the rest of Scandinavia decreases due to import of wind energy.
The transmission capacity between wind-dominant countries and hydro-dominant countries is therefore essential for a larger penetration of wind, to avoid volatile and some times even negative prices, as explained in Section 4.3.4. By extending the transmission capacity, the effect of wind production on the prices would decrease, as the hydro producers in Norway would adjust their production accordingly [29].

The energy-storing nature of hydro reservoirs gives hydro producers the possibility to make strategic bidding on the day-ahead market, in order to maximize their producer surplus. Instead of bidding according to their marginal cost, hydro producers can bid according to their opportunity cost. The opportunity cost consists of two factors.
Firstly, the opportunity cost of opening the sluices and producing hydro power is the value of water in the future. When producing now, there is less water in the reservoirs saved for future production. The value of water in the future therefore both depends on future demand, reservoir constraints, and water inflow to the reservoir. However, as demand is inelastic and much more predictable, the inflow uncertainty has a high

influence on the prices. The inflow has large variation and uncertainty, because it depends on exogenous factors such as rain and snowfall [31].
Some argue that hydro plants take advantage of the high and inelastic demand during winter time, and produce more than needed during summer solely to force the prices up during winter, as the water in the reservoirs suddenly becomes a scarce resource [31]. This strategy is affected by the uncertainty of the amount of water inflow and is therefore not without risk.
Secondly, another element in the hydro plants' opportunity cost is the equilibrium price, which most of the time is determined by the coal price, as coal power plants usually tend to be the marginal plant setting the price (see Figure 4), as mentioned in Section 4.3.2. The opportunity for strategic bidding due to their energy-storing nature allows the hydro plants to submit bids which are marginally lower than the coal price, in order to undercut the thermal producers and maximize their own producer surplus. Because of the uncertain water inflow, the strategic bidding can however increase the risk of system outages due to empty reservoirs [32].

To summarize: strategic bidding of the hydro reservoir plants changes the structure of the merit order curve in two ways, as the hydro producers do not necessarily submit bids according to their marginal cost of power generation, but according to their opportunity cost. The bidding from hydro reservoirs depends both on thermal power production and on wind power production. When placing bids slightly below the coal price, the hydro plants produce the amount they want and the thermal producers are only put into operation when demand is very high, or when supply from other producers is low. Apart from undercutting thermal plants, the hydro producers can also exploit the volatility and transient nature of wind power. The storage opportunity of hydro can compensate imbalances of wind producers and make a large penetration of wind production possible, as the hydro plants are able to exploit their position [29].

### 4.3.6 Flexibility of production

A final part of the bidding behaviour of the power generators is their differing ability to meet either peak load or base load.
Gas-fired plants are adaptable and can change their production within minutes. Similarly, hydro reservoirs can be brought into operation within seconds, almost without any costs [27]. This agile feature makes them suitable for peak load production.

Coal secures a stable supply of electricity, as the production of coal-fired plants can be prepared on the day-ahead market. However, coal-fired power plants are less flexible compared to gas-fired plants, as their start-up and shut-down time is longer, and they are therefore more suited to base load operation [27].

Similarly, nuclear power plants are characterized by having long and costly start-up and shut-down times, which effectively makes nuclear a must-run capacity [25]. This implies that nuclear is not suitable for peak or fluctuating loads, where the production load changes often and suddenly [27]. Instead, nuclear is more suitable for base loads. As described in Section 4.3.4, power prices some times turn negative if demand is low and supply is high, for instance if there is a large amount of wind during a summer night in Denmark. Agora Energiewende [33] examines causes of negative electricity prices, and find that they do not arise solely because of large amounts of renewable energies, but also because of lack of flexibility for power plants such as nuclear. In times with excess supply, nuclear power plants do not shut down their production entirely, because it is too costly. They only reduce their production by around 35%, and remain running despite of the possibility of negative prices that they temporarily receive. In situations like this, the lack of flexibility for nuclear creates further excess supply, driving down the prices even more [33].

### 4.3.7 The merit order effect

As more production comes from renewable energy sources such as wind, hydro, and solar, a larger share of the generation mix has marginal costs close to zero. This makes the merit order curve shift to the right, and lowers the equilibrium price on the spot market. In other words, a larger share of the demand is covered by cheaply produced renewable energy, and more expensive production such as coal and oil becomes outperformed, as they are pushed to the right hand side of the demand curve. This is called the merit order effect [4]. Figure 6 shows an example of the merit order curve shifting to the right, and the corresponding price reduction.

The structure of the merit order curve implies that production types with the lowest marginal costs, i.e. renewable energy sources and nuclear, are used first, with coal being taken into play only if they do not cover the demand. Due to their high marginal cost, oil, and gas plants are only taken into use if the demand is very high, or production from other plants is low [20].
Two real life examples of demand and supply curve on two different days in the peak hour from 17:00-18:00 are shown in Figure 16a and 16b in Appendix. On January 22nd, it was more windy than on January 15th, causing the merit order curve to shift to the right.

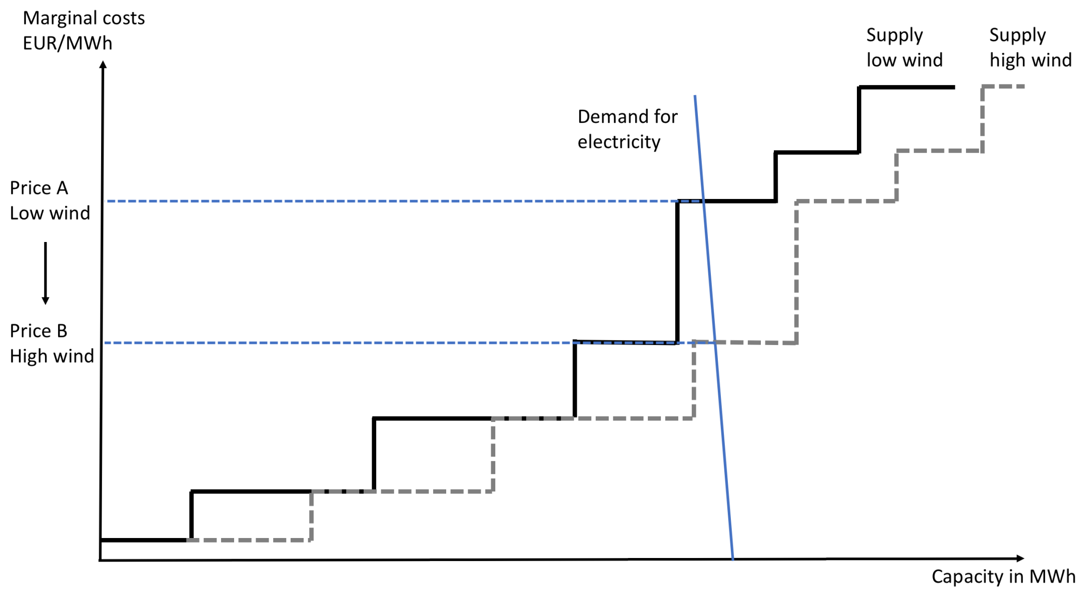



**Figure 6:** The merit order effect

In recent years, wind power has become increasingly important due to a larger market share, especially in Denmark [7]. Increased wind production contributes to a merit order effect by outperforming expensive production types and lowering the price. However, wind is a very volatile power source and subject to a high degree of unpredictability [26]. Even though wind forecasts are relatively reliable, it is hard to predict the amount of wind with 100 percent certainty [28]. In areas dependent on wind power, this uncertainty can create problems for the TSO. As explained in Section 3.2, the role of the TSO is to maintain a stable supply of electricity, and the unpredictability of wind can make this a difficult task for the TSO when the market share of wind increases.

Furthermore, the Nord Pool day-ahead market is structured such that producers have to submit their bids 12 to 36 hours before the actual production and delivery of the power. This design favours producers such as nuclear and thermal power generators, as these plants can plan their production ahead and are relatively precise in producing the planned amount of power. As we have seen, wind power represents an increasing share of the total power production, and the design of the day-ahead market is not well-suited for wind power generators, that deal with unpredictable power production [12]. The development of the Nordic market with an increasing share of wind energy results in an increasing role of the intraday and balancing power markets, as described in Section 3.4.2.

Despite the obvious advantages of wind power, such as the positive welfare gains from the merit order effect, zero pollution, and the fact that wind is a renewable power source, the volatility and unpredictability of wind power raises concerns on how much a society can rely on such volatile energy sources to provide electricity, and how this unpredictability affects the volatility of electricity prices.

Various solutions that can cope with the volatility of wind power have been put forward. One solution is that other power producers will need to be on standby and must be able to switch on and off quickly [26]. Another solution is a flexible grid system, in which the power can flow freely in large regions. As mentioned above, the capacity constraints in the Nord Pool area occasionally result in negative prices when there is excessive wind production. In the same manner, the transmission constraints can cause price spikes, for instance in hours with high demand and a sudden outage of a production plant within a bidding area [20]. If capacity constraints were removed, the excess supply or demand of one area could flow freely between all Nord Pool areas, thus stabilizing the power price and removing differences between bidding areas, as mentioned in Section 3.3. A third solution that could possibly overcome some of the consequences of volatile wind production is a more flexible demand, which is already extending in the form of smart energy [34].

However, although theory predicts that increased unpredictability in power generation will increase price volatility, the storing nature of hydro reservoirs might help dampen this effect in the Nord Pool power market, and make a larger share of wind power possible through the battery effect. However, due to capacity constraints and the necessity of stand-by plants, society still seems to struggle to fully exploit cheap renewable energy from wind power.

## 4.4 Summary

As explained in the above, the generation mix and power producers' different marginal costs play an important role in the formation of power prices in Nord Pool. As the share of renewable energies such as wind power increases, the tendency is that coal remains price setting in peak-hours, but that renewable energy sources are more often price setting in off-peak hours, due to the merit order effect. The increasing importance of wind power in the Nord Pool area, and the political goodwill towards wind production, through expansion of windmill parks and subsidies, makes it interesting and relevant to go deeper into how wind production really affects electricity prices, both in terms of level and volatility. Theoretically, we expect that a larger share of wind production will lower the system price, but there is a risk that the volatility of wind power will also be reflected in the system price. In order to examine the effect of wind production on the system price, i.e. to calculate the merit order effect stemming from wind production, we set up econometric models using time series data from Syspower, Nord Pool, and Statnett. Subsequently, we model the effect of increased wind power on system price volatility.

# 5 Data

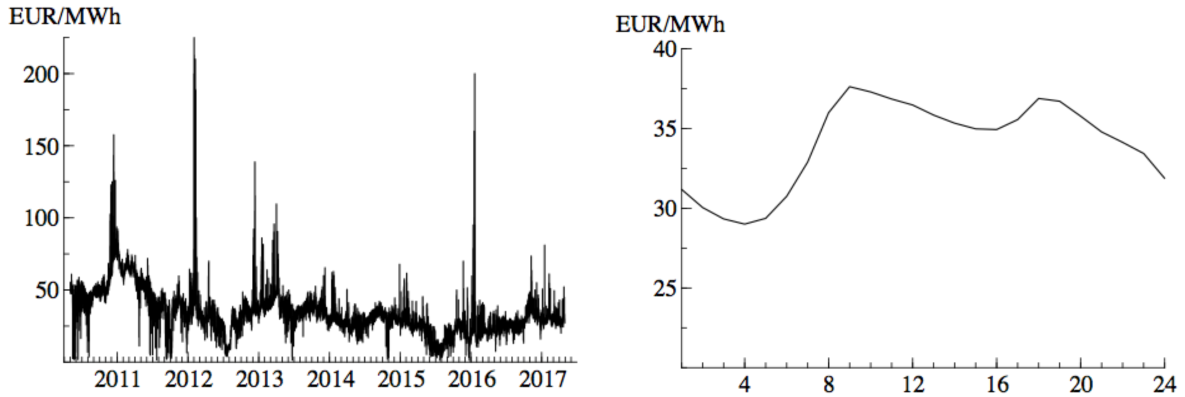
The data we use is composed of several time series data sets from Syspower, Nord Pool Spot, and Statnett. We analyse the day-ahead system price, and the data consists of 61,296 hourly observations of the Nord Pool spot price. Apart from the spot price, the data consists of other variables important for the analysis of the system price; namely different types of production, consumption, and the coal price.

We remove all observations for Saturday and Sunday from the data set for two reasons. Firstly, the spot price exhibits large seasonality over the week, due to higher demand in weekdays than weekends; by removing observations from weekends, this weekly seasonality is removed. Secondly, coal is only traded on weekdays, hence a unique coal price does not exist for weekends. The coal price is a crucial variable for determination of the spot price, and we do not expect including weekends to have a significant effect on the results of the analysis, as demand is low on weekends [25]. After removing weekends from the data set we have 43,776 hourly observations. The considered time period is chosen to be from the 4th of May 2010 to the 30th of April 2017, due to availability of data. Before this period, the coal price was only published on a weekly basis. After this period, there is a lack of publication of Swedish wind production.

## 5.1 Hourly electricity prices

Figure 7a shows the hourly electricity spot price for the Nord Pool area on an hourly basis over the period 2010-2017. The maximum hourly spot price in the period is 225 EUR/MWh, and the minimum hourly spot price is 1.4 EUR/MWh. Hourly electricity prices are in general characterized by four stylized facts: volatility, spikes, mean reversion, and seasonality [20].

Hourly electricity prices are in general highly volatile compared to other denoted volatile commodities such as oil, gas, treasury bills and notes [20]. One of the most prominent features of hourly electricity prices, accounting for a large part of the over-




(**a**) Hourly spot price.

(**b**) Average spot price per hour.

**Figure 7:** Spot prices in the Nord Pool area 2010-2017. Source: Syspower [1]

all volatility, is spikes, where the price suddenly jumps to an extreme level for a short time and then returns to its initial level. This is clearly visible in Figure 7a.
A price spike is defined as being 4 standard deviations from the mean day-ahead hourly price [20]. Spikes in electricity prices can partly be explained by inelastic demand. Spikes are rarely seen, but happen mostly in peak-hours in wintertime, where the demand is high. Due to the composition of the merit order curve, which is relatively flat when demand is low and relatively steep when demand is high, the price is more sensitive to demand shifts during high demand periods than low. In the case of no rain, no wind, and unforeseen outages of power plants, coincident with a high demand level, spikes can appear. The spikes often last for a very short time i.e. on and hourly or daily basis, and prices drop back to their initial level when the demand falls, weather conditions change, or the power plants come back in operation.
Inelastic demand and unforeseen supply conditions are not the sole cause of spikes, however. The auction structure on the day-ahead market permits bidding strategies that exploit the inelastic demand. As electricity is a good of necessity, retailers are willing to pay almost any price to meet the demand of their end-users. Hence, retailers must regularly place bids at the maximum allowed (3000 EUR/MWh) for their required amount of power. Examples of this strategy are shown in Figure 16a and 16b in Appendix that illustrate real life examples of demand and supply curves with bids at the maximum price level. Due to the uniform price structure, all buyers have to pay the spot price, regardless of their own bid. The suppliers can exploit this very inelastic demand by placing bids correspondingly to maximize their profit [20].

As seen in Figure 7a, another feature of energy prices is that they are generally mean reverting. This means that electricity prices are generally characterized by long range dependence, so the electricity prices will always revert to its natural mean despite external caused fluctuations. Mean reversion in electricity prices is most clearly seen in the case of spikes, where the mean reversion rate is very fast, and the prices almost immediately return to the previous level [20].

Hourly electricity prices exhibit seasonal fluctuations, mainly due to the seasonal behaviour of demand, and this seasonal pattern makes data for electricity prices very complicated. Because of climate variations in the Nordic region across seasons, the consumption peaks in winter due to increased heating requirements. This is reflected in the price, as can be seen in Figure 7a, where the prices are generally slightly higher during winter than during summer.
Apart from annual seasonality, electricity demand also varies throughout the week, with a higher consumption during weekdays than in weekends, and during working hours than at night. There is usually a morning peak around 9:00 and an evening peak around 18:00. Hours during night and weekends are called off-peak or base hours [20]. Figure 7b shows the average spot price per hour for the period 2010-2017, where the fluctuations in demand during the day is clearly reflected in the price. The price is low during off-peak hours and high during peak hours. The seasonality seen in the electricity prices is not as prominent as the seasonal behaviour of the demand, however, indicating that demand is not alone in determining the electricity price. Apart from seasonal fluctuations in demand, the supply side can also cause seasonal variations. Hydro and wind production are highly dependent of season and time of the day, as precipitation, snow melting, and wind velocity varies between seasons [20].

## 5.2 Daily average of hourly electricity prices

Although day-ahead spot prices are generated on an hourly basis, we convert the hourly prices to daily averages. The daily averages are calculated as follows:

$$SPOT_t = \frac{\sum_{h=1}^{H} SPOT_h}{H}, \tag{1}$$

where $h$ is an hour of the day and $H$ is the total observations of the day. By dividing the sum of hourly observations by $H$ instead of 24 we take possible missing hourly observations into account, and get a more accurate estimate of the daily average. [2]

[2] When calculating daily averages, the switch between summer and winter time and vice versa also have to be handled. From summer to winter time, an extra hour arises from 2 to 3 am. We choose to replace the 3rd hour with an average of these two prices and then calculate the daily average by averaging over the 24 hours. From winter to summer time, an hour between 2 and 3 am is lost. When calculating daily averages, the average of the specific day is taken over the 23 hours that are available.

In this way we can reduce unwanted noise caused by the nature of the hourly electricity prices, explained by the stylized facts in Section 5.1. Another argument for using daily averages is that all prices for the next 24 hours are set at the same time on the day-ahead market. Hence, all 24 prices are set from the same information from the preceding day, which is only updated every 24 hours [4]. Several similar studies have used daily averages based on the same arguments [3]–[5]. Apart from reducing unwanted noise caused by exceptional and temporary events taking place in a specific hour, daily averages add simplicity to our model, as less seasonal variation should be taken into account. However, wind production is very volatile over the day, and using daily average some of the variation will inevitably be lost [4]. In spite of this, we do not expect hourly variation to contribute significantly to the analysis of the long term effects of larger wind penetration on the spot price.

Figure 8 shows daily averages of the electricity spot price for the Nord Pool area over the period 2010-2017. As seen in the figure, volatility and spikes are reduced compared to figure 7a. The maximum daily average of the spot price over the period is now 103.3 EUR/MWh and the minimum is 6.2 EUR/MWh.

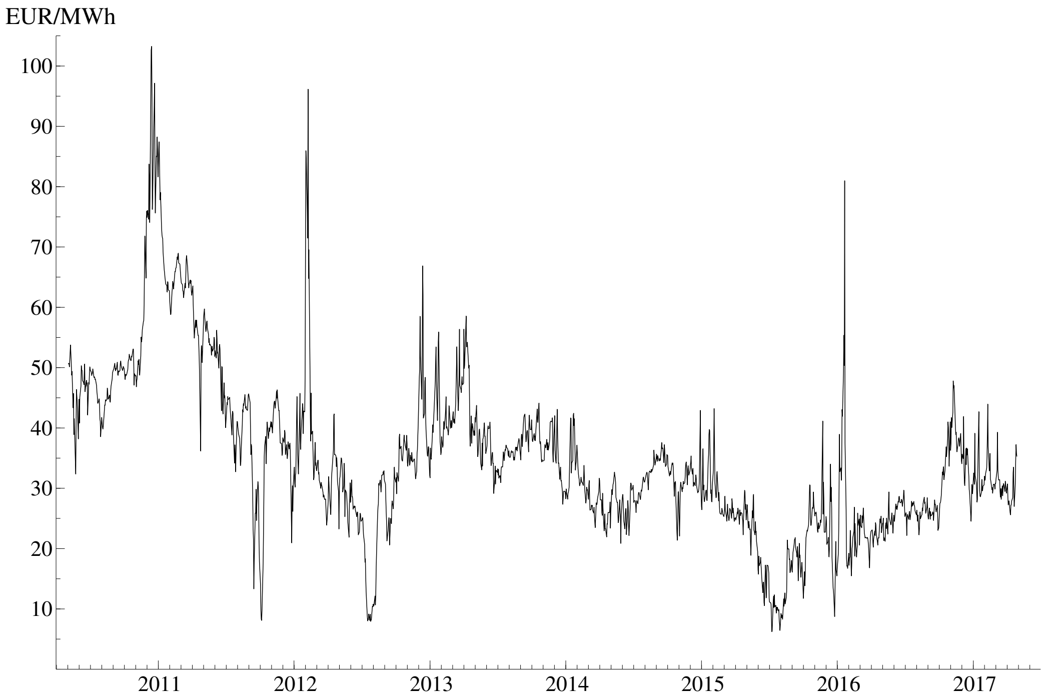



**Figure 8:** Average daily system price in the Nord Pool area 2010-2017. Source: Syspower [1]

**Table 1:** Descriptive statistics full sample.

| | All sample (N=1824) | | | | | |
|---|---|---|---|---|---|---|
| | Mean | Std. dev | Min | Max | Skewness | Kurtosis |
| SPOT | 35.1 | 13.7 | 6.23 | 103 | 1.13 | 5.49 |
| CONSUMPTION | 47,753 | 7,965 | 34,561 | 68,773 | 0.42 | 2.14 |
| PRODUCTION | 48,030 | 7,821 | 34,143 | 66,914 | 0.35 | 2.02 |
| WIND | 2,819 | 1,862 | 101 | 10,458 | 1.00 | 3.73 |
| HYDRO | 25,592 | 4,436 | 16,166 | 38,436 | 0.37 | 2.62 |
| NUCLEAR | 9,443 | 1,608 | 5,224 | 11,913 | -0.40 | 2.31 |
| THERMAL | 6,933 | 2,714 | 2,137 | 14,888 | 0.68 | 3.01 |
| COAL PRICE | 8.04 | 1.75 | 4.61 | 12.6 | 0.22 | 2.16 |

Notes:
SPOT and COAL PRICE are in EUR/MWh.
CONSUMPTION, PRODUCTION, WIND, HYDRO, NUCLEAR, THERMAL are in MWh.
Source: Syspower [1]

## 5.3 Descriptive analysis

Table 1 reports descriptive statistics of the daily averages of the spot price and seven other variables of interest for the period from May 2010 to April 2017. We have calculated daily averages of the variables using the same method as for the spot price in Equation (1). The table shows that we have 1,824 observations for each variable. Furthermore, it shows the mean, standard deviation, minimum value, maximum value, skewness and kurtosis of the variables. We have included the following 8 variables, as we expect them to have an impact on the spot price: total power consumption and total power production in the Nordic and Baltic countries, total production of hydro, nuclear, wind and thermal power in the Nordic countries, and a coal price. The spot and coal price are reported in EUR/MWh and the consumption and production variables are reported in MWh.

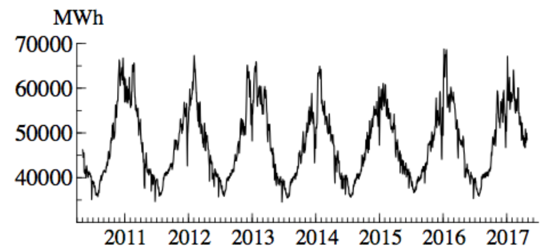
The spot price has a mean of 35.1 EUR/MWh during the period and a standard deviation of 13.7. The high kurtosis of 5.49 is caused by many outliers in terms of spikes, that are common for power prices as described in Section 5.1. Total consumption and total production are similar, as all the values in the table are relatively equal. The similarity is expected, because the net export varies around zero. The reason that the different production types do not include production from the Baltic countries is that we do not have production data from these countries split on type of production. As the total power production in the Baltic countries corresponds to only 5% of total generation in the Nord Pool area, we do not expect it to affect our results. The variables total production and consumption include not only the Nordic but also the Baltic countries. As the Baltic countries are included in the price setting of the spot price, they should also be included in the variables in our model if at all possible.

Table 1 shows that the smallest production type of the four considered is wind production, with a mean of 2,819 MWh, corresponding to 6% of total production. The reported wind production only considers Denmark and Sweden. The reason is that data for the Finnish wind production is only available from February 2012 and the Norwegian wind production is only available from January 2013. Furthermore, the Swedish and Danish wind production from 2013 to 2017 represent almost 90% of the total wind production in the Nordic countries, thus we expect to capture the most important features of the increasing wind production, even though we choose to disregard the Finnish and Norwegian wind production in our analysis. Table 1 also reports that the wind variable has the highest kurtosis, apart for the spot price, indicating many extreme values or outliers in wind production [35].

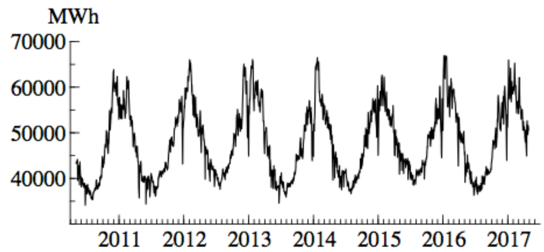
Hydro production is by far the largest production type, as also illustrated in Figure 3. The reported hydro production from 2010 to 2012 is calculated, as total production in Norway split on different production types is not available before January 1st 2013. We have calculated the total Nordic hydro production from 2010 to 2013 as an approximation of the Norwegian hydro production and added the actual hydro production in Finland and Sweden. We have approximated Norway's hydro production from 2010 to 2012 based on its share of hydro production in its total production from 2013 to 2017, which was 96%. Despite the fact that the share of hydro production is probably not constant throughout the year, we do not expect the approximation of the hydro variable to have an impact on our analysis.

The reported coal price is the daily coal price in EUR/MWh from Argus-McCloskey [36]. We have converted the coal price from USD/Ton into EUR/MWh by the EUR/USD exchange rate from ECB [37] and the conversion factor of 8.141 MWh/Ton [38]. The mean of the coal price is 8.04 MWh and it has a relatively low standard deviation of 1.75, compared to the spot price. Furthermore, it has a low skewness, indicating a symmetric distribution around its mean [35].

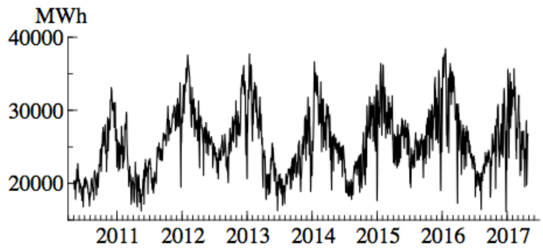
The coal price converted to EUR/MWh contains a number of missing values, due to bank holidays where currencies and commodities such as coal are not usually traded. To cope with these missing values we use linear interpolation, calculating an average between the observations before and after the day with no observation. In this way, the data set becomes suitable for time series analysis. We use the same method with potential missing values of the daily average spot price, the consumption variable and the production variables. This is only relevant in a few cases, and we therefore do not expect it to have an impact on our results.



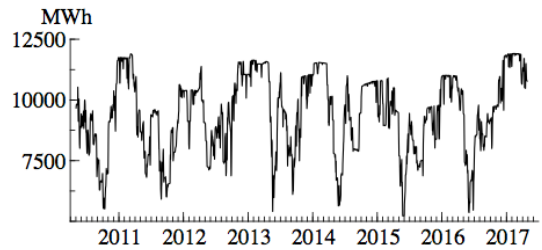

**(a)** Total Consumption.



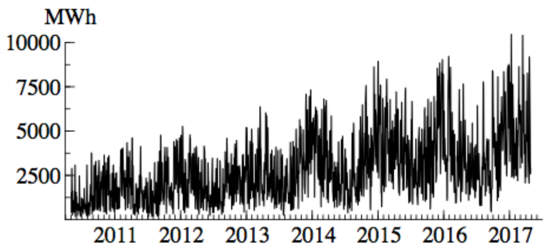

**(b)** Total Production.



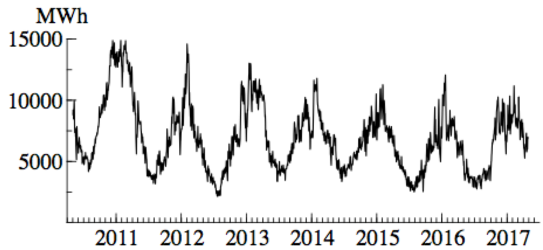

**(c)** Hydro Production.




**(d)** Nuclear Production.




**(e)** Wind Production.




**(f)** Thermal Production.

**Figure 9:** Consumption and production by production type in the Nord Pool area 2010-2017 in MWh. Source: Syspower [1]

Figures 9a-9f show total power consumption, total power production, and the total generation by the largest production types from Table 1. It is evident from the figures that the consumption and production in the Nordic and Baltic countries are very seasonally dependent, as explained in Section 5.1. Figures 9a and 9b show that the total consumption and production are relatively stable from year to year, as there is no tendency of the power consumption and production moving in an upwards or downwards direction. The same is true for hydro and nuclear production, where production is high in winter months and low in summer months.

In this regard, wind production stands out. Figure 9e shows total wind production in Denmark and Sweden from 2010 to 2017, and clearly illustrates an increasing trend and variance. The average daily wind production in Denmark and Sweden was 1,878

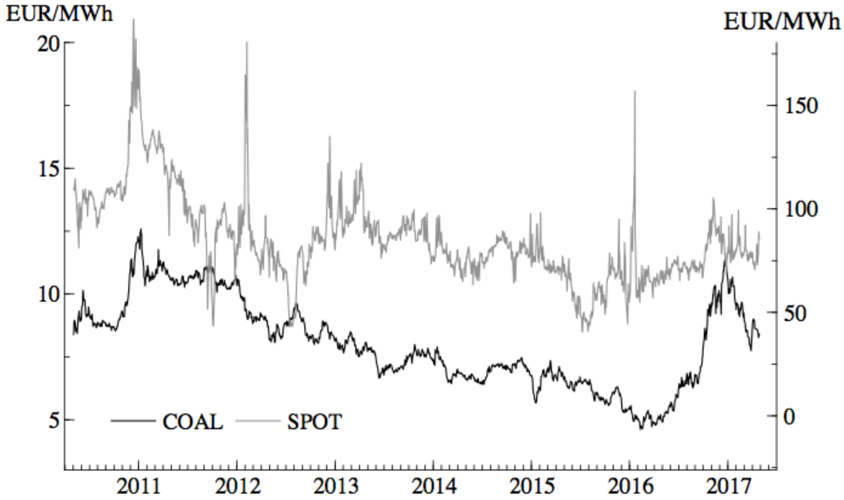



**Figure 10:** Coal and spot price in EUR/MWh. Spot price on secondary axis. Source: Argus-McCloskey [36] and Syspower [1].

MWh in 2011, whereas it has increased to 3,661 MWh in 2016, as reported in Tables 11 and 12 in the appendix. This is an increase of almost 200 percent. This increase in wind power production reflects an expansion of the installed wind capacity in the two countries [10]. Figure 9e shows that wind production has seasonal fluctuations similar to the other production plants, which are due to both fluctuations in consumption and to more wind during winter months compared to summer months[39].

Because of the constant consumption and production by year, and the increasing wind production from 2010 to 2017, the wind producers must have replaced other, more expensive, production types. Figure 9f shows that the production of thermal power has a decreasing trend when disregarding the yearly seasonality. This trend also appears in Tables 11 and 12 in the appendix. The average daily production of thermal power was 8,063 MWh in 2011, whereas it had fallen to 6,038 MWh in 2016. The outcome of less thermal power production, when wind power production increases, seems to be in accordance with the merit order effect explained in Section 4.3.7.

As explained above, there is a clear seasonal pattern in power consumption and production in the Nord Pool area. This clear pattern is not as evident in the spot price in Figure 8. Therefore, we expect some other variables to affect the spot price besides consumption and production. In Section 4.3.2, we explained how coal plants are often the marginal plant determining the price, hence we expect the price of coal to have an impact on the power price. Figure 10 shows the spot price and the Argus-McCloskey coal price. It is clear from the figure that the spot price follows the general trend of the coal price, although the daily spot price is more volatile than the coal price. The overall correlation between the spot price and the coal price could explain why the spot price does not follow the same clear seasonality as total consumption and production. We will return to the cointegrating relationship between the spot price and the coal price in Section 7.1.

## 5.4 Volatility of the spot price

Due to the volatile nature of electricity prices and the non-storing nature of wind power, it is not only relevant to analyse the level of the spot price, but also to test how more wind power in Nord Pool affects the price volatility in both the long and short term. In order to do that we calculate realized volatility.
The data we use to calculate realized volatility is different from the dataset for daily averages, as observations for weekends are now included. Weekends were removed when modelling variations in the spot price because the coal price, which is very important for that particular analysis, is not available during weekends. When analysing the volatility of the spot price, however, we choose to keep weekends in the dataset, as we only expect the coal price to have a significant effect on the spot price level and not volatility. Hence we do not have to deal with missing weekend observations in that variable. The reason for keeping the weekends when feasible is to have as much information in our data as possible. The dataset including weekends contains 2,552 daily observations, from May 4th 2010 to April 28th 2017.

The daily volatility is calculated based on Rintamäki et al. [6] and Mauritzen [7], who calculate daily volatility, $V_d$, using the following formula:

$$V_d = \left( \sqrt{\frac{1}{24} \sum_{h=1}^{24} \left( SPOT_h - \overline{SPOT}_d \right)^2} \right), \quad d = 1, \ldots, 2552, \tag{2}$$

where $\overline{SPOT}_d$ is the average daily price of day $d$, given by

$$\overline{SPOT}_d = \frac{1}{24} \sum_{h=1}^{24} SPOT_h. \tag{3}$$

Similarly, the weekly volatility, $V_w$, is calculated to evaluate price volatility in the longer term:

$$V_w = \left( \sqrt{\frac{1}{7 \cdot 24} \sum_{d=1}^{7*24} \left( SPOT_h - \overline{SPOT}_w \right)^2} \right), \quad w = 1, \ldots, 365, \tag{4}$$

where

$$\overline{SPOT}_w = \frac{1}{7 \cdot 24} \sum_{d=1}^{7\cdot 24} p_h \tag{5}$$

is the average price of week $w$. This leaves us with 365 observations of weekly volatility.

Figures 11a-11d illustrate the realized daily and weekly volatility in values and in logarithms, calculated based on Equations (2) and (4). The natural logarithm of the volatility is calculated as we wish to model the percentage change of increased wind energy in the analysis of volatility, presented in Section 9. The figures illustrate no clear seasonality in the volatility, but they illustrate a tendency of volatility clustering.

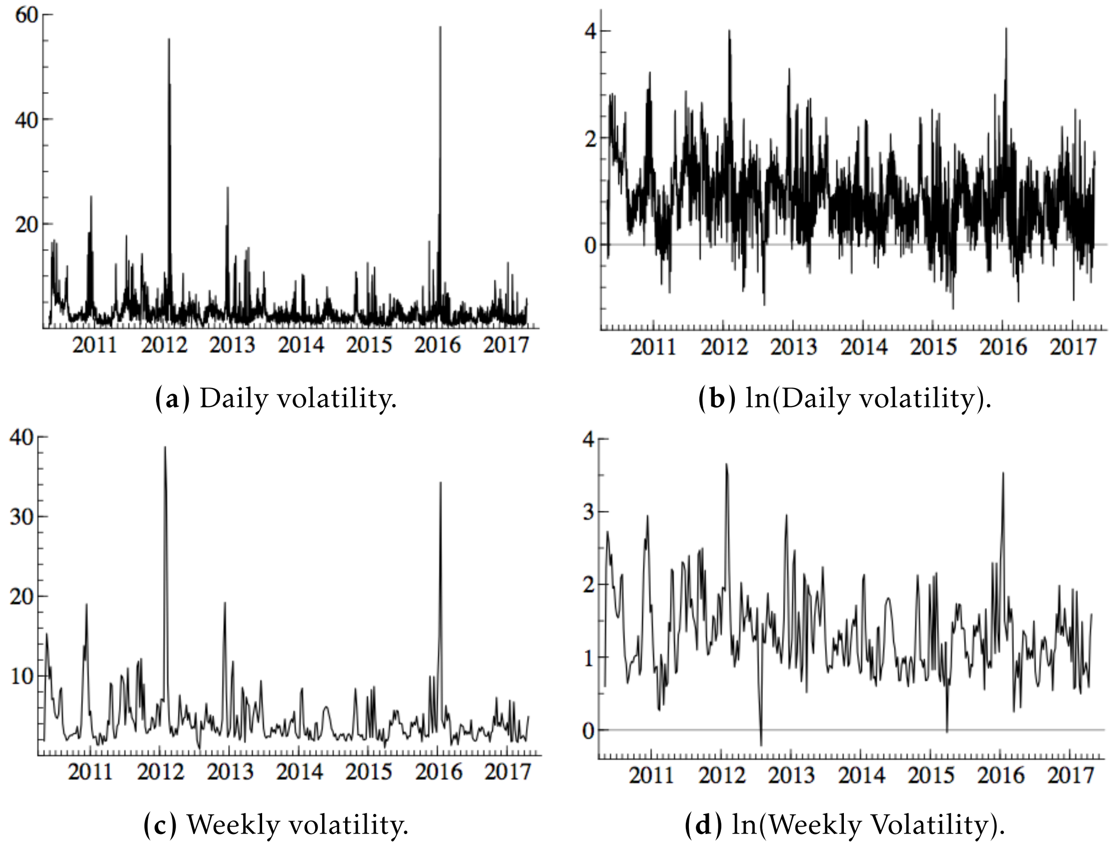



**Figure 11:** Daily and weekly volatility of Nord Pool's spot price 2010-2017. Source: Syspower [1]

Table 2 contains descriptive statistics of daily and weekly realized volatility. The table reports mean, standard deviation, minimum, maximum, skewness and kurtosis. Realized weekly volatility has a higher mean and standard deviation than realized daily volatility, but daily volatility has the highest maximum value. Both measures are characterized by very high skewness and kurtosis, indicating many extreme values and outliers, and non-symmetric distributions around their mean [35].

**Table 2:** Descriptive statistics of realized volatility.

| | Mean | Std. dev | Min | Max | Skewness | Kurtosis | N |
|---|---|---|---|---|---|---|---|
| Daily | 3.34 | 3.66 | 0.30 | 57.68 | 6.72 | 75.48 | 2552 |
| Weekly | 4.55 | 3.94 | 0.80 | 38.73 | 4.67 | 34.20 | 365 |

Source: Syspower [1]

# 6 Econometric Methods

In the following sections we present a series of regression models, with the ultimate goal of explaining the development of Nord Pool's spot price on the basis of the data and variables described in Section 5. The spot price volatility will be analysed in Section 9.

To analyse the level of the spot price we set up a number of models, both static and dynamic. In all cases we use the regression method of ordinary least squares (OLS) estimation. One advantage of OLS is that the estimation coefficients will be consistent and asymptotically normally distributed under a number of assumptions. Furthermore, it has a lower variance than other linear estimators. In the following section, we will go through the assumptions that must be fulfilled in order to ensure consistent and asymptotically normally distributed estimates in a general time-series data setting. In Section 6.2 we will look at time-series settings where the variables are not stationary; some modifications to the time-series are therefore required in order to maintain consistency and asymptotically valid estimation coefficients.

## 6.1 General time-series regression

A crucial requirement of the estimation coefficients is consistency; namely that

$$\text{plim } \hat{\beta}_j = \beta_j, \quad j = 0, 1, ..., k \quad \text{for} \quad T \to \infty. \tag{6}$$

In order for the estimators of our time-series data to be consistent, the following five assumptions need to be met: linearity, weak stationarity, weak dependence, no perfect collinearity, and zero conditional mean [40]. When these five assumptions are met, the law of large numbers and the central limit theorem apply and the OLS estimation coefficients are consistent, such that Equation (6) holds.

In addition to consistency, it is also necessary that the OLS estimators are asymptotically normally distributed. This implies that the OLS standard error and test statistics are asymptotically valid, and we can test hypotheses on the coefficients estimates [40]. The OLS estimator is asymptotically normally distributed if the error term is homoskedastic and has no autocorrelation. The conditions needed for consistency and asymptotic normal distribution will be described in detail below.

### 6.1.1 Consistency

**Assumption 1. Linearity:** This implies that the model of our dependent variable is linear in its parameters of $k$ explanatory variables. That is

$$y_t = \beta_0 + \beta_1 x_{t1} + \cdots + \beta_k x_{tk} + \epsilon_t \tag{7}$$

**Assumption 2. Weak stationarity:** According to Wooldridge [40], a time series $y_1, y_2, ..., y_T$ is weakly stationary if

$$E[y_t] = \mu \tag{8}$$

$$Var(y_t) = E[(y_t - \mu)^2] = \gamma_0 < \infty \tag{9}$$

$$Cov(y_t, y_{t-h}) = E[(y_t - \mu)(y_{t-h} - \mu)] = \gamma_h \quad \text{for} \quad h = 1, 2, .... \tag{10}$$

Weak stationarity implies that the mean and variance of the variable are constant, and the covariance is independent of time [3].

**Assumption 3. Weak dependence:** This imposes restrictions on the degree to which $x_t$ may depend on $x_{t-h}$, for large $h$, i.e. as the time distance between periods $t$ and $t-h$ increases. According to Wooldridge, there is no formal definition of weak dependence that covers all cases of time series [40]. Instead, we can rely on the intuitive definition that a stationary time series $x_t$ *for (t=1,2...T)* is weakly dependent if the correlation between $x_t$ and $x_{t-h}$ goes to zero when $h \to \infty$. As long as the convergence to zero is

[3] In the following, when we mention stationarity, we refer to weak stationarity.

sufficiently fast, this definition of weak dependence is adequate for our purpose [40].

**Assumption 4. No perfect collinearity:** None of the explanatory variables must be constant, or perfect linear combinations of each other [40].

**Assumption 5. Zero conditional mean:** The expected value of the error term $\epsilon_t$, conditional on the explanatory variables in all time periods, must be zero. That is

$$E(\epsilon_t \mid \mathbf{x}_t) = 0 \quad , \text{ t=1,2,...,n} \tag{11}$$

This implies that all variables correlated with both the dependent and explanatory variables must be included in the model, as explanatory variables. Furthermore, for Assumption 5 to hold, we must ensure a one way causality from $x_t$ to $y_t$ in the linear regression in Equation (7). We can rely on this causality if all the explanatory variables are exogenous.

### 6.1.2 Asymptotic normal distribution

Assumptions 1-5 ensure consistency. However, in order to get asymptotically valid test statistics, we need to know which standard errors to use, i.e. how to calculate the variance of the estimator [40]. We then need to know the specifications of the error term, which will be described in Assumptions 6 and 7.

**Assumption 6. Homoskedasticity:** This implies that the variance of the error term, $\epsilon_t$, conditional on the explanatory variables, is constant. This is as opposed to heteroskedasticity, which we must avoid. Thus, the errors are contemporaneously homoskedastic if:

$$Var(\epsilon_t|\mathbf{x}_t) = \sigma^2. \tag{12}$$

Heteroskedasticity does not cause bias or inconsistency of the OLS estimator, but it invalidates the normal standard errors and test statistics as the true variance and covariance are underestimated [40].

The most common test for heteroskedasticity is a White test. Another test is the Breusch-Pagan test, of which the White test is a special case. The difference between the two is that Breusch-Pagan tests for linear heteroskedasticity by regressing the squared residuals on its past, whereas White tests for more types of heteroskedasticity by regressing the squared residuals on all distinct regressors, cross-products, and squares of regressors. If the errors are not normally distributed, the White test is preferred. However, the White test is difficult to calculate in a regression with many explanatory variables, because of the squares and cross-products [40].

If Equation (12) is violated and the error term is characterized by heteroskedasticity, one must use White standard errors, which are robust to heteroskedasticity, in order to rely on the test statistics.

**Assumption 7. No autocorrelation:** This means that the errors in two different time periods are uncorrelated, conditional on $\mathbf{x}_t$ and $\mathbf{x}_s$.

$$Corr[\epsilon_t, \epsilon_s | \mathbf{x}_t, \mathbf{x}_s] = 0 \quad for\ all \quad t \neq s. \tag{13}$$

This is basically the same as considering whether there is some correlation between $\epsilon_t$ and an arbitrary error term $\epsilon_s$, thereby ignoring the conditioning on $\mathbf{x}_t$ and $\mathbf{x}_s$, i.e.:

$$Corr(\epsilon_t, \epsilon_s) \neq 0 \quad for\ all \quad t \neq s \tag{14}$$

This is detected by the estimated residuals from the regression model, $\hat{\epsilon}_t$ *for (t=1,2,...,T)*, where $Corr(\hat{\epsilon}_t, \hat{\epsilon}_s) \neq 0$ is the residual autocorrelation.

When there is no autocorrelation in the error term we can say that the model is dynamically complete. Testing for autocorrelation in time series models is, in other words, to test whether the model is dynamically complete [41].

The model is a complete dynamic model if the regressors contain all relevant information in the available information set. This means that all systematic information in the past of $y_t$ and $x_t$ is included in the model. If this is not the case, some of this information is included in the error term of the model, and the error term is correlated with some of the independent variables $x_t$. To be able to interpret the systematic variation in $y_t$ over time using the variables in $x_t$, we cannot have any systematic variation remaining in the error term [40].

A complete dynamic model is formally written as:

$$E[y_t | x_t, y_{t-1}, x_{t-1}, y_{t-2}, x_{t-2}, ..., y_1, x_1] = E[y_t | x_t] = x_t' \beta. \tag{15}$$

In practice, a test for no autocorrelation of the error terms is done by running the auxiliary regression model:

$$\hat{\epsilon}_t = x_t'\delta + \gamma\hat{\epsilon}_{t-1} + u_t, \tag{16}$$

where $\hat{\epsilon}_t$ is the estimated residual from a regression. The explanatory variables $x_t$ are included to allow that they not be strictly exogenous. This test is called a Breush-Godfrey test and the null hypothesis for no autocorrelation is $\gamma = 0$. If $\gamma$ is significantly different from zero we have autocorrelation in the error terms, as they are correlated across time, meaning that the model is not dynamically complete.

If both Equation (12) and (13) are violated, heteroskedasticity and autocorrelation robust standard errors (HAC) must be used when estimating the model. Both Cludius et. al [4], Clò et al. [5], and Galabert et. al [3] used HAC standard errors when estimating the effect of wind power in the electricity price. Under Assumption 1 through 7, usual OLS standard errors and test statistics are asymptotically valid [40].

Although we can attain valid test statistics by using HAC standard errors in case of autocorrelation and heteroskedasticity, autocorrelation often appears due to a more serious problem with the model specification. It is therefore useful to change the model to avoid autocorrelation. The interpretation and possible correction of the residual autocorrelation depends on the source for autocorrelation. Four possible reasons autocorrelation may appear in the error term are [41]:

1. The error terms of the dynamic general process (DGP) are autoregressive, of the form: $\epsilon_t = \rho\epsilon_{t-1} + v_t$.
2. If the model is dynamic misspecified, meaning that the relationship between the dependent variable and the explanatory variables is better explained by including lagged values of some or all variables, the error terms will be autocorrelated. The solution is to include lagged values by estimating an autoregressive distributed lag model (ADL)

$$y_t = \theta_1 y_{t-1} + x_t'\beta_0 + x_{t-1}'\beta_1 + \epsilon_t. \tag{17}$$

3. If the functional form of the regression is misspecified and the true relationship between the dependent variable and the explanatory variables is non-linear, the error terms from a linear regression are typically autocorrelated. The solution is to respecify the model with the true relation.

4. If some relevant variable which is correlated with the explanatory variables is omitted, and therefore included in the error term, the error terms will be autocorrelated. The solution is to include this variable as an explanatory variable in the regression.

## 6.2 Non-stationary time series

Section 6.1 examined the assumptions needed in order to make the OLS estimates consistent and asymptocially normally distributed in a setting with stationary time-series data. However, there are multiple reasons for the assumption of stationarity to fail. In our data three potential reasons are trend-stationarity, level shifts, and unit roots. When one of these features is present the OLS estimator will not be consistent. There are different solutions to make the estimator consistent, depending on the reason for non-stationarity [42].

**Trend-stationarity**: If a variable has an increasing or decreasing trend over time, the variable is not stationary. This is because the unconditional expectation of Equation (8) changes over time. To overcome this problem a trend needs to be added to the regression, so that the variable becomes trend-stationary [40].

**Level shifts**: If a variable is characterized by a change in the unconditional mean at a given point in time, we will see a level shift. Such a shift violates Equation (8) and makes the variable non-stationary. There are many reasons for a shift in level to appear, eg. institutional changes, or changes in computation or definition of a variable. To take level shifts into account, a dummy can be inserted in the regression so the coefficients can be consistently estimated [42].

**Unit roots**: An autoregressive unit root process can be written as:

$$y_t = \delta + \sum_{i=1}^{p} \theta_i y_{t-i} + \epsilon_t, \tag{18}$$

where $\sum_{i=1}^{p} \theta_i = 1$ [35]. The problem with a unit root process is that the LLN and the CLT, which are both required in order to ensure consistency of OLS estimates, do not apply [42].
One approach for testing for a unit root is the augmented Dickey-Fuller test, that tests for an unit root up to $p$ lags. The null hypothesis of the augmented Dickey-Fuller test is $H_0 : \sum_{i=1}^{p} \theta_i = 1$, with the one-sided alternative $H_A : \sum_{i=1}^{p} \theta_i < 1$. As the CLT does not

apply under $H_0$, the t-statistics do not follow the asymptotic standard normal distribution. Instead, the t-statistics under $H_0$ follow the Dickey-Fuller distribution [40]. If the variables are characterized by a unit root process, the solution could either be to model first differences or to use cointegration. If we have modelled an autoregressive distributed lag model as Equation (17), and $\theta_1 = 1$, first differences can be used. Then the change in the dependent variable from period $t$ to period $t-1$ is modelled instead of the absolute value, and the OLS coefficient estimators will be consistent. Another solution of a unit root is to use the method of cointegration, which we will examine in the next section.

### 6.2.1 Cointegration

The challenge with a unit root is that the error terms of a regression will not be stationary, hence the standard results do not hold for OLS. However, we are able to obtain consistent (super-consistent) results if we use the concept of cointegration. Two variables are said to be cointegrating if they follow the same deterministic trend [43]. When two variables are cointegrating, a linear combination of the two will be stationary, thus the error term will also be stationary [40]. A test of cointegration in a static regression is essentially a test of stationarity of the estimated residuals, and the test is called the Engle-Granger two-step procedure. First, the dependent variable is regressed on the explanatory variables:

$$y_t = \delta + \beta_1 x_{1t} + ... + \beta_2 x_{2t} + \epsilon_t. \tag{19}$$

Then, stationarity in the estimated residuals is tested using the augmented Dickey-Fuller test:

$$\hat{\epsilon}_t = \sum_{i=1}^{p} \theta_i \hat{\epsilon}_{t-i} + \eta_t, \tag{20}$$

where the null hypothesis is $H_0 : \sum_{i=1}^{p} \theta_i = 1$. The null hypothesis of a unit root in the estimated residuals is the same as a hypothesis of no-cointegration [35]. The critical values of the Dickey-Fuller distribution move to the left when more explanatory variables are included in Equation (19). The reason is that more explanatory variables will decrease the variance of $\hat{\epsilon}_t$, and make it look more stationary. Therefore, the Dickey-Fuller distribution is shifted to the left to take the reduced variance into account. If no-cointegration is rejected, it can be concluded that there exists a cointegrating relation in the model, and Equation (19) can be consistently estimated by OLS. However, the coefficient estimate of the cointegrating variable will not be standard consistent as the coefficients of stationary explanatory variables. Instead, the cointegrating coefficient will be super-consistent, as it converges at a faster rate [35].

The Engle-Granger two-step procedure only applies to static regressions. An alternative approach for dynamic models is to test for no-cointegration in the error-correction-model (ECM) [43]. First, the dynamic model is rewritten as an ECM

$$y_t = \delta + \theta_1 y_{t-1} + \beta_0 x_t + \beta_1 x_{t-1} + \epsilon_t \tag{21}$$

$$\Leftrightarrow y_t - y_{t-1} = \delta + (\theta_1 - 1)y_{t-1} + \beta_0(x_t - x_{t-1}) + (\beta_0 + \beta_1)x_{t-1} + \epsilon_t \tag{22}$$

$$\Leftrightarrow \Delta y_t = \delta + (\theta_1 - 1)y_{t-1} + \beta_0 \Delta x_t + (\beta_0 + \beta_1)x_{t-1} + \epsilon_t. \tag{23}$$

If $(\theta_1 - 1) < 0$, the variables in Equation (23) error correct and move towards the long-run solution, when deviations have appeared. If $(\theta_1 - 1) = 0$, the model does not error correct, and the long-run solution will not be sustained, hence no cointegration. A test for no-cointegration is therefore a test of the null hypothesis $H_0 : (\theta_1 - 1) = 0$, against the one-sided alternative of cointegration $H_A : (\theta_1 - 1) < 0$. With regards to the Engle-Granger two-step procedure, the distribution of the test statistics follows a Dickey-Fuller distribution. This depends on the number of variables in $x_t$ and whether a constant or a trend are included [40]. If no-cointegration is rejected and $(\theta_1 - 1) < 0$, it is possible to determine the long-run solution by setting $y_t = y_{t-1} = y^*$ and $x_t = x_{t-1} = x^*$:

$$y^* = \frac{\delta}{1 - \theta_1} + \frac{\beta_0 + \beta_1}{1 - \theta_1} x^*. \tag{24}$$

Under some regulatory conditions the long-run multipliers are asymptotically normally distributed, thus reliable test-statistics of Equation (24) can be performed.

# 7 Empirical analysis

In this section we build six linear econometric models to explain the development of the level of the Nord Pool spot price. The volatility will be studied in Section 9. We begin with selecting variables for the models and subsequently present the models themselves.

## 7.1 Variable selection

In order to use OLS regression, we must first determine if our dependant variable is stationary or not. The spot price shown in Figure 8 indicates a unit root process, which makes the variable non-stationary. Therefore, we test for the presence of a unit root in the daily spot price using the augmented Dickey-Fuller test in different specifications of the test[4].

The result of the test is not straight forward. For a high number of lags, the test suggests that we can not reject the null hypothesis of a unit root at a 5% critical value of the Dickey-Fuller distribution. The economic interpretation of a unit root is that shocks have permanent effects, which can explain the change in levels from year to year as shown in Tables 11 and 12 in the Appendix.

Because of the ambiguity of the test and the high number of observations in our dataset, that increases the requirements for the significance level, we will treat the spot price as a unit root process. One solution is to find another variable characterized by a unit root process that cointegrates with the spot price and include it in the model. Figure 10 indicates a common underlying trend between the coal and spot price, suggesting that variations in the coal price can partly explain variations in the spot price. When that is the case, we can apply cointegration and consistently estimate the model using OLS regression of the daily spot price on the coal price [40]. First, we need to test whether the coal price has a unit root. We perform the augmented Dickey-Fuller test, and the null hypothesis of a unit root can not be rejected[5]. Therefore, we will include the coal price as an exogenous explanatory variable in our regressions [5]. The intuition for the influence of the coal price is clear: residual production is all dependent on fuel cost, and if these costs increases, the power generators require a higher price for producing power, thus resulting in an increase in the spot price. Therefore, we expect positive and significant estimates for the variable of the coal price. We will perform the Engle-Granger two-step procedure or the test for no-cointegration in the ECM in each of our models, to make sure that we can interpret our estimation results correctly.

[4]We choose to include 24 lags in the augmented Dickey-Fuller test, based on Banerjee et al. who, according to Gelabert et al. [3], suggest that the optimal maximum number of lags to include in the test is

$$p = \text{int}[12 \cdot (T/100)^{1/4}], \tag{25}$$

where T is the total number of observations in the dataset. We choose the number of lags where AIC is minimized, which is 24. We also perform other specifications of the test. For instance, inclusion of more lags, with and without trend and constant. All the specifications suggest the same unclear result.

[5]As for the spot price, we perform different specifications of the test, where we include more lags, a trend and a constant. All specifications have the same conclusion; namely that the coal price is a unit root process.

As we wish to analyze the effect of increasing wind power on the spot price, we include wind production in the models. As explained above, we do not have data for wind power production for Norway and Finland from 2010, so we choose to model the impact of Swedish and Danish wind power on the spot price. Like Clò et al. [5], Cludius et al. [4] and Gelabert et al. [3], we include realized wind generation in our models instead of forecasts, even though the wind producers' bids at Nord Pool are based on forecasts. The reason that we use realized production is that data for wind forecasts are not available from 2010. We therefore use realized wind production as an approximation of forecasted wind power. Similarly to Mauritzen [29], we do not see this approximation as a problem for our estimation results as today's forecasts are generally very good at predicting actual wind production. Clò et al. [5] and Cludius et al. [4] argue that, in order to run OLS regression and ensure a one-way causality, we need to assume exogeneity of the explanatory variables. They reason that as wind power depends solely on weather conditions, exogeneity of the wind power production should be a valid assumption.
According to the merit order principle introduced in Section 4.3.2, we expect that a larger wind production will lead to a decrease in the spot price, by pushing out more expensive production forms; a merit order effect. Furthermore, existing literature, presented in Section 2, consistently finds a merit order effect when estimating the effect of increased renewable energy on the electricity price in Spain, Germany, and Italy, respectively [3], [4], and [5]. We therefore expect to find negative and significant coefficients for the wind variable in our models.

We do not necessarily expect wind production to have a linear effect. There may instead be a non-linear effect, depending on the level of wind production. The reasoning is as follows: if there is a lot of wind, then wind power or another inexpensive power generator is typically the price-setting type of production. In this situation, additional wind will only have a small effect on the spot price. In the opposite situation, where there is very little wind, expensive power plants such as oil or gas will usually be price-setting. In that case, additional wind will push out the most expensive production types, and the effect on the spot price of extra wind will be substantial. Because of this non-linear effect, it may be desirable to study percentage changes of wind production and not absolute changes.

As just described, the effect from wind depends on the price-setting production plant. Therefore, we assume production from other power plants to affect the spot price. To capture production from other power plants we include residual production in our model, which is calculated as total production in the Nord Pool area minus wind production in Denmark and Sweden. The advantage of including residual production instead of total production is that we avoid any problems of collinearity between the explanatory variables, as wind is part of total production [6]. Existing literature on the subject, such as Cludius et al. [4], Galebert et al. [3] and Clò et al. [5] have chosen to include power demand in their regression models. By including residual production, the effect of demand is still captured, because the variables are closely correlated. The correlation coefficient between total consumption and residual production in the Nord Pool area is 0.96, with a significance level of $p < 0.0001$. According to Clò et al. [5], we need to assume exogeneity in order to use demand as an explanatory variable in the estimation as this will ensure a one-way causality. This seems like a valid assumption, as demand is very price insensitive and inelastic, especially in the short-run, where it is unlikely that consumers adjust their everyday consumption based on spot market prices [4].

Even though hydro production is a green and renewable energy source like wind, we do not expect hydro reservoirs to have the same impact on prices as wind. The reason is that hydro producers have the ability to store power, and hence wait to generate power until a time of high prices, which gives them a positive opportunity cost [3]. The positive opportunity cost implies that the hydro producers affect the spot prices in the same way as other power plants, like thermal power plants. The correlation coefficients between hydro production in the Nord Pool area and thermal and nuclear production are both positive and significant different from zero ($p < 0.0001$), suggesting that they behave similarly. Therefore, we include the hydro production in the residual production.

As residual production consists of power generation dependent on fuel costs, as explained in Section 4.3.3, we expect positive and significant estimates for this variable in all estimated models. These plants are either directly dependent on fuel costs, like thermal, nuclear and gas plants, or indirectly dependent on fuel costs, like hydro reservoirs plants that are able to strategically place bid slightly below the marginal costs of coal plants. As explained in Section 4.2 the demand is fixed and does not change with the price. Often, wind production is not large enough to fully cover demand at a specific time, and other more expensive production forms come into play. This can happen either due to low wind, or if demand is too high for the wind capacity to fully cover

[6] As the production of Estonia, Latvia, and Lithuania is not included in the variables of production types, we would not get perfect collinearity if we inserted the total production and the different production types. However, the production of the Baltic countries is relatively small, so inclusion of both total power production and production split on different production types as explanatory variables could create problems for the estimation.

demand. The switch in production types increases the spot price relative to situations where wind power can fully cover demand.
Another way of interpreting this is to consider residual production as a measure for demand, and, according to standard economic theory, a marginal positive change in demand will increase the price.

As explained in Section 5.1, power prices are characterized by clear seasonal patterns, which complicates the analysis. To cope with seasonality we include yearly, monthly, and daily dummies in the model, which will control for the large seasonal fluctuations in the variables. Moreover, we include a trend in our models when significant to potentially obtain trend-stationarity as explained in Section 6.2.

As described in Section 3.1, Nord Pool expanded its spot market to include Lithuania in 2012 and Latvia in 2013. This implies that the mechanisms from these markets became a part of the spot price determination. Also, the production variable contains the production in Lithuania and Latvia from 2012 and 2013, respectively. This could lead to a level shift as described in Section 6.2. Even though it is not visible in Figures 9a and 9b, we choose to include a dummy for Lithuania's participation from June 18th, 2012, and a dummy for Latvia's participation from May 23rd, 2013.

## 7.2 Models

Having selected which explanatory variables relevant to include in the analysis of the spot price, we will build six models to ascertain how the merit order effect is best examined. Each model will be presented separately, along with reasons for the underlying decisions. The results of the models will be presented in Section 8. All the models in this section are run in PcGive using automatic model selection, where different combinations of the models are tested against each other and insignificant variables are removed to find the best simplified model that fits the data, using a general-to-specific approach [44], [45]. We include a trend in the models and treat it as the other variables, i.e. it is only included in the model if it is not removed by automatic model selection. Furthermore, we control for large outliers by including dummies.

The first model is based on the models by Cludius et al. [4] and Clò et al. [5]. We regress the spot price on the following explanatory variables: residual production, wind production, coal price, seasonal dummies and a trend.
The interpretation of the estimation coefficient of the wind variable is complicated, because we do not know its distribution. We can interpret the level of the estimation

result, but can not test significance. Thus, although we cannot interpret the test statistics, the model does not take into account any non-linear effect of the wind variable, and we do not believe a static cointegration relation to be the best model explaining the DGP, we chose to run the model to see if we can get consistent results with previous literature and findings. A comparison is presented in Section 8.

**Model 1:**

$$SPOT_t = \delta + \phi_0 resPRO_t + \beta_0 WIND_t + \gamma_0 COAL_t + \alpha D_t + \kappa t + \epsilon_t. \tag{26}$$

$SPOT_t$ represents the Nord Pool spot price in period t. $resPRO_t$ is residual production, $WIND_t$ is wind production, $COAL_t$ is the Argus-McCloskey coal price. Finally, $D_t$ makes up seasonal dummies, and $t$is a trend.
In Section 7.1 we tested that neither the spot price nor the coal price are stationary, although they follow the same underlying trend. In order to interpret the coefficient results, we need to formally test for cointegration. We use the Engle-Granger two-step procedure to test for no-cointegration by testing whether the residual, $\hat{\epsilon}_t$, has a unit root. Again, we test for unit roots using an augmented Dickey-Fuller test. We choose the number of lags to include in the test based on AIC, and get a t-statistic of $-5.006$, which we can reject on a 1 percent significance level ($p < 0.001$). Thus, we reject the null hypothesis of a unit root and conclude that there exists a cointegrating relation in this model and that $\gamma_0$ will be super-consistent, hence it converges at a very fast rate.
We do not test for autocorrelation and heteroskedasticity in Model 1, because the super-consistency overrides potential non-linear variance or misspecification of the error term.

In Section 7.1 we argued that there might not be a linear relation between spot price and wind production. Therefore, we replace $WIND_t$ with the natural logarithm to wind, $lnWIND_t$, in the next model. By taking the natural logarithm to wind, the coefficient measures the elasticity, i.e. the impact on the spot price of a 1% change in wind production, which may be a better way to interpret the impact of wind on the spot price. This transformation makes the wind variable homoskedastic.

**Model 2:**

$$SPOT_t = \delta + \phi_0 resPRO_t + \beta_0 lnWIND_t + \gamma_0 COAL_t + \alpha D_t + \kappa t + \epsilon_t. \tag{27}$$

The variable $lnWIND_t$ now represents the natural logarithm to wind production. We test for no-cointegration in Model 2 by testing whether the residual, $\hat{\epsilon}_t$, has a unit root. Again, we use an augmented Dickey-Fuller test and choose 4 as the number of lags in the test, based on AIC. We get a t-statistic of $-6.053$, which we compare with the 1% critical value of $-4.96$ of the Dickey Fuller distribution with four 4 lags. Thus, we reject the null hypothesis of a unit root on a 1% significance level. Therefore, we conclude that there exists a cointegrating relation between the variables in this model As with Model 1, we do not test for autocorrelation and heteroskedasticity, due to super-consistency.

In the following we extend our model to a dynamic model. The advantages of an ADL model are that we can calculate short and long-run dynamics, and test hypotheses on all the parameters.

We start with a very simple ADL model, where we regress the spot price on itself, lagged, and the coal price, also with lags, as Figure 10 indicates the importance of coal when estimating variations in the spot price.
We start by including five lags in the ADL model as we expect a weekly seasonality of five in this dataset, given that we have removed weekends.

**Model 3:**

$$\begin{aligned} SPOT_t = \delta + \theta_1 SPOT_{t-1} + \ldots + \theta_5 SPOT_{t-5} \\ + \gamma_0 COAL_t + \gamma_1 COAL_{t-1} + \ldots + \gamma_5 COAL_{t-5} + \alpha D_t + \kappa t + \epsilon_t. \end{aligned} \quad (28)$$

In Model 3,we test for no-cointegration, which is done by testing for no-cointegration in the ECM. We test the null hypothesis of $H_0 : (\theta_1 - 1) = 0$ or $\theta_1 < 1$, which is strongly rejected. If $\theta_1 = 1$ we would continue with the analysis by using first differences of the spot variable, as done by Gelabert et al. [3]. In our case, $|\theta_1| < 1$, so we will not use first differences, but conclude that there exists a cointegration relation between spot and coal in Model 3.

As explained in Section 6.2.1, a feature of the ADL model when $|\theta_1| < 1$ is that it is possible to determine the long-term relation of a model by setting $SPOT_t = SPOT_{t-1} = SPOT^*$, and $COAL_t = COAL_{t-1} = COAL^*$. The long-run solution of Equation 28 is[7]:

$$SPOT^* = \frac{\delta}{1-\theta_1} + \frac{\gamma_0 + \gamma_1}{1-\theta_1} COAL^*. \quad (29)$$

[7]We disregard trend and dummies when calculating long-run solutions.

As lags are included in the model, there is no autocorrelation in Model 3. We test for heteroskedasticity in Model 3 using a White test performed by PcGive. The White test indicates that heteroskedasticity is present in Model 3, as the null hypothesis of no heteroskedasticity cannot be rejected ($p < 0.001$). To make the estimates robust to heteroskedasticity, we use White's heteroskedastic robust standard errors [40].

We now extend Model 3 by including the logarithm of wind production and residual production with lags of both variables in the model. The importance of these two variables when explaining the spot price was discussed in Section 7.1. Again, we include seasonal and outlier dummies and a trend if significant. The objectives are that Model 4 will be dynamic well-specified, i.e. able to capture the dynamic effects of the variables, and that we are able to analyse the effect on the spot price of a change in wind production.
When estimating Model 3, the lags of the explanatory variables that are not removed by automatic model selection are: $SPOT_{t-1}$, $SPOT_{t-4}$ and $COAL_{t-1}$. That $COAL_{t-1}$ is chosen above $COAL_t$ will be elaborated on in Section 8. We do not see the intuition why $SPOT_{t-4}$ should have an effect on $SPOT_t$, so we choose to leave it out of Model 4. However, we do keep $SPOT_{t-1}$, $COAL_t$, and $COAL_{t-1}$ in the regression.

**Model 4:**

$$\begin{aligned} SPOT_t = \delta + \theta_1 SPOT_{t-1} + \phi_0 resPRO_t + \phi_1 resPRO_{t-1} + \beta_0 lnWIND_t + \\ \beta_1 lnWIND_{t-1} + \gamma_0 COAL_t + \gamma_1 COAL_{t-1} + \alpha D_t + \kappa t + \epsilon_t. \end{aligned} \tag{30}$$

We strongly reject no-cointegration in Model 4, again indicating the cointegration relation between the variables. We subsequently test for heteroskedasticity in our model. The White test of PcGive indicates that heteroskedasticity is present in the model, as the null hypothesis of no heteroskedasticity cannot be rejected ($p < 0.001$). To make the estimates robust to heteroskedasticity we use White's standard errors [40] as before.

The long-run solution is given by

$$SPOT^* = \frac{\delta}{1-\theta_1} + \frac{\gamma_0 + \gamma_1}{1-\theta_1} COAL^* + \frac{\beta_0 + \beta_1}{1-\theta_1} lnWIND^* + \frac{\phi_0 + \phi_1}{1-\theta_1} resPRO^*. \tag{31}$$

Regression of Model 4 with standard errors that are robust to heteroskedasticity will generate consistent and asymptotically valid results, implying that we are able to use t-statistics of the model. However, we still want to examine if we can improve the model by taking natural logarithm of all the variables, including the dependent variable. Thus, we run the ADL model from Model 4 with all the variables in logarithms. When we run the model in logarithms, the variables $COAL_t$ and $COAL_{t-1}$ both become insignificant and are removed from the model during the selection process. We know from previous analysis that the spot price is non-stationary, thus we can only use the OLS estimation results if there exists cointegration, i.e. $COAL$ needs to be included in the model.

Before discarding this model, we test for a long-run relationship of the model, as Gelabert et al. [3] argue that the relation between the natural gas market and the electricity price is the error correction term related to the long-run relationship, because most combined cycle plants have long-term gas price contracts. In contrast to Gelabert et al. [3], we do not find any long-run relationship between the coal price and the spot price, and for that reason we do not continue with the model nor report the results.

In the following we try model the spot price in a different way. In Models 1-4, the spot price was modelled as a linear function of a number of explanatory variables relevant for describing the spot price. Now, we aim to model the ratio between the coal and spot price. This variable is shown in Figure 13. Due to the fact that the coal and spot price follow the same stochastic trend, it is possible to analyse the effect of wind energy by making a new variable. Hence, instead of creating a model to explain variations in the spot price, Model 5 is created to explain the deviation from the cointegration coefficient or the long-run solution between the spot and coal price, calculated as the spot price divided by the coal price. We expect the explanatory variables $lnWIND$ and $lnresPRO$ to be able to explain deviations. We include the explanatory variables as elasticities by taking the natural logarithm of $resPRO_t$ and $WIND_t$, because the dependent variable is a ratio.

**Model 5:**

$$\frac{SPOT_t}{COAL_t} = \delta + \phi_0 lnresPRO_t + \beta_0 lnWIND_t + \alpha D_t + \kappa t + \epsilon_t. \tag{32}$$

Because of the cointegration relation between COAL and SPOT we know that the ratio between the two variables should be stationary. However, to ensure stationarity we test for the presence of a unit root using the augmented Dickey-Fuller test. We use AIC to choose the optimal number of lags in the test, and get a t-statistics of $-8.176$, which we compare with the 1% critical value of $-3.43$ in the Dickey-Fuller distribution. Thus, we reject the null hypothesis of a unit root on a 1% significance level, which is supported by a graphical display of the variable as shown in Appendix 13.

Therefore, we conclude that the variable $\frac{SPOT_t}{COAL_t}$ is stationary, and that we can use general time-series regression from Section 6.1 to consistently estimate the OLS coefficients of $lnresPRO_t$ and $lnWIND_t$, as Assumption 1-5 are fulfilled. In order to use test statistics of Model 5, we need asymptotic normal distribution by ensuring no autocorrelation and homoskedasticity, as described in Section 6.1.2. We run the Breush-Godfrey test for no autocorrelation in Model 5 and the null hypothesis of no autocorrelation is rejected. Therefore, we must use HAC standard errors, that are robust to autocorrelation and heteroskedasticity. Another method to cope with autocorrelation of Model 5 is to change the specification of the model to include lags of the dependent and explanatory variables, which is done in Model 6. Additionally, a dynamic model can possibly explain the DGP better.

**Model 6:**

$$\begin{aligned}\frac{SPOT_t}{COAL_t} = \delta + \theta_1 \frac{SPOT_{t-1}}{COAL_{t-1}} + \phi_0 lnresPRO_t + \phi_1 lnresPRO_{t-1} \\ + \beta_0 lnWIND_t + \beta_1 lnWIND_{t-1} + \alpha D_t + \kappa t + \epsilon_t \quad (33)\end{aligned}$$

As the model is now dynamic, we do not face problems with autocorrelation. We run White's test for heteroskedasticity, which we cannot reject. To cope with this, we use White's standard errors that are robust to heteroskedasticity, which enables us to rely on test-statistics from the OLS estimator.

We now test if $\theta_1 = 1$, which is rejected on a 1% significance level ($p < 0.001$). As $|\theta_1| < 1$, we are able to calculate the long-run solution of Model 6:

$$\frac{SPOT^*}{COAL^*} = \frac{\delta}{1-\theta_1} + \frac{\phi_0 + \phi_1}{1-\theta_1} lnresPRO^* + \frac{\beta_0 + \beta_1}{1-\theta_1} lnWIND^*. \quad (34)$$

# 8 Results

Table 3 reports the test results from the OLS regressions described in Section 7.2. All models are run over the period 2010-2017.

Model 1 includes residual production, the coal price and wind production. Additionally significant seasonal dummies and outliers are included. As the linear trend is significant in the model, it is included as well. Model 1 is similar to the models run by Clò et al. [5] and Cludius et al. [4] and hence the results shown in Table 3 are compa-

Table 3: Results of OLS regressions for the period 2010-2017.

| | Model 1 SPOT | Model 2 SPOT | Model 3 SPOT | Model 4 SPOT | Model 5 SPOT/COAL | Model 6 SPOT/COAL |
|---|---|---|---|---|---|---|
| $resPRO_t$ | 0.00051*** (4.909e-05) | 0.00054*** (5.453e-05) | | 0.0007*** (2.853e-05) | | |
| $COAL_t$ | 2.98*** (0.238) | 2.46*** (0.3151) | | | | |
| $WIND_t$ | -0.00086*** (0.0001) | | | | | |
| $lnWIND_t$ | | -2.12*** (0.299) | | -0.66*** (0.091) | -0.19*** (0.043) | -0.08*** (0.012) |
| $SPOT_{t-1}$ | | | 0.95*** (0.009) | 0.97*** (0.007) | | |
| $resPRO_{t-1}$ | | | | -0.0006*** (2.874e-05) | | |
| $COAL_{t-1}$ | | | 0.28*** (0.053) | 0.19*** (0.051) | | |
| $lnWIND_{t-1}$ | | | | 0.43*** (0.093) | | 0.04** (0.013) |
| $lnresPRO_t$ | | | | | 3.43*** (0.366) | 4.00*** (0.169) |
| $lnresPRO_{t-1}$ | | | | | | -3.83*** (0.167) |
| $(SPOT_{t-1}/COAL_{t-1})$ | | | | | | 0.94*** (0.009) |
| Weekday dummies | NO | NO | YES | YES | NO | YES |
| Monthly dummies | YES | YES | YES | YES | YES | YES |
| Yearly dummies | YES | YES | YES | YES | YES | YES |
| Latvia dummy | NO | NO | NO | NO | YES | NO |
| Lithuania dummy | NO | NO | NO | NO | YES | NO |
| Outlier dummies | 30 | 29 | 29 | 26 | 25 | 22 |
| Trend | YES | NO | YES | NO | YES | YES |
| Standard error | HAC | HAC | White | White | HAC | White |
| $R^2$ | | | | | 0.6799 | 0.967 |
| log-lik | -5908.91 | -5925.11 | -4156.53 | -3540.49 | -1959.96 | 123.53 |
| AIC | 3.6851 | 3.702 | 1.765 | 1.087 | -0.640 | -2.934 |
| HQ | 3.7296 | 3.745 | 1.808 | 1.128 | -0.593 | -2.894 |
| N | 1824 | 1824 | 1823 | 1823 | 1824 | 1823 |

Notes:

Standard errors in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

$R^2$ is only calculated when a constant is included in the model.

The test statistics and p-values can not be used for Model 1 and 2 as we do not know the distribution of the standard errors.

rable to these previous studies.
However, one need to be careful with the interpretation of the results of this model, as we do not know the distribution of the standard errors. Hence, we cannot use the test statistics and p-values, but only comment on the size of the coefficients.

As expected, the coefficient for residual production is positive, showing that a marginal increase of 1 GWh in residual production increases the spot price by 0.51 EUR/MWh. The coefficient for coal price indicates that an increase in the coal price of 1 EUR/MWh increases the spot price by 2.98 EUR/MWh. Finally we find that a marginal increase of 1 GWh in wind production decreases the spot price by 0.86 EUR/MWh.

All coefficients for Model 1 are consistent with the results from Cludius et al. [4] and Clò et al. [5]. However, both studies find larger effects than -0.86. Cludius et al. estimate merit order effects from -0.97 to -2.27 for Germany over the period 2008-2012, and Clò et al. finds a merit order effect of -4.2 EUR/MWh for Italy. The reason for this can be that neither Italy nor Germany have the same access to flexible hydro production as the Nord Pool area has. As explained in Section 4.3.5, hydro reservoirs have the possibility to store electricity. This enables them to have a flexible production by producing when it is not windy, or closing the sluices and importing excess wind power from neighbouring bidding areas during windy times. The price fall in Nord pool from increased wind power will be smaller than if hydro reservoirs were not able to adjust their production. Hence, a large share of flexible power generation in the power system will *ceteris paribus* dampen the effect of increased wind power on the spot price. The lower coefficient in Model 1 compared to Cludius et al. [4] and Clò et al. [5] is therefore consistent with the theory and our expectations.

In Model 1, we show that we get results in accordance with both theory and previous studies estimating a merit order effect. However, instead of measuring the merit order effect in absolute terms as in Model 1, we argue that estimating the effect of a percentage change in wind production is more useful. Additionally, it takes into account a possible non-linear effect of wind production, as explained in Section 7.1. This result is shown for Model 2 in Table 3, indicating that a 1% increase in wind production decreases the spot price by 2.12 EUR/MWh, supporting a merit order effect. The coefficients for residual production and coal price are very similar to the coefficients in Model 1.

Despite the fact that the results in Model 1 and 2 are in line with our expectations and previous studies, we argue in Section 7.2 that one way of improving the regression models is to include dynamic effects, which is done in Model 3 and 4. This improves the models and enables us to interpret the test statistics.

Model 3 is a very simple ADL model, which includes only the spot and the coal price and lagged values of those variables. Using automatic model selection for Model 3 in PcGive removes the coal price in period $t$, while retaining the lagged coal price with a significant coefficient. This only shows that it does not make any difference to the model whether we include $COAL_t$ or $COAL_{t-1}$, but that if we include both, one of them becomes insignificant. As expected, we get positive and significant coefficients for both the lagged coal and spot price.

Model 4 extends Model 3 by also including residual production, the natural logarithm to wind production, and the lagged values of all the variables. Again automatic model selection does not allow both $COAL_t$ and $COAL_{t-1}$ to be included in the model, and removes the insignificant $COAL_t$. In line with the theory, and our expectations, the coefficient for residual production is positive and significant and the wind variable is negative and significant.

By estimating both Model 3 and 4 we are able to compare the results of the two models and test whether wind power has an effect or not. The significant coefficients for wind and residual production makes it clear that Model 3 is not the best model to explain variations in the spot price, and implies that wind production does indeed have an effect on the spot price.

Models 5 and 6 have a different dependent variable, which gives a different interpretation. Models 5 and 6 estimate the ratio between the spot and coal price. If the ratio is suddenly high, the reason could be very low wind production, which results in high spot prices, even though the coal price is unchanged. Model 5 is a static model run with HAC standard errors, due to autocorrelation in the error term. Model 6 includes dynamic effects by adding lagged values of the dependent variable, wind production, and residual production. The coefficient for wind production is negative and significant, indicating that a larger wind production decreases the ratio between the spot and coal price, which is in line with our expectations. The opposite applies for residual production, which increases the gap between the two prices by a positive coefficient. This shows that the results in Models 1-4 are also robust to this transformation of the dependent variable.

Due to the lagged values of the variables, Models 4 and 6 are better dynamically specified than the static models. However, we still find heteroskedasticity in the error terms and run the regressions using White's standard error. Because of the dynamics of the models, interpretation of the estimates in ADL models are in general complicated, and the coefficients in Table 3 only reflect the short run effects in one period. Therefore, we will not go further into detail with the interpretation of the specific coefficients in Table 3. However, an advantage of ADL models is that long run solutions of the models, taking all dynamic effects into account, can be calculated from the estimates of the original model, as shown in Equations (31) and (34). The long run solution of a dynamic model gives the long run relationship between the dependent variable and the explanatory variables in a static setting.

## 8.1 Long run solution

**Table 4:** Long run solutions.

| | Model 1<br>SPOT | Model 2<br>SPOT | Model 3<br>SPOT | Model 4<br>SPOT | Model 5<br>SPOT/COAL | Model 6<br>SPOT/COAL |
|---|---|---|---|---|---|---|
| *resPRO* | 0.00051*** | 0.00054*** | | 0.0009*** | | |
| | (4.909e-05) | (5.453e-05) | | (0.0002) | | |
| *COAL* | 2.98*** | 2.46*** | 5.13*** | 5.85*** | | |
| | (0.238) | (0.315) | (0.353) | (0.907) | | |
| *WIND* | -0.0009*** | | | | | |
| | (0.0001) | | | | | |
| *lnWIND* | | -2.12*** | | -7.1*** | -0.19*** | -0.71*** |
| | | (0.299) | | (1.184) | (0.043) | (0.181) |
| *lnresPRO* | | | | | 3.43*** | 3.95*** |
| | | | | | (0.366) | (0.660) |

Notes:
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The test statistics and p-values can not be used for Model 1 and 2 as we do not know the distribution of the standard errors

The long run solutions of Models 1-6 are listed in Table 4. For the static models (Models 1, 2, and 5), the results are the same as in Table 3, but for the dynamic models, the long run solutions differ from the short run solutions in Table 3. All coefficients in Models 3, 4, and 6 are significant on a 1% level. All coefficients in Model 3 and 4 change significantly compared to those from Model 1 and 2. This indicates that the static models do not represent the DGP very well.
Although Model 3 is not chosen as the best model to explain variations in the spot price, the results in Table 3 and Table 4 indicate that there is both a short and long run relationship between the spot and coal price.
The results for the long run solution of Model 4 show that a 1% increase in wind production decreases the spot price by 7.1 EUR/MWh. Additionally, an increase of 1 GWh in residual production increases the spot price by 0.9 EUR/MWh. As expected, the coal price has a positive effect on the spot price, and an increase of 1 EUR/MWh in

the coal price increases the spot price by 5.85 EUR/MWh. This coefficient can seem a bit high, but is consistent with results from Model 3.

The coefficient −7.1 for the wind variable in the long run solution of Model 4 in Table 4 can be interpreted as the merit order effect, as explained in Section 4.3.7. The negative and significant coefficient are consistent with the theory. However, Gelabert et al. [3] argue that the merit order effect is not only the decrease in the spot price as a result of more wind, but the effect on the spot price from a switch between energy sources. The reason is that power demand is fixed, so increased wind power will substitute more expensive power producers due to the merit order principle of the supply curve. As the marginal effect of residual production in the spot price is positive, this coefficient needs to be subtracted in order to take into account the decreased residual production produced under increased wind production.
As we examine the wind variable in percentage and the residual production in absolute terms, we are not able to calculate the average effect of a switch between energy sources as seen in Gelabert et al. [3], but only the marginal effect of an increase in wind production, which we continuously will refer to as the merit order effect.

The long run solution of Model 6 is also shown in Table 4. The dependent variable in this model is the ratio between the spot and coal price; namely how much the spot price deviates from the coal price. We find that an increase of 1% in wind production decreases the ratio by 0.71, i.e. reducing the ratio between the spot and coal price. This means if the ratio is 4, a 1% increase in wind would make the ratio fall to 3.29. An increase of 1% in residual production increases the ratio by 3.95, thus bringing the spot and coal price further away from each other. There is a significant change in the coefficients of wind power from Model 5 to Model 6, again indicating that the static model does not represent the DGP.

Summing up: after improving the regression model from Model 1 to Model 4, by including dynamic specifications and taking the natural logarithm to the wind variable, it is not straight forward to compare the results in Table 4 directly with the results from existing literature.
However, including dynamic effects enables us to use the test-statistics, and the results of Model 4 are still consistent with results from previous literature in that we also find a negative and significant effect from increased wind power production on the electricity prices. Furthermore, previous studies by Cludius et al. [4] and Clò et al. [5] also find a positive effect of both demand and fuel costs on prices. So, although we cannot directly compare the size of the effect, we consistently find a merit order effect as both theory and previous literature predicted.

The long run solution of Model 6 has, as expected, a negative and significant coefficient for wind and a positive and significant coefficient for residual production. However, the interpretation of the merit order effect is complicated when considering the ratio between spot and coal price. Here Model 4 provides a more intuitive interpretation of how increased wind production affects the spot price. Furthermore, the models in previous literature all use the spot price as the dependent variable when estimating the merit order effect. Therefore, we will now proceed by focusing on the results from Model 4.

The merit order effect of -7.1 EUR/Mwh can reflect both increased wind power production and capacity. A new wind farm, called Vesterhav Syd Havmøllepark, is currently under construction in Western Jutland, extending the total wind capacity by nearly 200 MW [46]. This means that the park can maximally produce 200 MWh with optimal wind conditions. Hence, with the estimated merit order effect of increased wind power in the spot price from Model 4, the effect from this specific wind mill park can be calculated.
In 2017, the highest daily average of wind production was around 10,000 MWh. We assume that this is very close to the total maximum wind power capacity in Nord Pool today. The average daily price on that specific day was 27,7 EUR/MWh. In a scenario like that, where all wind power capacity is utilized, the new wind farm, with a capacity of 200 MW, would increase capacity by 2%. If we assume that all capacity of the new wind farm is also fully utilized, and there is no transmission constraints, the total wind production would then be 10,200 instead of 10,000. The 2% increase in wind production would, according to the estimated merit order effect, decrease the spot price by 14.2 EUR/MWh, and the spot price would fall to 13.5 EUR/Mwh, corresponding to a price fall of 51%.
In a less windy scenario, where the total wind production is lower, the new windmill park would probably not be able to produce at its maximum capacity. This would imply that a 2% change in capacity would correspond to a lower absolute change, and the corresponding effect on the price would be lower.

However, the results of the long run solution of Model 4 appear to be sensitive to whether a trend is included or not. So far we have not included a trend in the model, as it becomes insignificant. If we include a linear trend anyway, the effect from both the coal price and wind production in Table 4 decreases. There is a risk of multicollinearity by including both the wind variable, characterized by an increasing trend, and a linear trend in the model. If a linear trend is included, there is a risk that the negative relationship between wind production and the spot price is captured by the

linear trend and not by the increase in the wind variable. Hence, by removing the linear trend, the increasing trend in the wind variable gets more power in explaining the decreasing spot price, and the effect of the wind variable increases. However, even when including a linear trend, the effect of wind production is negative and significant with a coefficient of -4.8, still supporting a merit order effect.
This implies that if a trend is included in the model, the effect of the new wind farm Vesterhav Syd Havmøllepark would be smaller when the capacity is fully utilized. In this scenario, the daily average price would fall from 27,7 to 18,1 EUR/MWh, corresponding to a price fall of 35%. As the result is sensitive to this change it is difficult to establish any specific merit order effect in the case of Vesterhav Syd Havmøllepark, although one can get an idea of an expected decrease in the spot price as a result of increased wind power capacity.

## 8.2 Extended models

The results that we have found for all the models in Sections 7.1 and 8 are all consistent with theory and previous literature in terms of sign and significance. However, the results are sensitive to inclusion of a trend. We will now make some extensions to Model 4, testing different variations of the wind variable and hence the robustness of our results[8].

### 8.2.1 Non-linear effect of wind power

As explained in Section 7.1, we do not expect wind power to have a linear effect on the spot price in terms of absolute changes. In Models 2 and 4, we took the natural logarithm to the wind variable to overcome this absolute non-linearity and interpret the effect of percentage changes. Another way of estimating the effect of percentage changes in wind power is by including the variable wind penetration, instead of the logarithm of wind production. We will now do that to see if the same results are obtained. We calculate wind penetration as the ratio between wind production and total production:

$$WIND\_PEN_t = \frac{WIND_t}{TOTALPRODUCTION_t}, \tag{35}$$

where total production is a measure of total demand. Ketterer [8] argues that the combination between power demand and wind production is particularly important,

[8]All following models are run in PcGive using automatic model selection.

**Table 5:** Results of extended models.

| | Model 4 SPOT | Model 4a SPOT | Model 4b SPOT | Model 4c SPOT |
|---|---|---|---|---|
| $resPRO_t$ | 0.0007*** | | 0.0007*** | 0.0007*** |
| | (2.853e-05) | | (2.892e-05) | (2.835e-05) |
| $lnWIND_t$ | -0.66*** | | -0.56*** | -0.53*** |
| | (0.091) | | (0.095) | (0.089) |
| $SPOT_{t-1}$ | 0.97*** | 0.95*** | 0.96*** | 0.959*** |
| | (0.007) | (0.008) | (0.008) | (0.007) |
| $resPRO_{t-1}$ | -0.0006*** | | -0.0006*** | 0.0007*** |
| | (2.874e-05) | | (2.893e-05) | (2.790e-05) |
| $COAL_{t-1}$ | 0.19*** | 0.20*** | 0.20*** | 0.13** |
| | (0.051) | (0.042) | (0.050) | (0.043) |
| $lnWIND_{t-1}$ | 0.43*** | | 0.46*** | 0.41*** |
| | (0.093) | | (0.094) | (0.093) |
| $WIND\_PEN_t$ | | -0.48*** | | |
| | | (0.017) | | |
| $WIND\_PEN_{t-1}$ | | 0.42*** | | |
| | | (0.017) | | |
| $WQ4_t * lnIWND_t$ | | | -0.06*** | |
| | | | (0.012) | |
| $CQ4_t * lnWIND_t$ | | | | -0.64*** |
| | | | | (0.171) |
| $CQ4_t$ | | | | 4.99*** |
| | | | | (1.400) |
| Weekday dummies | YES | YES | YES | YES |
| Monthly dummies | YES | YES | YES | YES |
| Yearly dummies | YES | YES | YES | YES |
| Outliers | 26 | 32 | 24 | 25 |
| Trend | NO | NO | YES | NO |
| Standard error | White | White | White | White |
| Log-likelihood | -3540.49 | -3727.49 | -3556.76 | -3544.1 |
| AIC | 1.087 | 1.30 | 1.11 | 1.09 |
| HQ | 1.128 | 1.35 | 1.14 | 1.13 |
| N | 1823 | 1823 | 1823 | 1823 |

Notes:

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

because the ratio shows the effect of wind production relative to the level of demand. The wind penetration variable replaces wind production and residual production in Model 4, which becomes:

**Model 4a:**

$$SPOT_t = \delta + \theta_1 SPOT_{t-1} + \beta_0 WIND\_PEN_t + \beta_1 WIND\_PEN_{t-1} + \gamma_0 COAL_t + \gamma_1 COAL_{t-1} + \alpha D_t + \kappa t + \epsilon_t. \quad (36)$$

The short run results of Model 4a are shown in Table 5. The coefficients are very consistent with the results from Model 4, suggesting that the model is robust to this transformation of the wind variable. We still see a positive effect from the coal price on the spot price, and a larger share of wind power seems to decrease the spot price, indicating a merit order effect.

**Table 6:** Long run solutions of extended models.

| | Model 4 | Model 4a SPOT | Model 4b SPOT | Model 4c SPOT |
|---|---|---|---|---|
| $resPRO$ | 0.0009*** | | 0.0006*** | 0.0006** |
| | (0.0002) | | (0.0001) | (0.0002) |
| $COAL$ | 5.85*** | 4.223*** | 4.688*** | 3.091*** |
| | (0.907) | (0.290) | (0.788) | (0.565) |
| $lnWIND$ | -7.1*** | | -2.326* | -2.928*** |
| | (0.0001) | | (1.136) | (1.116) |
| $WIND\_PEN$ | | -1.462*** | | |
| | | (0.280) | | |
| $WQ4 * lnWIND$ | | | -1.278*** | |
| | | | (0.322) | |
| $CQ4 * lnWIND$ | | | | -15.599*** |
| | | | | (3.587) |
| $CQ4$ | | | | 122.210*** |
| | | | | (29.15) |

Notes: Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The long run solution of Model 4a is shown in Table 6. The long run relationship between the coal price and the spot price does not change significantly from Model 4, and the wind penetration coefficient is negative and significant as expected. It is, however, much smaller than the coefficient of the wind variable in Model 4. The size of the coefficient might seem slightly more realistic, suggesting that wind penetration could be a better variable capturing the effect of increased wind power. We find that an increase of 1 percentage point in the share of wind production out of total production will decrease the spot price by 1.46 EUR/MWh. The result is very similar to Ketterer [8], who finds that an increase of 1 percentage point in wind penetration will decrease the German spot price by 1.49 EUR/MWh.

Apart from the possible non-linear effect of absolute changes in wind production, one might think that the effect of percentage changes could also be characterized by non-linearity relative to the absolute size of wind production at a specific time. To capture this effect we calculate quartiles of wind production and include them in Model 4. The quartiles will enable us to estimate and interpret the merit order effect in the different quartiles of wind production. This is done by including dummies for the different quartiles of wind production, and interaction terms of quartile dummies and the wind variable.

**Model 4b:**

$$\begin{aligned} SPOT_t = \delta + \theta_1 SPOT_{t-1} + \phi_0 resPRO_t + \phi_1 resPRO_{t-1} \\ + \beta_0 lnWIND_t + \beta_1 lnWIND_{t-1} + \gamma_0 COAL_t + \gamma_1 COAL_{t-1} \\ + \beta_2 WQ2_t \cdot lnWIND_t + \beta_3 WQ3_t \cdot lnWIND_t + \beta_4 WQ4_t \cdot lnWIND_t \\ + \beta_5 WQ2_t + \beta_6 WQ3_t + \beta_7 WQ4_t + \alpha D_t + \kappa t + \epsilon_t \end{aligned} \tag{37}$$

The quartile dummies of wind production are included as WQ2, WQ3, WQ4 with WQ1 as reference. The result of Model 4b is shown in Table 5. Again, we find consistent coefficients for the coal price, wind, and residual production compared to those from Model 4 in Table 3. The dummies for the different quartiles of wind production all turn out insignificant when running the model. This suggests that being in a period with high wind production does not in itself affect the level of the spot price. However, the interaction term capturing a dummy for the fourth quartile of wind production and the natural logarithm becomes negative and significant. This indicates that the marginal effect of a percentage change in wind production is not linear, and that the effect of 1% more wind production on the spot price is higher when wind production is high.
When looking at the long run solution of Model 4b, in Table 6, we see that compared to the first three quartiles of wind production, being in the fourth quartile contributes to an additional effect of −1.28 EUR/MWh for a 1% increase in wind production. Thus,

the total effect of a 1% increase in wind production in the fourth quartile of wind production is a decrease of 3.6 EUR/MWh in the spot price. Again this effect is lower than when calculating the average effect in Model 4, supporting our suspicion that the coefficient in Model 4 seems too high.

When wind production is high, a 1% increase corresponds to a higher absolute change, leading to a larger decrease in the price. The result could indicate that wind generators only become price setters if wind production is in the fourth quartile. Due to the merit order structure of the supply curve, a jump appears when the price setting plant goes from being a coal or hydro plant to being a wind power generator. This could explain why the effect of a marginal percentage increase in wind production could be the last straw causing a downward jump in the price.

The result of Model 4b makes it clear that the level of demand or total consumption, and not necessarily the level of wind production, is crucial for catching a non-linear effect of wind production on the spot price. In the next section, we will therefore attempt to capture the non-linear effect by modelling the effects of wind power on the spot price during different levels of consumption.

### 8.2.2 Merit order effect during peak vs. off-peak

When the demand is high, the price is determined by power producers with high marginal costs, and when the demand is low, the price is determined by renewable energy sources with low marginal costs. Therefore, we expect that the size of the merit order effect differs between times with high and low demand, so called peak and off-peak. Specifically, we expect wind power to give a higher merit order effect during times with peak demand, i.e. a stronger negative impact on the spot price. This is because low cost wind power will substitute more expensive power generators in a peak period [3]. We include dummies for different quartiles of consumption and interaction terms with the dummies and the wind variable in the model.

**Model 4c:**

$$\begin{aligned} SPOT_t = \delta + \theta_1 SPOT_{t-1} + \phi_0 resPRO_t + \phi_1 resPRO_{t-1} \\ + \beta_0 lnWIND_t + \beta_1 lnWIND_{t-1} + \gamma_0 COAL_t + \gamma_1 COAL_{t-1} \\ + \beta_2 CQ2_t \cdot lnWIND_t + \beta_3 CQ3_t \cdot lnWIND_t + \beta_4 CQ4_t \cdot lnWIND_t \\ + \beta_5 CQ2_t + \beta_6 CQ3_t + \beta_7 CQ4_t + \alpha D_t + \kappa trend + \epsilon_t. \end{aligned} \tag{38}$$

The quartile dummies of consumption are included as CQ2, CQ3, CQ4 with CQ1 as reference. The short run results of Model 4c are shown in Table 5. The coefficients for the coal price, residual production, and wind production are again consistent with those of Model 4 in Table 3, with positive and significant coefficients for $COAL_t$ and $resPRO_t$, and a negative and significant coefficient for the wind variable. Only the fourth quartile of consumption becomes positive and significant, indicating that when demand is high, the level of the spot price is generally high as well. The coefficient of the interaction term with the wind variable and the fourth quartile of consumption is negative and significant. This indicates, as expected, that when the consumption is high, a marginal percentage increase in wind production will have a stronger effect on the spot price relative to times with lower consumption.
However, when looking at the long run solution of Model 4c in Table 6, the coefficients for the fourth quartile dummy and the interaction term seem unreasonably high. In the long run, the total effect of a 1% increase in wind production during peak times will cause a decrease in the spot price of 18.5 EUR/MWh. In the three lower quartiles the spot price decreases by 2.9 EUR/MWh when wind production increases by 1%. Despite the high coefficients, we notice that the sign and significance level is in line with our expectations and theory.

# 9 Volatility of the Nord Pool spot price

Until now we have looked at the level of the spot price, and how this level is affected by increasing wind production. We will now direct our attention towards the volatility of the spot price, and how it is affected by an increased wind production. As shown in Section 8, increased wind production tends to lower the spot price, and it is obvious to expect that it will also have an affect on price volatility. As we move towards a more renewable energy system, it is crucial for investors, power companies and regulators, not only to understand the changes in price levels, but also how the uncertainty of wind power affects the price volatility.

Previous literature examining price volatility in Germany and Denmark, such as Rintamäki et al. [6], Mauritzen [7], and Ketterer [8], have found that the daily price volatility will decrease as wind power increases. However, they find that wind power increases long term price volatility on weekly or monthly periods. The argument for the decreasing daily volatility is that wind power results in a lower average daily price in general, and hence also at peak times. The lower peak prices will possibly decrease investment in production suitable for peak times, due to a lower expected pay off. If less peak generation is built based on the price signals, when the wind is not blowing at peak hours a larger wind penetration in the generation mix could increase volatility in the long term, by causing large price spikes and stress [7].

Electricity price volatility will in general affect the profitability of conventional power plants [6]. A low and volatile spot price will make it more risky to invest in new capacity, which could delay the transformation to a more CO2 neutral energy system [8]. Furthermore, it could threaten the stability of the power system as a whole. Thus, to prevent a higher price volatility and deal with the uncertainty of wind production, flexible production such as gas fired plants, improvement of transmission capacity, flexible energy use, and more adjustable markets are required in the future [6].

Transmission flows can also affect price volatility. For instance, transmission capacities makes it possible for Norwegian and Swedish hydro reservoirs to exploit the increased volatility, by closing the sluices and importing energy from Denmark when it is windy, hence functioning as large batteries for less windy times. This mechanism will *ceteris paribus* dampen the effect of wind power on the spot price, as explained in Section 8. This will also, in principle, decrease the overall price volatility in Nord Pool. However, if transmission capacities are fully utilised, increased wind power will still lead to increased volatility. This sums up the importance of transmission capacities on the price volatility. The hydro reservoirs' dampening effect on the volatility in Nord Pool implies that decreasing daily volatility from wind production is not found in power exchanges with less hydro power, such as Germany [6].

Because of the relatively large consequences of volatility in the electricity price explained above, it is important to test how more wind power in Nord Pool has affected the price volatility in both the long and short therm.

In the following sections, we will go through different methods of modelling volatility. We will introduce the method of GARCH and ARMA. To begin with we will introduce theory of GARCH models; we will then extend Model 4 from Section 7.2 to include ARCH effects. We will discuss the implications of modelling volatility using the GARCH method and discuss an alternative method, ARMA, which is a method to model realized volatility, introduced in Section 5.4. We will present theory of ARMA models and examine realized volatility on a daily and weekly basis.

## 9.1 GARCH-X volatility models

One feature of financial data is that there often seems to be a trade-off between mean and variance. This trade-off could very well be present in the case of Nord Pool's spot price. Furthermore, data could be expected to have volatility clustering, i.e. a high probability of a shock or deviation from the expected value of the spot price in period $t$, after a shock to the price in period $t-1$. When the variable is characterized by a non-constant variance it is said to be heteroskedastic, as explained in Section 6.1.2. One method of dealing with time varying heteroskedasticity is to build an autoregressive conditional heteroskedasticity, or GARCH model [40].

Equations (39) and (40) show the GARCH($p,q$)-X model:

$$y_t = x_t'\theta + \epsilon_t \tag{39}$$

$$\sigma_t^2 = \omega + \sum_{j=1}^{p} \alpha_j \epsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \psi x_t, \tag{40}$$

where $\epsilon_t = \sigma_t z_t$ and $z_t$ is identically and independently distributed for all t, with mean zero and a variance of one. Equation (39) represents the mean equation of the GARCH model, and Equation (40) is the variance equation. To ensure that the variance is always positive, the conditions $\alpha_i$, $\beta_j >= 0$ and $\omega > 0$ must be fulfilled [8]. To ensure stationarity, $\sum_{j=1}^{p} \alpha_j + \sum_{j=1}^{q} \beta_j < 1$ must be fulfilled.
The GARCH model is an extension of the ARCH model by inclusion of lags of the variance and potentially other explanatory variables, $x_t$, in the variance equation. In Equation (40), the estimation of $\psi$ measures the effect from a change in an explanatory variable, $x_t$, for example wind power, on the variance of $SPOT_t$. The GARCH model is estimated by maximum likelihood, which requires a distribution on $z_t$. Normality can be assumed, i.e. $z_t \sim N(0,1)$, as done by Ketterer [8]. Other distributions can also be used; for example the student t(v) distribution that is commonly used because of its fat tails, compared to the normal distribution [47].

In Section 8, we examined Model 4 to explain the effect of wind power on the spot price. However, the model exhibited ARCH effects, which suggests running Model 4 from Equation (30) as a GARCH model, in order to model volatility in the spot price. We therefore insert wind power as an explanatory variable in the variance equation to estimate if wind power affects the volatility of the spot price. Again we include seasonal dummies (yearly, monthly, and daily), and dummies for Latvia and Lithuania. As found in the results of Model 4, only one of the variables $COAL_t$ or $COAL_{t-1}$ becomes

significant. We choose to include the coal price in period $t-1$, as it is more significant than $COAL_t$ in Model 4.
The GARCH models differ from Model 4 in that we did not take ARCH and GARCH effects into account, and the conditional variance of $SPOT_t$ was assumed to be constant. In Models 7 and 8 we allow for a non-constant conditional variance, $\sigma_t^2$. The same dataset from Nord Pool [9] and Syspower [1] that was used in the analysis of the merit order effect is used here.

**Model 7:**

$$SPOT_t = \delta + \theta_1 SPOT_{t-1} + \phi_0 resPRO_t + \phi_1 resPRO_{t-1} + \gamma_0 COAL_{t-1} + \beta_0 lnWIND_t + \beta_1 lnWIND_{t-1} + \alpha D_t + \epsilon_t \quad (41)$$

$$\sigma_t^2 = \omega + \sum_{j=1}^{p} \alpha_j \epsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \psi lnWIND_t. \quad (42)$$

To begin with we run Model 7 with multiple ARCH and GARCH lags, but the Akaike Information Criterion (AIC) suggests that ARCH and GARCH lags above one worsen the model. We regress the model with 1 ARCH and 1 GARCH lag, as done by Ketterer [8], who chose the number of lags in the variance equation based on minimising the Bayesian Criterion. We run the model using PcGive, estimating Model 7. The dummies are removed one by one, starting with the most insignificant, i.e. following the method of general-to-specific when eliminating dummies [45].
We estimate a non-normal error distribution, which is better for fat-tailed distributions. In Section 5.1 we explained how power prices are characterized by spikes. We therefore use the student t(v) distribution, where the degrees of freedom $v$ are estimated, indicating how fat the tails are [47].
In PcGive we impose stationarity by enforcing $\sum_{j=1}^{p} \alpha_j + \sum_{j=1}^{q} \beta_j < 1$. The coefficient of the wind variable must also be positive to ensure that $\sigma_t^2$ is always positive. As we want to estimate the wind coefficient for our specific dataset, and not use the results for forecasting, it is sufficient for us to check if the conditional variance is always positive, as argued by Ketterer [8].

As a robustness check we replace $lnWIND$ and $resPRO_t$ with wind penetration, $WIND\_PEN$, i.e. the ratio of wind power to total production, as an explanatory variable in both the mean and variance equation of Model 7. Ketterer [8] argues that, besides wind power production, another critical factor for price determination is the demand of power, which is why a combination of the two in $WIND\_PEN$ could affect the price and its volatility [8]. Additionally, the long run solution of Model 4a in Section 8.2 indicated that wind penetration might be a better variable to capture the effect of increased wind power. As with Model 7, Model 8 is run by PcGive, which estimates a non-normal error distribution and imposes stationarity. The final model is determined by the general-to-specific approach, leading to:

**Model 8:**

$$SPOT_t = \delta + \theta_1 SPOT_{t-1} + \gamma_0 COAL_{t-1} + \beta_0 WIND\_PEN_t + \beta_1 WIND\_PEN_{t-1} + \alpha D_t + \epsilon_t \quad (43)$$

$$\sigma_t^2 = \omega + \sum_{j=1}^{p} \alpha_j \epsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \psi WIND\_PEN_t. \quad (44)$$

### 9.1.1 Results of GARCH-X volatility models

Table 7 shows the results of the GARCH models 7 and 8, as well as the results of Model 4 from Section 8. The results of the mean equation of Model 7 show coefficients consistent with those for Model 4, suggesting that taking ARCH effects into account does not change the coefficients significantly. Similar to Model 4, the coefficient for the wind variable is negative and significant, showing that an increase in wind production decreases the spot price. This again confirms the finding of a merit order effect in Section 8 and in several previous studies as Gelabert [3], Cludius et al. [4], and Clò et al. [5]. The coefficients for both residual production and the coal price are positive and significant, which is also in line with theory. However, the coal price is only significant on a 5% level.

Looking at the variance function of Model 7, we find that the variance parameters $\alpha_1$ and $\beta_1$ are both positive and significant, and their sum is smaller than one, ensuring stationarity. $\alpha$ and $\beta$ represents the impact of new shocks and the persistence of past shocks [8]. The wind variable $\psi$ is not, however, significant, indicating that a change in wind production does not affect the daily volatility of the spot price.

Model 8 is similar to Model 7, but the wind variable is now characterized by wind penetration, i.e the ratio of wind production to total production. This transformation changes the significance of the coal price, which is now significant on a 1% level. The results of the variance equation does not change. The coefficient of wind penetration is still insignificant. This result is not in line with previous literature studying how wind

**Table 7:** Results for GARCH-X models.

| | Model 4 SPOT | Model 7 SPOT | Model 8 SPOT |
|---|---|---|---|
| *Mean equation* | | | |
| $SPOT_{t-1}$ | 0.97*** (0.007) | 0.98*** (0.004) | 0.97*** (0.005) |
| $lnWIND_t$ | -0.66*** (0.091) | -0.44*** (0.055) | |
| $lnWIND_{t-1}$ | 0.43*** (0.093) | 0.31*** (0.050) | |
| $resPRO_t$ | 0.0007*** (2.853e-05) | 0.0005*** (3.105e-05) | |
| $resPRO_{t-1}$ | -0.0006*** (2.874e-05) | -0.0005*** (3.083e-05) | |
| $COAL_{t-1}$ | 0.19*** (0.051) | 0.05* (0.026) | 0.10*** (0.028) |
| $WIND\_PEN_t$ | | | -0.35*** (0.013) |
| $WIND\_PEN_{t-1}$ | | | 0.31*** (0.012) |
| Trend | NO | NO | NO |
| Seasonal dummies | YES | YES | YES |
| *Variance equation* | | | |
| $Constant$ | | 0.66 (0.587) | 0.50** (0.160) |
| $\alpha_1$ | | 0.50*** (0.042) | 0.46*** (0.057) |
| $\beta_1$ | | 0.50*** (0.042) | 0.54*** (0.057) |
| $lnWIND_t$ | | -0.03 (0.074) | |
| $WIND\_PEN_t$ | | | -0.004 (0.019) |
| Student-t df | | 3.27*** (0.214) | 3.24*** (0.188) |
| log likelihood | -3540.5 | -3242.9 | -3521.7 |
| AIC | 1.09 | 3.59 | 3.88 |
| N | 1823 | 1823 | 1823 |
| Standard errors | White | Robust | Robust |

Notes:

Standard errors in parentheses

$^{a}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

power affects volatility in the electricity price. Ketterer [8] and Rintamäki [6] find that increased wind production increases daily price volatility in Germany, whereas Mauritzen [7] and Rintamäki [6] find that an increased wind production decreases daily price volatility in Denmark.

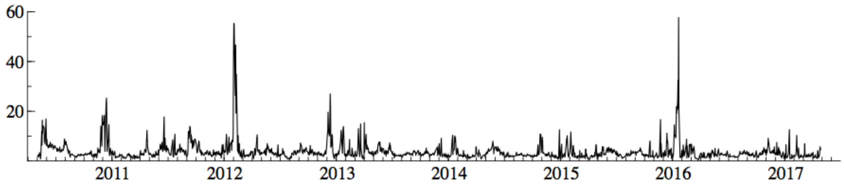
The estimation of degrees of freedom in the student's t distribution is 3.27 and 3.24 in Models 7 and 8, respectively. Both degrees of freedom are very low, indicating many extreme observations in the dataset. This is consistent with the stylized fact of spikes that characterizes electricity prices, as described in Section 5.1. In Models 7 and 8 we did not include dummies for large outliers, as done in Model 4, instead the low estimates of degrees of freedom seem to capture the outliers in the spot price.

As we look at the whole Nord Pool area and volatility in the system price, access to flexible hydro production and the large share of wind energy in Denmark and parts of Sweden could explain why our results differ from those in the literature.
As argued by both Mauritzen [7] and Rintamäki [6], wind production decreases the spot price, especially during peak hours. This should in principle make the daily volatility more smooth and imply a decrease in volatility as a result of more wind power. They find this for the area prices DK1 and DK2 in Denmark. For Germany, Ketterer [8] and Rintamäki [6] find the opposite result; wind production increases daily volatility.

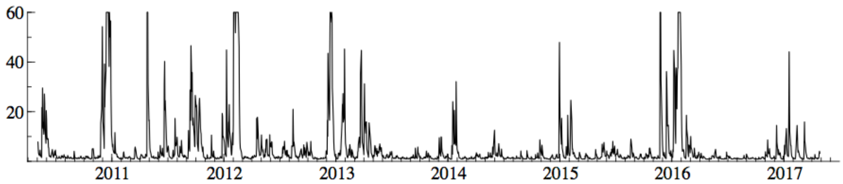
Germany and Denmark differ from the whole Nord Pool area in different ways. Germany does not have the same access to flexible hydro production the countries in Nord Pool have. This can explain why wind power seems to increase daily price volatility in Germany. When flexible hydro reservoirs are not present, the electricity price is much more sensitive to whether it is windy or not, which increases volatility.
Denmark has a very large share of wind energy: more than 40 % of total Danish power production [1]. Hence, it is reasonable to assume that the dampening effect on electricity prices from an increased wind production is larger in DK1 and DK2 than for the Nord Pool system price, where wind production accounts for a much smaller share of the total production. Furthermore, transmission capacities has a larger effect on the area prices than on the Nord Pool spot price. This could also explain why we do not find that wind power decreases daily price volatility in the Nord Pool spot price.
However, a more likely explanation is that the GARCH-X model is not the best way to model volatility in the spot price.

Figures 12a and 12b illustrate daily realized volatility from Equation (2) and conditional variance from Model 7, respectively. The figures show that the estimated $\sigma_t^2$

from Model 7 captures the variations in the realized volatility, but the models overestimate the volatility, especially in periods of high volatility. Additionally, extreme values above 60 of the estimated conditional variances from Model 7 are set to 60 for comparison with realized volatility in Figure 12a, which implies an even larger overestimation of $\sigma_t^2$ in Model 7 compared to realized daily volatility. Therefore, we will now build four models to explain the realized volatility, as another method to examine whether the increased wind production has an effect on spot price volatility. By modelling the realized volatility instead of the estimated conditional variance it is also possible to include weekends in the data, as the model is no longer dependent on the coal price. This adds accuracy to the model as more information is included.




**(a)** Realized volatility of daily average spot price based on Equation (2).




**(b)** Estimated conditional variance $\sigma_t^2$ from Equation (42) in Model 7.

**Figure 12:** Realized and estimated volatility 2010-2017. Extreme values above 60 of the estimated conditional variances from Model 7 are set to 60 for comparison with realized volatility in Figure 12a. This change is done 33 times in Figure 12b.

## 9.2 ARMA models for realized volatility

In this section we model a number of general autoregressive, moving average (ARMA) models of the realized volatility. The general ARMA model with p autoregressive lags, q lags of moving-average, and explanatory variables $x_t$ is written as [35]:

$$y_t = \delta + \sum_{i=1}^{p} \theta_i y_{t-i} + \epsilon_t + \sum_{j=1}^{q} \alpha_j \epsilon_{t-j} + \psi x_t. \tag{45}$$

In this equation, the dependent variable, $y_t$, can be different measures of volatility, for instance daily or weekly. The dynamics of an ARMA model are useful, as we expect volatility clustering. The estimation of $\psi$ in Equation (45) measures the effect from a change in an explanatory variables, $x_t$, for instance wind power on realized volatility. Equation (45) can be consistently estimated by maximum likelihood or non-linear least squares (NLS) [35]. Due to computational time, we estimate the ARMA models by NLS.

The method of ARMA allows us to model both short and long term volatility. We will start with daily realized volatility, calculated in Equation (2). In Section 9.2.3 we present the ARMA models of volatility in a longer run; weekly realized volatility. The results of the short and long run ARMA models will be presented in Section 9.2.2 and 9.2.4.

### 9.2.1 ARMA model of daily realized volatility

Rintamäki et al. [6] and Mauritzen [7] calculate realized daily volatility based on the formula:

$$lnV_d = ln\left(\sqrt{\frac{1}{24}\sum_{h=1}^{24}(SPOT_h - \overline{SPOT}_d)^2}\right), \quad d = 1, ..., 2552, \tag{46}$$

where $\overline{SPOT}_d$ is the average daily price of day $d$, $\overline{SPOT}_d = \frac{1}{24}\sum_{h=1}^{24} SPOT_h$, and $SPOT_h$ is the spot price of hour h of a given day. We take the logarithm to the daily volatility to get the estimation results in percentages. Rintamäki et al. [6] argue that the relationship between wind production and daily volatility is characterized by a constant elasticity and not in absolute terms. We test stationarity of the logarithm of realized daily volatility by performing an augmented Diskey-Fuller test, and we reject the null hypothesis of a unit root on a 1% significance level. Now, we build the model with $lnV_d$ as our dependent variable, which we regress on its past, a moving average, an explanatory variable for wind power, and seasonal dummies.

When building the ARMA model, we need to specify the number of AR lags and the number of MA lags to include in the model. As we are trying to explain daily volatility, a seasonality of 7 is expected, as there are 7 days per week in this dataset. We select the lags based on the autocorrelation (ACF) and partial autocorrelation functions (PACF) of the dependent variable, as done by Rintamäki et al. [6] and Mauritzen [7]. The ACF and PACF of $lnV_d$ are shown in Figure 14 in the appendix. We see a clear trend in both the ACF and PACF function with spikes at 1, 7 and 14 lags, and we start by including all AR and MA lags up to 14. In order to reduce computing time of PcGive and to ensure an outcome of results, we upscale the daily volatility by 10 before taking the natural logarithm.

**Model 9**[9]**:**

$$lnV_d = \delta + \sum_{i=1}^{14} \theta_i lnV_{d-i} + \epsilon_d + \sum_{j=1}^{14} \alpha_j \epsilon_{d-j} + \psi lnWIND_d, \quad d = 1, ..., 2552, \tag{47}$$

where $d$ denotes daily intervals. We run the model using PcGive and use the method of general-to-specific, excluding the insignificant lags in the regression one by one. While removing the lags, we evaluate the models according to AIC, log-likelihood, and the Portmanteau test for no autocorrelation, such that the final model has a minimized AIC, minimized log-likelihood value and no autocorrelation[10]. All seasonal dummies (yearly, monthly, and daily) and a trend are initially included, and we keep the seasonal dummies in the model even if they become insignificant. The reason for this is that the model experiences autocorrelation if seasonal dummies are removed.

The dummies and trend are included in the model as having a one-to-one impact on realized daily volatility, while the explanatory variable, $lnWIND_d$, is modelled as having an innovative impact (as the error terms $\epsilon_j$). Alternatively, $lnWIND_d$ can be modelled as having one-to-one impact as the dummies. We will use the terminology of PcGive when referring to the wind variable being included in the model as either innovative (Z) or one-to-one (X).

Model 9 with $lnWIND_d$ as X becomes:

$$(lnV_d - lnWIND_d \psi) = \delta + \sum_{i=1}^{14} \theta_i (lnV_{d-i} - lnWIND_{d-i} \psi) + \epsilon_d + \sum_{j=1}^{14} \alpha_j \epsilon_{d-j}, \quad d = 1, ..., 2552. \tag{48}$$

We now replace $lnWIND_d$ in Model 9 with $WIND\_PEN_d$ to see if the model can be improved, as done in Section 9.1 with the GARCH-X model. Again, we start with a general model from Equation (45) with 14 AR terms, 14 MA terms, seasonal dummies and the explanatory variable $WIND\_PEN_d$ as Z:

[9]For simplicity, dummies and trend are not contained in the formulas, but they are included in all the ARMA models.

[10]Portmanteau is the default test of PcGive for test of no autocorrelation in ARMA models.

**Model 10:**

$$lnV_d = \delta + \sum_{i=1}^{14} \theta_i lnV_{d-i} + \epsilon_d + \sum_{j=1}^{14} \alpha_j \epsilon_{d-j} + \psi WIND\_PEN_d, \quad d = 1,...,2552. \tag{49}$$

When specifying the model, the method of general-to-specific to select which AR and MA terms to exclude from the model is used. We choose the best model based on minimized AIC, minimized log-likelihood value and no autocorrelation. As with Model 9, we do not remove seasonal dummies if they become insignificant.

As done with Model 9, we now model $WIND\_PEN_d$ as an X variable:

$$\begin{aligned}(lnV_d - WIND\_PEN_d\psi) = \delta + \sum_{i=1}^{14} \theta_i (lnV_{d-i} - WIND\_PEN_{d-i}\psi) \\ + \epsilon_d + \sum_{j=1}^{14} \alpha_j \epsilon_{d-j}, \quad d = 1,...,2552. \end{aligned} \tag{50}$$

### 9.2.2 Results of daily realized volatility

Table 8 shows the results of Models 9 and 10, estimating the daily realized volatility in the spot price as an ARMA model with wind production and wind penetration as explanatory variables, respectively. We first estimate Model 9 and assume that the wind variable has an effect on daily price volatility best captured as having an innovative impact (Z). Next, we estimate the same model, but allow the wind variable to have a one-to-one effect (X). In both models, we remove insignificant AR and MA terms one by one and end up with the lags reported in Table 8. The trend turns out insignificant and is removed from both models.
In both models, the 1st and 7th autoregressive terms become significant, which is also indicated by the ACF function in Figure 14 in the appendix. Apart from those lags, there is no clear tendency that can explain which lags become significant when we make the different modifications to the models. It is worth noting that the coefficient for the wind variables is not affected by the selection of lags; only the information criteria and the portmanteau test statistic change with different lag selection.

Model 9 estimates daily volatility with the natural logarithm of wind as explanatory variable. The coefficient only becomes significant if we include it as having a one-to-one impact (X). The result indicates that an increase of 1% in wind production de-

**Table 8:** Results for realized daily volatility in the spot price.

| | Model 9 | | Model 10 | |
|---|---|---|---|---|
| | $lnV_d$ (Z) | $lnV_d$ (X) | $lnV_d$ (Z) | $lnV_d$ (X) |
| $lnWIND_t$ | -0.016 | -0.09*** | | |
| | (0.011) | (0.016) | | |
| $WIND\_PEN_t$ | | | -0.0055* | -0.017*** |
| | | | (0.003) | (0.003) ) |
| $ARterms$ | 1,3,5,7,9,12,13 | 1,3,5,7,9,12,13 | 1,3,5,7,9,12,13 | 1,2,3,4,5,7,9,11,12,13 |
| $MAterms$ | 1,3,4,5,8,9,12,13 | 2,3,4,5,8,9,12,13 | 1,3,4,5,8,9,12,13 | 1,2,3,4,5,8,9,10,12,13,14 |
| Seasonal dummies | YES | YES | YES | YES |
| Trend | NO | NO | NO | NO |
| Portmanteau test statistic | 0.093 | 0.093 | 0.108 | 0.247 |
| log-likelihood | -1393.93 | -1378.73 | -1392.72 | -1370.74 |
| AIC | 1.125 | 1.113 | 1.124 | 1.112 |
| N | 2552 | 2552 | 2552 | 2552 |

Notes
Standard errors in parentheses
[a] $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The p-value of the Portmanteau test for no-autocorrelation is reported in the table

creases the daily price volatility by 0.09%.

In Model 10, the wind variable is changed to wind penetration. The coefficient becomes negative and significant regardless of whether we include it in the model as having an innovative or one-to-one impact (Z or X), although, the latter is the most significant.

When including the $WIND\_PEN_d$ as X, i.e. having a one-to-one impact, the total effect is

$$\frac{\partial V_d}{\partial WIND\_PEN_d} = \psi = -0.017. \tag{51}$$

That is, a 1% increase in wind penetration leads to a 0.017% decrease in daily volatility.

When the variable is included as having an innovative impact (Z) in Model 10, we need to take into account the innovative effects when calculating the total marginal effect of wind power, given by

$$\frac{\partial V_d}{\partial WIN\_PEN_d} = \frac{\psi}{1-\theta_1-\theta_3-\theta_5-...}. \tag{52}$$

This gives a total effect of $-0.08$, that is a 1% increase in wind penetration leads to a 0.08% decrease in daily volatility. Although this coefficient is higher than the effect of wind power if we assume a one-to-one effect (X), we believe that the best reflection of the DGP is to include the wind variable as X because the result is more significant in both Model 9 and 10.

The negative impact of wind penetration on daily price volatility differs from the results of the GARCH-X models in Section 9.1.1, which find no effect of wind power on estimated daily volatility. However, realized volatility is a more accurate variable than the estimated conditional variance, and the results of the ARMA model are consistent with the findings of Mauritzen [7] and Rintamäki et al. [6], who find decreased short run volatility in the spot price due to a generally lower price level during the day, especially in peak hours. However, they find that wind power increases volatility in the longer term. We therefore estimate weekly volatility.

### 9.2.3 ARMA models for weekly realized volatility

We calculate weekly volatility by the formula:

$$lnV_w = ln\left(\sqrt{\frac{1}{7*24}\sum_{d=1}^{7*24}(SPOT_h - \overline{SPOT}_w)^2}\right), \quad w = 1,...,365, \tag{53}$$

where $\overline{SPOT}_w = \frac{1}{7\cdot 24}\sum_{d=1}^{7\cdot 24} SPOT_h$ is the average price of week $w$, and $SPOT_h$ is the spot price of hour h of a given day. This leaves us with 365 observations of weekly realized volatility. A unit root in weekly volatility is rejected on a 1% significance level. When building the ARMA model of weekly volatility, we do not expect a clear seasonal pattern as we did for daily volatility. Therefore, we include 5 AR lags and 5 MA lags, suggested by plots of ACF and PACF of weekly volatility in Figure 15 in the appendix. Additionally, we include a trend, and yearly and monthly dummies.

The model for weekly realized volatility with $lnWIND_w$ as having an innovative impact (Z) becomes:

**Model 11:**

$$lnV_w = \delta + \sum_{i=1}^{5}\theta_i lnV_{w-i} + \epsilon_w + \sum_{j=1}^{5}\alpha_j\epsilon_{w-j} + \psi lnWIND_w, \quad w = 1,...,365, \tag{54}$$

where $w$ denotes weekly intervals. We remove the lags one by one, starting with the most insignificant, according to the method of general-to-specific. A minimized AIC, minimized log-likelihood value and no autocorrelation is ensured in the final model. As for Models 9 and 10, the seasonal dummies are retained to avoid autocorrelation.

As with daily volatility, we replace $lnWIND_w$ with $WIND\_PEN_w$ in the model for weekly volatility. Again we start by including 5 AR lags and 5 MA lags.

**Model 12:**

$$lnV_w = \delta + \sum_{i=1}^{5} \theta_i lnV_{w-i} + \epsilon_w + \sum_{j=1}^{5} \alpha_j \epsilon_{w-j} + \psi lnWIND\_PEN_w, \quad w = 1, ..., 365. \tag{55}$$

As done in Section 9.2.1 for short run realized volatility models, we also run Models 11 and 12 with the explanatory variables $lnWIND_w$ and $WIND\_PEN_w$, respectively, as having one-to-one impact (X) instead of innovative impact (Z).

### 9.2.4 Results of weekly realized volatility

**Table 9:** Results for realized weekly volatility in the spot price

| | Model 11 | | Model 12 | |
|---|---|---|---|---|
| | $lnV_w$ (Z) | $lnV_w$ (X) | $lnV_w$ (Z) | $lnV_w$ (X) |
| $lnWIND_t$ | -0.043 | -0.087 | | |
| | (0.039) | (0.069) | | |
| $WIND\_PEN_t$ | | | -0.036** | -0.023* |
| | | | (0.013) | (0.011) |
| $ARterms$ | 1,2 | 1,2 | 1,2 | 1,2 |
| $MAterms$ | 1 | 1 | 1 | 1 |
| Seasonal Dummies | YES | YES | YES | YES |
| Trend | NO | NO | NO | NO |
| Portmanteau test statistic | 0.8587 | 0.8401 | 0.7895 | 0.8089 |
| Log-likelihood | -218.07 | -217.88 | -214.38 | -216.38 |
| AIC | 1.3264 | 1.3254 | 1.3062 | 1.3171 |
| N | 365 | 365 | 365 | 365 |

Notes:
Standard errors in parentheses
$^a$ $p < 0.10$, $^*$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$
The p-value of the Portmanteau test for no-autocorrelation is reported in the table

The results of Model 11 and 12 are shown in Table 9. In keeping with Figure 15 in Appendix, only the first two autoregressive lags and the first moving average term become significant in those models. The wind variable in Model 11 becomes insignificant regardless of whether we allow it to have an one-to-one impact, as X, or an innovative impact, as Z. However, when changing the wind variable to wind penetration, in Model 12, the coefficient becomes significant and negative, both when it is included as X and Z. Again we need to calculate the total dynamic effect if it is included as having an innovative impact (Z), given by

$$\frac{\partial V_d}{\partial WIN\_PEN_d} = \frac{\psi}{1 - \theta_1 - \theta_2}. \tag{56}$$

This gives an effect of $-0.048$, which suggests that a 1% increase in wind penetration decreases the weekly realized volatility by 0.048%.

When including the wind variable as having a one-to-ome impact (X) we find that a 1% increase in wind penetration decreases weekly price volatility by 0.023%. Although the effect is relatively small, the result is opposite to both previous literature and expectations. The results in Tables 8 and 9 suggest that Nord Pool does not face the potential challenges of increased wind penetration on price volatility in the long run.
The result that wind power's effect on weekly price volatility differs from previous studies might still be due to the hydro reservoirs dampening the consequences of volatility in wind production.
Another possible reason is that wind power only accounts for 8.3% of total production in the Nordic area [1]. Mauritzen [7] estimates the effect of wind power on price volatility in Denmark, and Rintamäki et al. [6] did the same for Denmark and Germany. As wind power makes up a larger share of total production in both Denmark [1] and Germany [4], it is likely that those areas experience larger effects due to changes in wind production, both in terms of price level and in terms of volatility than we see in our results for the Nord Pool system price.
It is also worth noticing that Mauritzen [7] and Rintamäki et al. [6] use a different method to calculate weekly volatility. They use average daily price movement over the week; we use hourly price movements over the week.

### 9.2.5 ARFIMA estimation of volatility

Overall, the results of the different specifications of the ARMA models presented in Table 8 and 9 indicate that, with the level of wind production in the Nord Pool area present in the estimation period, increased wind production decreases price volatility. When looking at an autocorrelation function for realized volatility, one would suggest modelling the volatility by an ARMA model, if the convergence of the autocorrelation function to zero was exponential. However, the convergence of the autocorrelation function of daily realized volatility, shown in Figure 14 in the appendix, does not seem to be obviously exponential, but instead slow and persistent towards zero. This suggests that daily volatility in the spot price is characterized by long memory. Hence, it could be relevant to model daily volatility as an ARFIMA model, which will be done in this section. An ARFIMA model is another way of taking the long lag structure of the variable into account, rather than simply including even more lags in the ARMA model. We will see if the results change from Model 10 if we take this long memory into account. The basic ARFIMA model can be written as [48]:

$$\Theta(L)(1-L)^d(Y_t - X_t'\psi) = \alpha(L)\epsilon_t, \quad t,...,T. \tag{57}$$

The difference between ARMA and ARFIMA is that we now estimate the parameter $d$, instead of assuming $d = 0$. The term $(1-L)^d$ is called the fractional difference operator, with the interpretation

$$(1-L)^d Y_t = Y_t - dY_{t-1} + \frac{d(d-1)}{2!}Y_{t-2} - \frac{d(d-1)(d-2)}{3!}Y_{t-3} + ..., \tag{58}$$

such that the process has an infinite memory, ensuring that all relevant dynamics are included in the model, which is basically the same as including infinitely many lags. The variable $d$ can be between 0 and 1, where $d < 1/2$ ensures stationarity of the process. If $d = 1$ the model becomes an ARIMA model with normal first differences [48], [49].

The autocorrelation function for weekly volatility converges much faster towards zero than daily volatility, and does not indicate any long memory in the variable. However, we re-estimate Model 12 to see if the results change when taking the full dynamics of the variable into account.

The results of the ARFIMA models are shown in Table 10, where wind penetration is included in both models as having a one-to-one impact (X). When estimating Model 10 as an ARFIMA model, some of the AR and MA terms become insignificant (reported with parentheses), and are thus captured in the $d$ parameter. This suggests that taking long memory into account improves the model. However, the coefficient of the wind variable does not change from the results in Table 8, so the result of the effect of wind penetration is robust to the different estimation method.

As expected, the results for weekly volatility estimated as an ARFIMA model do not indicate any long memory, as $d$ becomes highly insignificant. The insignificance suggests to remove it and return to the results from the previous ARMA(2,1) model in Table 9. Thus, it does not improve the model to include the $d$ parameter. As for the ARFIMA model of daily realized volatility, neither the significance level or the coefficient size of the wind variable in Model 12 change significantly from the results in Table 9. Thus, we still find that increased wind penetration decreases both daily and weekly price volatility.

**Table 10:** Results of long memory in volatility of the spot price.

| | Model 10 | Model 12 |
|---|---|---|
| | $lnV_d$ (X) | $lnV_w$ (X) |
| $WIND\_PEN_t$ | -0.017*** | -0.029* |
| | (0.003) | (0.011) |
| $dparameter$ | -0.39 | 0.00 |
| | (0.236) | (0.0004) |
| $ARterms$ | 1,(2),3,4,(5),7,9,11,(12),(13) | 1,2 |
| $MAterms$ | (1),2,3,(4),5,8,9,10,(12),(13),(14) | 1 |
| Seasonal dummies | YES | YES |
| Trend | NO | NO |
| Portmanteau test statistic | 0.192 | 0.807 |
| log-likelihood | -1369.27 | -220.42 |
| AIC | 1.11 | 1.34 |
| N | 2552 | 365 |

Notes:
Standard errors in parentheses
$^{a}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$
Insignificant lags are reported in parentheses
The p-value of the Portmanteau test for no-autocorrelation is reported in the table

# 10 Conclusions and policy implications

The increased awareness on climate change in recent decades has launched a political interest in renewable energy sources. Especially the Nordic countries have been pioneers in this area, which has been expressed in terms of political debate, investments, and subsidies related to renewable energy.

This thesis contributes to previous research within the field, studying the effect of increased renewable energy production on electricity prices. We have estimated the effect of increased wind power on the price level and the price volatility in Nord Pool using time series data for the period 2010-2017. Based on an autoregressive distributed lag (ADL) model, we find evidence of the merit order effect in the Nord Pool spot price. Our results suggest that a 1% increase in wind production leads to a decrease of 7.1 EUR/MWh in the spot price if including the variable $lnWIND$ in the model, and a decrease of 1.5 EUR/MWh if including the variable $WIND\_PEN$. Additionally, we find a non-linear effect of wind power both for different quartiles of wind production and consumption.

The size of the coefficients of the wind variables are sensitive to different specifications, which makes it difficult to conclude on the size of the effect. However, all models provide negative and significant coefficients supporting a merit order effect.

We also investigate the impact of wind power on price volatility, and find that a marginal increase in wind penetration in Nord Pool decreases both daily and weekly volatility in the spot price. A 1% increase in wind penetration decreases daily price volatility by 0.017% and weekly price volatility by 0.023%. This is contrary to previous literature, which lead us to expect increased wind power to increase price volatility, at least on weekly basis.

There are some limitations related to our models that could be improved on in further research. We assume that the impact of wind power can be estimated with only a single coefficient; namely wind power production. Other important factors may play a part in determining the effect of wind power on the electricity price, such as political reforms, market situations, capacity etc. Furthermore, as the price on the day-ahead market is determined on the basis of wind forecasts, it might give more accurate results to use wind forecasts as a variable, instead of actual production. We have studied the effect over the whole time period of our dataset, but it may change over time, and it could therefore be informative to estimate the effect in different years. Previous studies have estimated the merit order effect in different years for Germany [4] and Italy [5], concluding that the effect diminishes with increasing wind penetration, but there is still some ambiguity in the results.

There is also a risk of omitted variables in the model. We have, for example, not included a macro variable such as GDP or inflation, which could take into account the overall picture of the economic situation during the period of study. In recession, where demand is generally low in society, it is likely that the demand for electricity, primarily from the industries forced to lower their production, is also lower. Ultimately, it is preferable to have more data available than less, and having access to data for a longer time period could possibly improve the estimated long term effects of wind power.

Evidence of a merit order effect is very useful for policy makers when designing tariffs and making investments in renewable energy. Previous studies compare the estimated price savings with the cost of support schemes and subsidies paid by the final consumer. For Italy and Germany, respectively, Clò et al. [5] and Cludius et al.[4] find that support schemes for wind power are fully covered by monetary savings, due to a decrease in the spot price for both Italy and Germany. This direct comparison for the Nord Pool area is beyond the scope of this thesis, but could be relevant for further studies. However, as we consistently find evidence of the merit order effect in Nord Pool, one might conjecture that the subsidies given in Nord Pool are also at least partly outweighed by monetary savings.

The result is also useful for policy makers' investment decisions in wind power capacity, as the merit order effect both reflects the effect of increased wind power production and capacity. Hence, before investing in new wind farms, the total effect of the increase in wind power capacity can be measured on the basis of the estimated merit order effect, as done in the example of Vesterhav Syd Havmøllepark in Section 8. However, for a total cost-benefit analysis of wind energy one would also need to take into account the construction cost of wind farms, and the maintenance cost related to wind energy in the transmission grid. Therefore, the overall welfare consequences can only be fully analysed when including those factors.

Although our analysis suggests further investment in wind power due to a lower price level and reduced volatility, a general problem of wind power is the non-storing nature. This challenge might increase as the share of wind energy in Nord Pool increases. Currently wind power accounts for 8.3% of total production in the Nordic countries [1], but it is likely that the challenges associated with wind power will appear when the share increases to for example 15% or 20%.
As explained throughout the thesis, a specific advantage of the Nord Pool system relative to other systems is the access to a large share of flexible hydro production. This partly solves the problem, by functioning as a large battery for the whole Nord Pool

area. Thus, hydro reservoirs store energy and import when it is windy in areas with a high share of wind production. When the wind is not blowing, the hydro reservoirs generate power and export. As long as the transmission capacities are large enough, this mechanism can smooth out the volatile wind production. As we find a decreasing price volatility in the system price when wind penetration increases, there is no indication that the transmission capacities meet significant constraints when importing and exporting power between bidding areas with the current level of wind production.

It is important to note that development in wind penetration and transmission capacities must follow each other. It is likely that price volatility of both the system price and area prices would increase if wind production increases without a corresponding increase in transmission capacities, enabling the battery effect to function optimally. Because of this, policy makers have to plan investment in grid improvements and extensions along with investment plans in wind farms. Ultimately, the larger the transmission grid, the higher capacity for wind production in an electricity system. This is because wind power can be distributed more efficiently between areas, reducing the likelihood of negative prices and price volatility. As an example, a 770 km long electricity cable, called the Viking Link, is currently being built between Denmark and the United Kingdom. This will give a more efficient exploitation of wind energy and increase the security of supply [2].
Likewise, the location of wind farms can be an important consideration. By distributing wind farms over different areas in the Nord Pool area, the likelihood for a more constant total wind production increases, as the wind might blow at different times in different areas. If all wind production was located in one place, the impact on price volatility would probably increase. This could also be an explanation as to why we see a different effect in price volatility in the whole Nord Pool area, compared to that which Mauritzen [7] and Rintamäki [6] find for Denmark alone.

An alternative, or addition, to improved power transmission between areas is demand response, also called smart energy. Policy makers can incentivize consumers to use less energy in peak hours and more in off-peak hours, by letting the consumer electricity price vary and reflect price signals. Such an initiative was introduced in Denmark on December 1st 2017, where electricity prices are generally lowered in most hours in the year, but increased to about double in the winter season between 5-8 pm [50].
Technologies such as timers, heat pumps, electric cars, and private solar cells can make demand response possible. With timers, for instance, washing machines can start automatically in off peak hours where wind generators are price setting. Likewise, private actors can take a flexible approach to charging their electric vehicles. Smart energy is

expected to increase the flexibility of power demand, which is normally very inelastic. However, to fully capitalize on the advantages of the technology, large scale pilot studies need to be conducted, for example the vehicle-to-grid initiative reported in [51].

In this thesis we focus on the Nord Pool system price and estimate level changes and volatility in that price. As the system price is only a clearing price, reflecting the total demand and supply, it would be relevant to further study the effect of increased wind power on the different bidding area prices. The share of wind production differs a lot from area to area, and it is very likely that the effect of a marginal change in wind power is related to this share. In DK1, wind production accounts for more than 40% of total energy production [1], and accordingly Mauritzen [7] and Rintamäki [6] find that increased wind power increases long run price volatility in DK1. Hence, it would be interesting to study how the different area prices differ from the system price, and how this deviation is affected by increased wind power.

Along with higher wind penetration, a larger investment in stand-by plants is required as Nord Pool relies more on expensive peak hour production such as gas plants, in peak hours without wind. The associated costs also need to be taken into account when evaluating the economic feasibility of wind power [7].
However, the general development in electricity prices is crucial for investments in different technology. The merit order effect shows that increased wind power leads to a decrease in the electricity price. A generally lower electricity price also implies a lower price in peak hours. Hence, the expected return of investment in production suitable for peak hour generation falls. This will *ceteris paribus* mean decreasing investment in such technology, which could become a challenge for both security of supply and price volatility. Similarly, the feasibility of already existing stand-by plants decreases significantly if the price is so low that they nearly never come into play [52].

In Nord Pool, flexible hydro reservoirs can meet the requirement of stand-by capacity to a certain extent, which also gives the opportunity for hydro producers to largely benefit from this. But despite these obvious advantages, the hydro generation method is also associated with high environmental consequences [26]. When building a dam and corresponding reservoir, there is a risk that it significantly changes the environment in the area: housing may need to be relocated; biodiversity can be threatened, both by filling the reservoir and changing the natural water course; and increased sediment transport will gradually reduce the efficiency of the hydro plant. These potential drawbacks can be mitigated by careful planning when developing new plants, although increased environmental awareness has made the realisation of larger plants more difficult [26]. Thus, even hydro reservoirs have their limits in the longer term.

On a longer time horizon, increased wind production will have implications for the market structure. Forecast errors of wind power gives rise to deviations between bids on the day-ahead market and actual production in delivery hour. Although forecasts are precise, the timing of the day-ahead market is not suitable for a large wind penetration, as forecast errors will have greater significance. Hence, the intraday and balancing power market will become more important, as larger imbalances will occur with larger wind penetration [12]. It will be a focus in the future to include more participants in the balancing power market. To meet the need for a change in the market structure, Ketterer [8] suggests later gate closure on the day-ahead market, or to offer not only hourly but 15 minute electricity blocks, which was realized on the German intraday market in December 11.

In conclusion, according to the data examined in this thesis, wind power seems to both decrease the level and volatility of the Nord Pool system price. Thus, as long as the transmission grid is extended along with wind power extensions, and the market structure is adjusted to cope with increased wind penetration, it seems possible to further exploit the benefits of wind power in Nord Pool in the future.

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# A Appendix

**Table 11:** Descriptive statistics 2010-2013

| | 2010 (N=174) | | 2011 (N=260) | | 2012 (N=261) | | 2013 (N=261) | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. dev | Mean | Std. dev | Mean | Std. dev | Mean | Std. dev |
| SPOT | 53.22 | 13.59 | 47.99 | 14.54 | 32.52 | 12.38 | 39.11 | 5.61 |
| COAL PRICE | 9.35 | 0.93 | 10.73 | 0.40 | 8.84 | 0.55 | 7.55 | 0.42 |
| WIND | 1,333 | 951 | 1,878 | 1,181 | 2,031 | 1,134 | 2,591 | 1,529 |
| CONSUMPTION | 46,334 | 8,965 | 47,341 | 7,852 | 48,064 | 8,162 | 47,499 | 8,162 |
| PRODUCTION | 44,494 | 8,267 | 46,619 | 7,024 | 49,393 | 7,704 | 47,300 | 8,202 |
| NUCLEAR | 8,596 | 1,455 | 9,178 | 1,731 | 9,534 | 1,282 | 9,892 | 1,619 |
| THERMAL | 8,273 | 3,016 | 8,063 | 3,485 | 6,434 | 2,810 | 7,460 | 2,506 |
| HYDRO | 22,826 | 4,168 | 23,797 | 3,822 | 27,722 | 3,783 | 24,259 | 4,538 |

Source: Syspower data [1]

**Table 12:** Descriptive statistics 2014-2017

| | 2014 (N=261) | | 2015 (N=261) | | 2016 (N=261) | | 2017 (N=85) | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. dev | Mean | Std. dev | Mean | Std. dev | Mean | Std. dev |
| SPOT | 30.46 | 4.00 | 21.86 | 7.27 | 27.94 | 7.51 | 31.29 | 3.37 |
| COAL PRICE | 6.96 | 0.31 | 6.26 | 0.47 | 6.69 | 1.95 | 9.16 | 0.78 |
| WIND | 3,065 | 1,674 | 3,977 | 1,953 | 3,661 | 2,015 | 4,955 | 2,060 |
| CONSUMPTION | 46,956 | 7,457 | 47,135 | 6,604 | 48,130 | 8,377 | 54,934 | 4,841 |
| PRODUCTION | 47,861 | 7,705 | 48,376 | 6,260 | 48,385 | 8,259 | 56,009 | 4,657 |
| NUCLEAR | 9,694 | 1,641 | 8,790 | 1,308 | 9,440 | 1,508 | 11,564 | 457 |
| THERMAL | 6,651 | 1,873 | 5,739 | 2,114 | 6,038 | 2,285 | 7,921 | 1,194 |
| HYDRO | 25,529 | 4,259 | 27,096 | 3,462 | 26,244 | 4,826 | 27,867 | 3,716 |

Source: Syspower data [1]

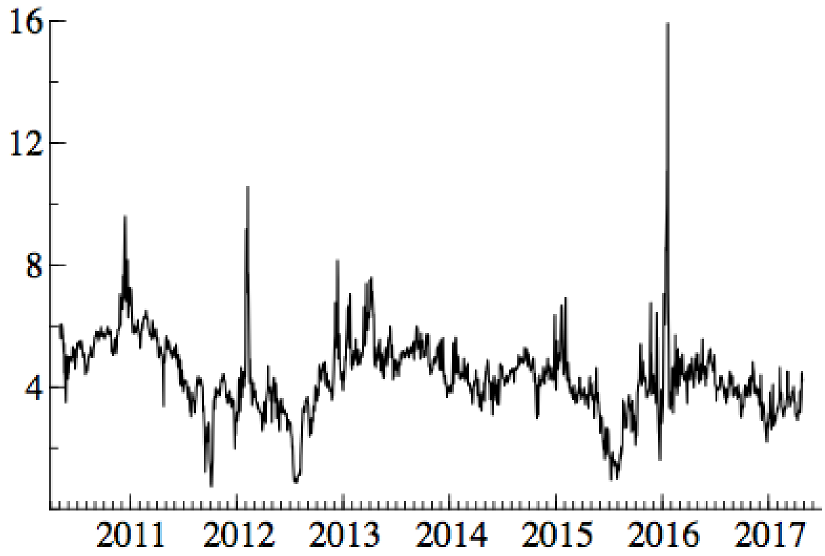



**Figure 13:** The ratio between spot and coal price. Syspower data [1]

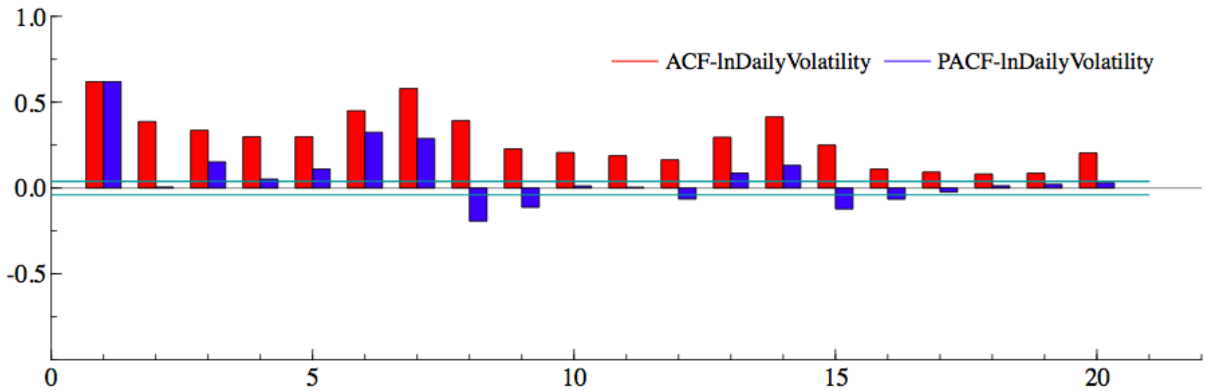



**Figure 14:** Autocorrelation and partial autocorrelation function for intraday volatility

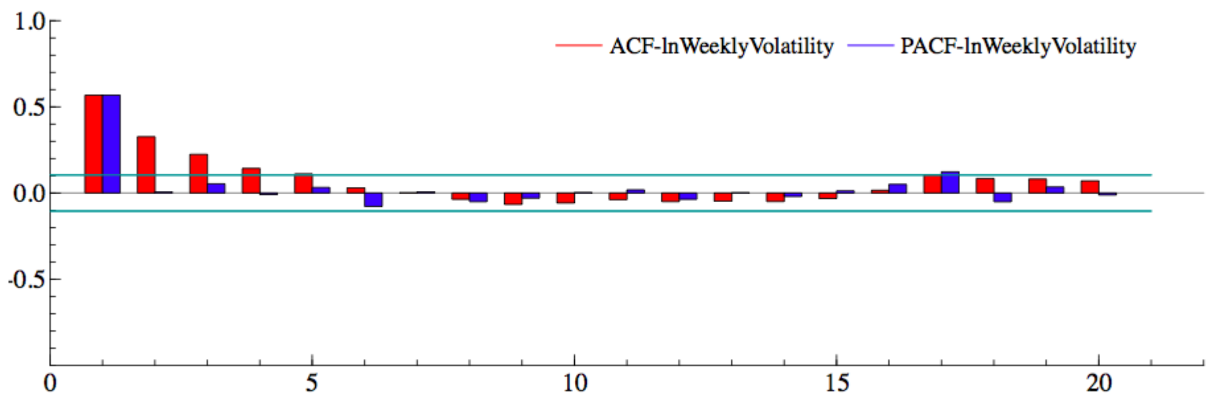
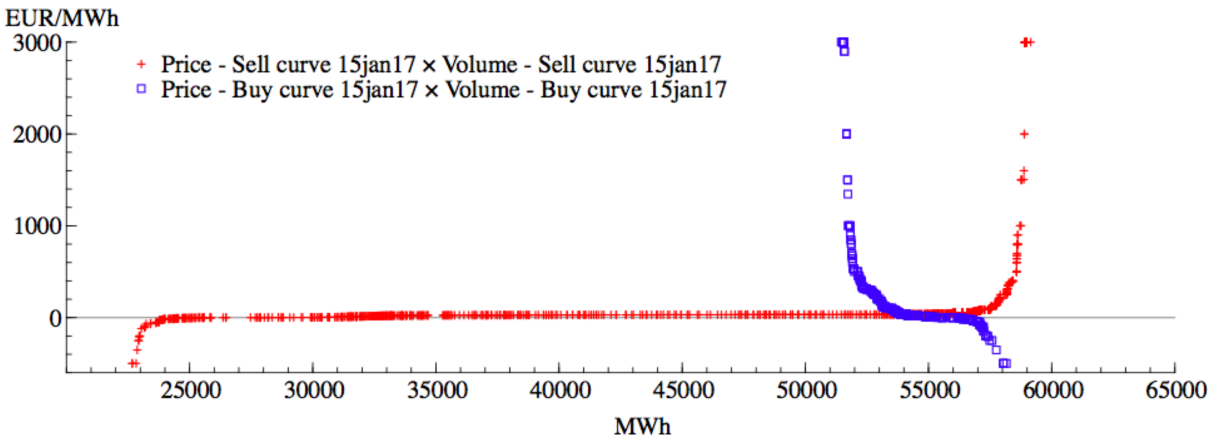
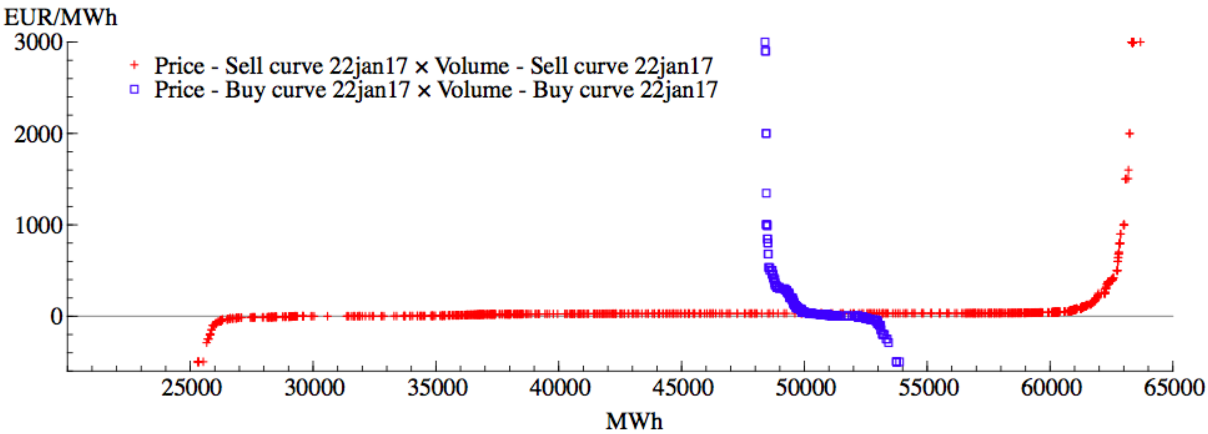



**Figure 15:** Autocorrelation and partial autocorrelation function for weekly volatility




**(a)** Hour with low wind from January 15th 2017 17:00-18:00.




**(b)** Hour with high wind from January 22th 2017 17:00-18:00.

**Figure 16:** Real life examples of System Price Curve Data. Source: [9].