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Master Thesis

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The main drivers of variations in the day-ahead spot price in the Nordic market, and how each driver change intraday.

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Abstract

This thesis studies the drivers of variations in the day–ahead spot price Nordic market and how they change intraday. The study uses variables of power production from wind and photovoltaics (PV), residual load, hydrological balance, and the short run marginal costs (SRMC) of coal and gas with the price of CO_2 included. The data spans from January 2014 to December 2018. A vector autoregressive (VAR) model was used together with a supplementing generalized impulse response function (GIRF). The VAR is resolved as 24 individual matrixes, one for every hour of the day, containing all the variables. Our findings reveal that the impact of renewable energy sources on the day–ahead spot price vary intraday. The main drivers explaining most of the price variations are found to be from the price itself, followed by residual load. We also find that the VAR model achieves the highest explanatory power during the most volatile hours of the day.

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1. Introduction

This thesis analyzes the dynamic interrelationship between intraday variations of the day–ahead spot price in the Nordic power market and the variables driving these variations. In recent years the focus on renewable energy has been increasing and the Nordic power market leads Europe when it comes to including renewable energy sources in the production mixture (Regulators, 2019). Renewable energy sources are prone to unstable exogenous effects, mainly weather, and higher production from renewable sources will lead to higher volatility in prices, according to Hirth (2018) and Linkenheil and Göss (2017). Combined with the non–storability of electricity, it is difficult to immediately balance out production and consumption. Mismatches in this balance lead to spikes in the price and high volatility in the spot price is experienced (Birkelund, Haugom, Molná, Opdal, & Westgaard, 2015). This makes the hourly behavior of the electricity price difficult to fully explain. The societal and political dependence on electricity is substantial (Ward, Green, & Staffell, 2019). For participants to better adjust to the power market, a thorough understanding of the intraday behavior of the day–ahead spot price and its drivers is crucial.

To our knowledge there is no available academic literature looking directly at the Nordic power market and the main drivers of hourly change in one of the most important factors for revenues–the power price. Research that investigates price drivers often uses data on daily average frequencies in its models (Clò, Cataldi, & Zoppoli, 2015; Gelabert, Labandeira, & Linares, 2011; Gianfreda, Parisio, & Pelagatti, 2016; Mosquera-López & Nursimulu, 2019; Mosquera-Lopez, Uribe, & Manotas-Duque, 2017; Würzburg, Labandeira, & Linares, 2013) or semi–daily average frequencies (Paschen, 2016). This is both because of its statistical convenience and, as Clò et al. (2015) and Gelabert et al. (2011) emphasized, to reduce the unwanted noise and volatility that arises from periodical volume shocks to production on an hourly frequency. The daily average electricity price is also an important measure for financial instruments and is commonly used as a reference price (Raviv, Bouwman, & Dijk, 2015). Still, there is an issue with this approach, since the power market is an extremely dynamic market and power are traded at an hourly frequency. A lot of information about the price variations would be forgone by averaging the data into daily frequencies, as Raviv et al.

(2015) suggested. When hourly data is averaged out to daily data it cannot provide any information about which variables are driving price changes through volatile hours and calm hours. It also cannot explain whether the effects of the variables stay positive or negative throughout the day, or if their effects are changing. We will address this frequency gap in the data used in the modelling of power market prices to enlighten the hourly behavior of the variables.

1.1 Research question

Based on the literature (Mosquera-López & Nursimulu, 2019; Paschen, 2016; Raviv et al., 2015; Würzburg et al., 2013) and the advice of Wattsight AS and Montel AS, we will enlighten the behavior of the variables they refer to as the most important drivers of the day–ahead spot price. We will also follow up on Würzburg et al. (2013, p. 168) and the suggested extension of their study. They noted that “an analysis of the factors that drive the price effects (such as the pattern of peak hours and prices, or the cost of fuels) would be an interesting extension of this research.”

In order to address these issues, the main research question to be studied is:

‘’What are the main drivers of variations in the day–ahead spot price in the Nordic power market, and how do each driver change intraday?’’

This paper will present results that will further help to explore the dynamics of the Nordic power market, especially the intraday variations. We will analyze the significance of the variables and the strength of their coefficients through hours of high and low volatility. Consequently, we can provide information about the variables with a model and a systematic setup that has not been used in the previous literature. This might help investors to gain a better understanding of which variables are expected to impact price variations and when. This will improve the foundation for how they process exogenous information that affects these variables. Thus, it can help them to make more accurate price estimations on an hourly frequency and strengthen their positions in the bid/ask trading.

1.2 Approach and main results

We will be looking at residual load, which is the consumption minus the production of renewable sources of energy. Residual load also represents the production left for conventional power plants to take over after renewable energy, with its low marginal costs, has contributed its share. The residual load indicates the consumption and therefore the demand in the market. We also look at renewable power production from wind and photovoltaics (PV), or solar power. The hydrological balance, which is the level of water stored in dams, lakes and snow on mountains, represents the production capacity of hydro power plants neglecting mechanical constraints. We will look at the short–run marginal costs (SRMC) of coal and gas with the price of CO_2 emissions included.

We will proceed to address the variations in the day–ahead prices with a vector autoregressive (VAR) model in which we run 24 individual system regressions, one for every hour of the day. The results show that our model is more suitable for volatile hours, as the explanatory power, R^2, increases with the increases in kurtosis, skewness, and standard deviation presented by Table 3 on page 23. We also found that, as expected, the price itself and the residual load are the main drivers of the variations in the day–ahead spot price. They both have significant positive coefficients for every hour of the day. Wind power production showed negative significant coefficients for every hour of the day, with stronger coefficients during nighttime. PV showed significance during the most volatile hours in the morning and for one hour in the evening, but remained insignificant during the daytime. PV were negative for hours 5 and 6 but changed to positive for hours 7 and 23. The coal price was insignificant throughout the day. Gas coefficients were positive and showed significance from hour 8 through the rest of day but were not significant during the calm hours of the nighttime.

2. Theory and literature review

2.1 The Nordic power market

The Norwegian power market was as one of the first countries in the world to be deregulated in 1991. This cleared the way for the Nord Pool power exchange. Nord Pool was established in 1996 as a joint Norwegian–Swedish power exchange, but has experienced expansions since (Nord-Pool, 2019d). Today the Nord Pool day–ahead market operates in all the Nordic countries (Norway, Sweden, Denmark, and Finland), the UK, and the Baltics (Latvia, Lithuania, and Estonia) (Nord-Pool, 2019c). The Nordic countries are divided into several bidding areas: Norway has five, Sweden has four, Denmark has two, and Finland only has one. The UK and the Baltic countries all have one bidding area each (Nord-Pool, 2019a).

The electricity spot market at Nord Pool, also called the EL–spot market, is where investors can buy and sell physical power contracts. The day–ahead market covers electricity trades where transactions are settled on a supply and demand basis and the systematic day–ahead spot price is quoted when all transactions are settled. This is a theoretical, unconstrained price, and all prices and trades are reported in terms of Euro (EUR)/Megawatt hours (MWh). Then, Nord Pool calculates the day–ahead spot price for each bidding area. Differences in prices between different bidding areas arise because of differences in transmission constraints. Transmission constraints represent bottlenecks in the transmission lines. The price is the result of a bid/ask auction. The buyers must plan and inform Nord Pool upfront how much electricity they need and estimates what price they are willing to pay, hour by hour. At the same time, the sellers of electricity must inform Nord Pool how much they can deliver at a given time and at what price, hour by hour. Both sellers and investors must inform Nord Pool before 12:00 Central European Time (CET). Then it works like an auction-based exchange. At 12:42 CET an algorithm has calculated the systematic price for each hour of the day and the trades are settled. The delivery will then be from 00:00 CET the next day and continue for the next 24 hours, hence the name “day-ahead” spot price (Nord-Pool, 2019b).

Nord Pool also has an intraday market that is a supplement to the day-ahead market. Here corrections can be made within the current day if there are imbalances between the true and projected consumption or production (Nord-Pool, 2019e). Imbalances can arise because of strong winds, the shutdown of a nuclear power plant, or a fall in temperatures leading to a higher need for heating. The focus of this paper will be on the day-ahead market.

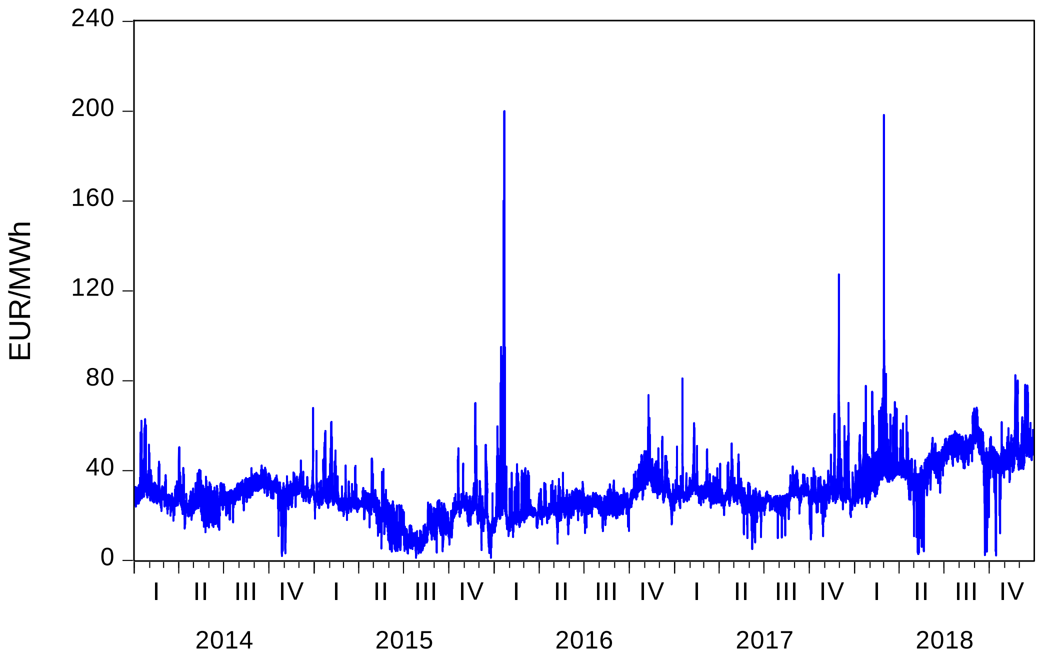
2.2 The day-ahead spot price

We are witnessing global climate change. The global temperature is rising and one of the goals of the Paris Agreement regarding temperature is to hold the global average increase below 2 degrees Celsius, with an aim of 1.5 degrees Celsius (Nations, 2015). To reach this goal, the focus on renewable sources of energy must continue to grow. Increased power production from renewable sources and reductions in the use of fossil fuel will also continue to change the behavior of the day–ahead spot price. The findings of Linkenheil and Göss (2017) and Hirth (2018) show that higher levels of renewable power production will lead to higher volatility in price variations. This is because renewable power sources are more prone to exogenous effects such as weather and temperature changes and the price response of power systems with mostly low marginal cost renewable electricity generation tends to be very sensitive to volume shocks. At the same time, more stable fossil fuel electricity production is being phased out.

"*Electricity is a non–storable commodity with an inelastic demand curve and the strong dependency on highly fluctuating energy suppliers causes the electricity price to be endowed with unique characteristics*" said Ziel, Steinert, and Husmann (2015, p. 100). These stylized facts about electricity prices are referred to by Huisman, Huurman, and Mahieu (2006) and Ziel et al. (2015) as seasonality, mean reversion, and high heteroscedastic volatility with extreme spikes.

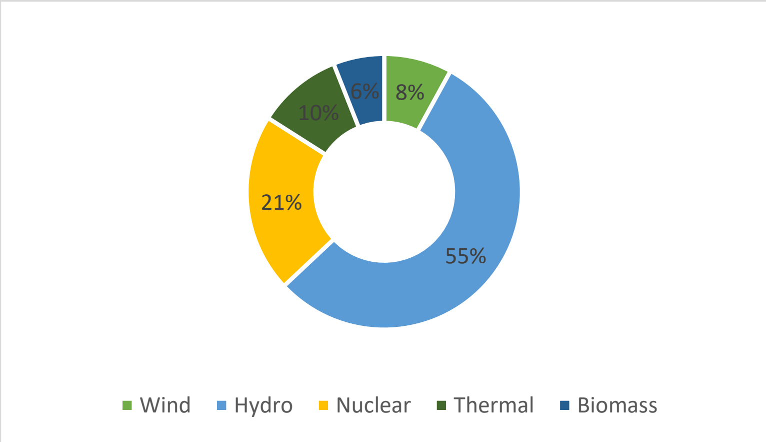
The weather is influential on the Nordic power market largely due to the level of hydro power production in Norway and Sweden (Norway, 2019). High levels of precipitation lead to an increased hydrological balance and increased supply from hydro power plants. This increase in supply leads to decreasing power prices, which is supported by general economic theory. Conversely, dry years will lead to high prices. These are some of the effects that can be seen from Figure 1 below, as 2015 was a very wet year and the electricity prices were low (Tigersted, 2018). On the other hand, in 2018, there was an unusual heat wave that spread across northern Europe (Attribution, 2018). Water reservoirs and lakes were dried up and electricity prices increased. This behavior of the hydrological balance in 2015 and 2018 are clearly presented by hydrology in Figure 4 on page 19. After the wet year of 2015, we can see that the price shows a trend of increasing from 2016 to 2018. The same response is found for the SRMCs of coal and gas in the same period (Figure 4, page 19). Since the prices of coal and gas are the main costs of fossil fuel power production, we expect to see some correlation between electricity price development and the prices of coal and gas. Mosquera–López and Nursimulu (2019) believe that the increase in price from 2016 to the end of 2017 in Germany was driven by an increase in electricity demand.

Figure 1. *The hourly day–ahead spot price at levels that are listed on Nord Pool from January 2014 to December 2018. The price is presented as EUR/MWh.*



The production mix in the Nordic countries has a strong presence of renewable energy. The hydropower production from Norway and Sweden is well developed and is the largest contributor to the Nordic power market, as shown in Figure 2 on page 10. Denmark has also an extensive wind power capacity. In Denmark, 41% of the power production in 2018 came from wind power (Green, 2019). Therefore, a high capacity for production from wind results in a high volatility of prices in Denmark, and the prices can even turn negative (Starn, 2018).

Figure 2*. The power production mixture from Nordic countries in 2018. Source: (Pöyry, 2018).*



2.3 Previous research

2.3.1 Introduction

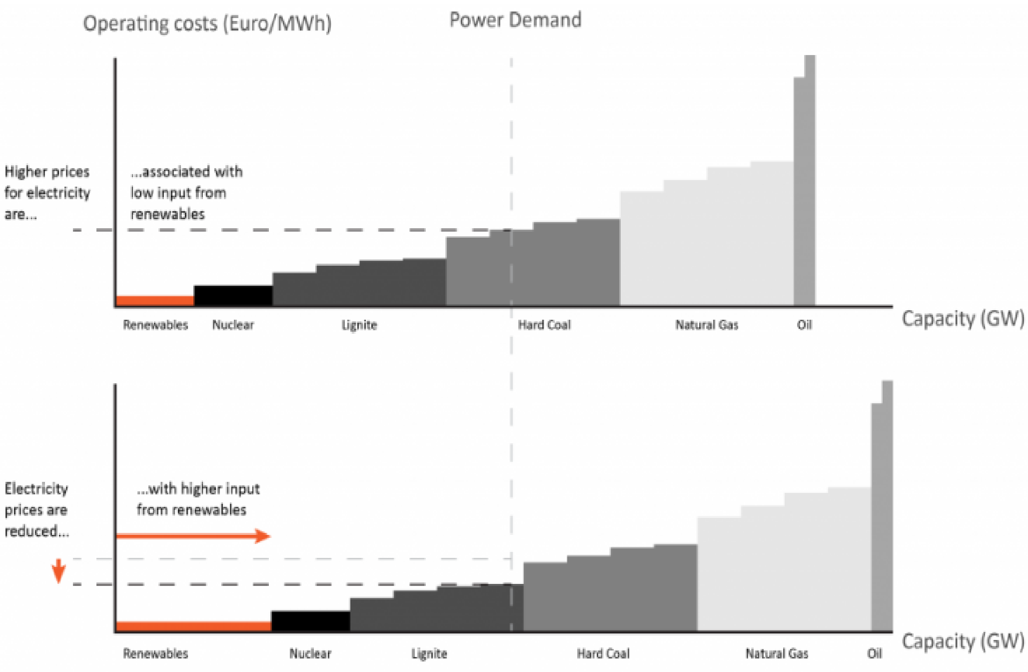
In this section we investigate what previous literature and research can explain about the effects of the main drivers of electricity price variation in the Nordic power market, and if they change during the day. We will go through findings in previous research before summarizing what it contains. Then we explain the gaps in relation to our research and how we will deal with the gaps. There have not been many previous studies on the main drivers of change in power prices in the Nordic power market. Most of the research is from the European market where the German market is highly represented (Bublitz, Keles, & Fichtner, 2017; Gürtler & Paulsen, 2018; Hirth, 2018; Kallabis, Pape, & Weber, 2016; Lagarde & Lantz, 2018; Mosquera-López & Nursimulu, 2019; Paraschiv, Erni, & Pietsch, 2014; Paschen, 2016; Sensfuß, Ragwitz, & Genoese, 2008; Würzburg et al., 2013). Würzburg et al. (2013) described that their reasons for looking at the German market were its size, its location in the core of Europe, and its influence on other energy areas that are closely integrated.

The mixture of electricity generation in Europe is different from that of the Nordic countries. The European market has more production coming from coal and gas. Among renewable sources, hydro power only represents 10%, and wind and solar together represent 16% of energy production (Energiewende & Sandbag, 2019). The Nordic power market has a larger share of renewable energy production with hydro power being the biggest production source and representing 55% of the energy mixture (Figure 2, page 10). The variables used in the studies in the European markets have an effect in the Nordic region, but their impacts are different (Hirth, 2018). It was further found by Würzburg et al. (2013) that the effect of fossil fuels was expected to show similar effects in the Nordic power market regardless of the high hydro capacity in Nordic countries. Hydro power is not as well documented in the literature as wind and solar power. This might be due to greater potential future production by solar and wind power in Europe (I. R. E. Agency, 2018). The European power market is continuously changing and the rate of new studies on electricity prices is increasing. Therefore, we are mostly focusing on newer studies to be better able to describe the drivers in today's market.

2.3.2 Findings

There are several researchers who have previously studied how the merit order effect (MOE) describes the mechanism of setting the market price, such as Gürtler and Paulsen (2018), Lagarde and Lantz (2018) and Sensfuß et al. (2008) in the German market; O'Mahoney and Denny (2011) in the Irish market; and Clò et al. (2015) in the Italian market. The MOE describes the ordering of which production sources start to produce electricity based on their marginal cost of production (Appunn, 2015). Renewable energy has a very low marginal cost and is therefore not dependent on a high market price in order to be profitable. On the other hand, fossil fuel is more expensive to consume and requires a higher market price to be profitable. Therefore, the marginal cost of the production sources decides when each source will start to produce power. The researchers all found that renewable energy sources like wind, PV, and hydro power are making up an increasing percentage of the electricity production mixture while the amount of fossil fuel is reduced. This reduces the wholesale electricity price due to the low marginal costs of renewable energy, which then means that it can be offered at a lower price and remain profitable (Appunn, 2015).

Figure 3. The graph shows the illustration of the merit order effect (MOE). On the x–axis is the capacity of the different sources used for electricity production. The different sources are natural oil, natural gas, lignite and hard coal which are (two different types of coal), nuclear and renewables. On the y–axis is the operating costs (marginal). The table shows that when the production of renewable energy increases, it leads to the production of sources with higher marginal cost to be decreasing, given the assumption that demand stays constant. Production from sources with higher marginal costs such as oil, natural gas, and hard coal are being squeezed out of the market by renewables. This causes the wholesale electricity prices to be reduced, as exemplified in the bottom graph (Appunn, 2015).



The findings in the study of the MOE were also supported by Mosquera-Lopez et al. (2017). Their non–linear factor model found that temperature and wind speeds, which largely drive production from renewable energy, show strong price declining effects. The analysis was conducted using data from 2013 to 2016 in. To analyze the up and downsides of weather changes they modeled quantile regressions. In addition to the MOE, they found that the influence of weather is strongest at the tails of the electricity price, where abnormally high and low prices are recorded. These findings coincide Gürtler and Paulsen (2018) study of the MOE from 2010 to 2016, who looked at the effects of wind and solar power production on electricity price forecasts in Germany. The findings of Mosquera-Lopez et al. (2017) were rationalized by defining the extreme lowest quantile as situations of high elasticity demand. The extreme highest quantiles were defined as situations of supply shortage. In situations of supply shortage, or higher demand than supply, fuels and other sources of energy production with higher marginal costs will be used to supply the market. During periods where prices are relatively stable, in the 40th to 70th percentile, higher PV energy production leads to lower prices, as expected. Further on, PVs end up having a positive effect on prices in the highest quantiles. The explanation for this revelation was that in the morning, the sun comes up and PV energy production begins. At the same time, the demand was found to be rapidly increasing (Mosquera-Lopez et al., 2017). This is because people are waking up, consumption increases, and this leads to a higher price. Mosquera-Lopez et al. (2017) believes that this leads to higher production from sources of high marginal costs, which further increases price. During these hours of the day, the increased production from PVs positively correlates with an increase in price.

Another study on the decline in electricity prices in Europe was done by Hirth (2018). He was looking at both Germany and Sweden in the period from 2008 to 2015. He found that the expansion of renewable energy was the largest single factor explaining the price declines in both Germany and Sweden. This was supported by Gelabert et al. (2011) in the Spanish market. Hirth (2018) also found the reduction in CO_2 and coal prices to be important for Germany. The effect of CO_2 and coal prices was not so prominent in Sweden due to the different power production mix. He found that the wet year of 2015, which increased the hydro power supply, and a reduction of electricity demand also lead to a strong reduction in electricity price in Sweden. He rationalizes that Sweden is more sensitive to volumetric shocks in power production compared to Germany due to higher levels of renewable power production in Sweden. This was also found by Linkenheil and Göss (2017). Further research on the decline in prices in the German market from 2011 to 2015 and 2007 to 2014 was done by Kallabis et al. (2016) and Bublitz et al. (2017) respectively. Contrary to the findings of Hirth (2018), Bublitz et al. (2017) and Kallabis et al. (2016) found that the reduction in CO_2 prices had the single strongest impact on the decline in electricity prices, and not the increasing renewable energy production.

In addition to looking at the effect of renewable energy production on day–ahead prices at European Energy Exchange (EEX), Paraschiv et al. (2014) also looks at the impact of coal, gas, and oil over time in Germany from January 2010 to February 2013. In their dynamic fundamental model, they found that the increase in wind power has a noticeably stronger impact in the evening and nighttime as demand is lower and the weather is often windier. The sensitivity of the electricity price to the coal remained constant while the sensitivity to oil was negligible. On the other hand, they found the sensitivity of electricity price to the price of gas to be decreasing over time. This was because gas is at the end of the merit order and is therefore the first to be replaced by renewables, decreasing the production from gas. When there is high demand, sources with high marginal costs were added to the production of electricity, which also supports the MOE. This coincides with Würzburg et al. (2013) who studied the price effects of renewables in Germany and Austria in the sample period of 2010 to 2012. They found gas to be significant in the short-term on days when demand for electricity was high. Contrary to Paraschiv et al. (2014), Gianfreda et al. (2016) found in the period from 2010 to 2014 that the production from coal in Great Britain and Spain were to a large extent reduced due to an increase in production of renewable energy sources. This is supported by Mosquera-Lopez et al. (2017), who found that coal had positive but statistically insignificant coefficients in almost all percentiles.

Similar approach to ours is used by Paschen (2016), who used a structural vector autoregression (SVAR). He analyzed the effects of wind and PV shocks and the impulse response functions on the day–ahead spot market in Germany. As opposed to our dataset, he does not approach data hourly, but rather divides the days into two, with a daytime ranging from 6:00 am–6:00 pm and a nighttime from 6:00 pm–6:00 am. In this way he reduced the possibility of biased results, as most wind production occurs at nighttime and solar production occurs at daytime. The results showed that wind power had a more persistent effect on spot price compared to PVs over time. Paschen (2016) believes that this might be because of the autocorrelation of wind power for larger lags. He also suggests that the increasing impact of PVs coincides with the demand in peak hours resulting in a steeper merit order curve. In other words, higher levels of production from PVs leads to less production from sources with higher marginal costs.

Mosquera-López and Nursimulu (2019) used daily average electricity prices when they looked at a multivariate model for daily average electricity price development in Germany between 2010 and 2017. The use of daily average spot price and not hourly prices is supported by Gelabert et al. (2011) and Clò et al.

(2015), who gave the grounds for their choice of daily average prices wanting to reduce unwanted noise that is temporal and might only take place at a particular hour. Mosquera-López and Nursimulu (2019) used wind, PVs, load, gas, CO_2 and coal as explanatory variables. These are very much the same variables we will examine in our approach. Mosquera-López and Nursimulu (2019) found that the main drivers for the spot price are the load and renewable infeed from PVs and wind power. In their presentation of structural breaks, they show that the effects of wind and PVs were negative on the price for all breaks with the exception for PVs, which had a positive effect in the first out of five break regimes. They reason for this reaction by saying that initial price–increasing effect of PVs may be attributed to the high cost of PVs at the beginning of this study. Load had a positive effect in all regimes. They conclude that the MOE is time–varying and that the price varies with the level of wind power and PVs, but the negative effect of wind is always stronger than PV.

2.3.3 Summary and conclusion

To sum up previous research there is a clear consistency in the literature supporting the MOE (Sensfuß, Ragwitz, & Genoese, 2008; Lagarde & Lantz, 2018; Gürtler & Paulsen, 2018; O'Mahoney & Denny, 2011; Clò, Cataldi, & Zoppoli, 2015). Wind and PV production are mainly found to have negative effects on electricity prices (Gelabert et al. 2011; Paraschiv, Erni, & Pietsch, 2014; Paschen, 2016; Kallabis et al., 2016; Bublitz et al., 2017; Hirth, 2018; Mosquera–López & Nursimulu, 2019). We found that the effects of hydro power on the day–ahead market price are not well documented in the literature on the Nordic power market. Studying the decline of wholesale electricity prices from 2008 to 2015, Hirth (2018) showed that the main driver in the decrease in power prices was the introduction of renewable energy in both Sweden and Germany. He also found that coal plays a greater role in Germany compared to Sweden. Coal is therefore not expected to play a crucial role in describing the price development in the day–ahead market in the Nordic power market because the Swedish production mix is similar to the Nordic one. According to Gianfreda et al. (2016), coal also had a decreasing effect over the period of 2010 to 2014 in Spain and Great Britain due to increases in renewable energy production. Mosquera-Lopez et al. (2017) found coal to be statistically insignificant in almost all percentiles.

Bublitz et al. (2017) and Kallabis et al. (2016) on the other hand, found CO_2 and coal prices to have the strongest effect in Germany from 2011 to 2015 and 2007 to 2014 respectively.

The sensitivity of the power price to changes in gas is expected to be decreasing due to solar and wind power production taking larger shares of the production mix, supporting the MOE. The production from gas would then decrease, according to Paraschiv et al. (2014). Würzburg et al. (2013) supports the findings of Paraschiv et al. (2014), as they found gas to be significant in the short–term when demand for electricity was high. Demand, which is often referred to as load, has a positive effect on electricity prices in studies using this variable (Bublitz et al., 2017; Clò et al., 2015; Gürtler & Paulsen, 2018; Hirth, 2018; Lagarde & Lantz, 2018; Mosquera-López & Nursimulu, 2019; Paraschiv et al., 2014; Paschen, 2016).

The paper by Paschen (2016) uses a structural vector autoregressive model (SVAR). Paschen (2016) divides the hourly data into two sets, taking an average of both the daytime and nighttime prices. His approach to methods and data is the one that is most similar to ours. Still, by taking an average of both daytime and nighttime prices, he eliminates valuable hourly information. He further only reports the impulse responses from shocks of wind and solar power on price. Therefore, we cannot compare our price variable with previous research.

With the exception of the study by Hirth (2018), who looks at the Swedish market, there is no research giving insight into the drivers in the Nordic day–ahead spot market as far as we can tell. The area most commonly emphasized is the German market such as Gürtler and Paulsen (2018), Lagarde and Lantz (2018), and Mosquera-López and Nursimulu (2019).

To our knowledge, the literature is only capable of explaining the main drivers of price variations of electricity by using mostly daily average data. Daily average data gives a good indication of the behavior of variables over time, but it does not show important short–term intraday behavior in a very volatile market. The gap in the frequency of the data being used in most research and what is traded on the power exchanges is something that we want to address. We also want to further explore the Nordic power market which is not as frequently addressed in Europe. There is a lot of important research on other European power markets that is relevant to the Nordic power market. However, the production mix in the Nordic countries is rather special because of the large extent of renewable energy, especially the production from hydro power (Pöyry, 2018). It is therefore expected that the day–ahead spot price in the Nordic power market shows different sensitivity towards changes in renewable energy production compared to other European markets (Linkenheil & Göss, 2017; Hirth, 2018). That is why we also include the variable hydrological balance, which represents the potential power production from hydro power plants based on reservoir levels and snow in the mountains.

3. Data

We will now present the data we are using, where the data is collected from, definitions of the variables, cross–correlations and descriptive data of the day–ahead spot price.

The selection of the variables is motivated by previous research by Mosquera-López and Nursimulu (2019), Paschen (2016), Raviv et al. (2015), and Würzburg et al. (2013) and recommendations from the expert advice of Wattsight AS and Montel AS. The data sample spans from the beginning of 2014 to the end of 2018. This horizon of five years of data is long enough to include recent years changes in the variables we are looking at, such as the gradual increase in CO_2 prices and the sudden drop in 2016 (W. Zhang et al., 2019). It also includes the wet year of 2015 (Tigersted, 2018) and the dry year of 2018 (Attribution, 2018) and their effects on the hydrological balance. Temperature changes, as we experience warm summers and cold winters, affect the residual load. At the same time the sample horizon is still short enough to present relevant data. This is very important as the power market is growing and changing at an extremely high pace. There has been an increase in the production of renewable energy sources in the Nordic countries, especially the production of wind power over the last couple of decades. Along with a phasing out of nuclear power production, the production mix has changed a lot and will continue to change in the near future (Lisk & Vehviläine, 2016). Changes in regulatory and legal constraints further induce network planning and investments (Research, 2010). In other words, a too long timespan for these kinds of data would not be representative for the situation of the most recent years. What was relevant in 2005 is not as relevant in 2018.

Table 1. *Overview of the variables used, their abbreviations, unit sizes, their frequency, and the sources of the data. The data sample spans from 2014 to 2018.*

Variables	Abbreviation	Unit	Frequency	Source
Nord Pool day-ahead spot price	Price	EUR/MWh	Hourly	Montel AS
Hydrological balance	Hydrology	GWh	Hourly	Wattsight AS
Residual load	Load	MWh	Hourly	Wattsight AS
Photovoltaics	PV	MWh	Hourly	Wattsight AS
Wind	Wind	MWh	Hourly	Wattsight AS
Coal ARA SRMC	Coal	EUR/MWh	Daily	Wattsight AS
Gas Dutch TTF SRMC	Gas	EUR/MWh	Daily	Wattsight AS

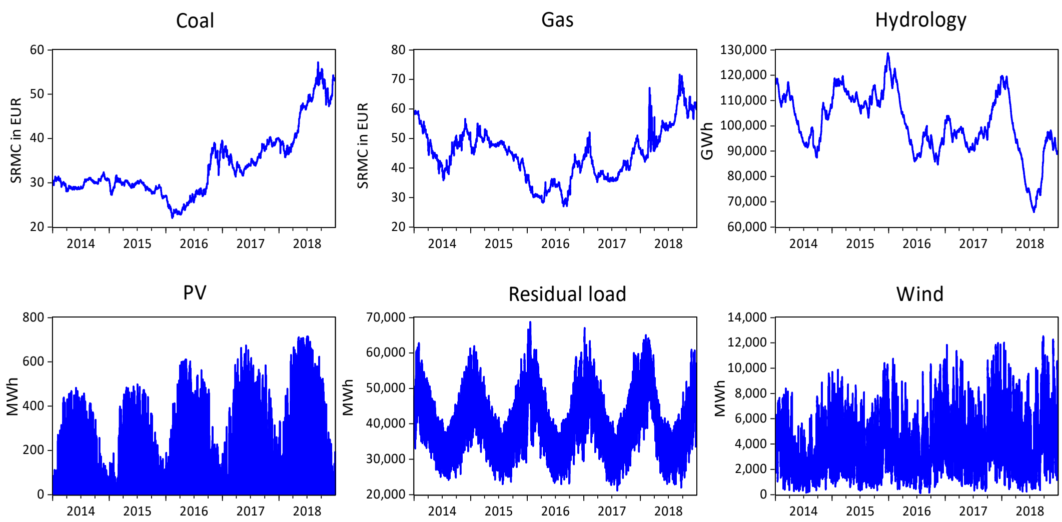
The data of the day–ahead spot price is provided by Montel AS and has been gathered directly from Nord Pool. "*Montel is a key information provider for the European energy markets*" (Montel-AS, 2019). Therefore, this data is considered reliable. The price of coal and gas are publicly available on a daily frequency, but not the SRMC with the cost of CO_2 emissions included. The same goes for hourly data of PV, wind, and hydrology. Therefore, we cannot compare and verify the reliability of the data, but rather trust the source Wattsight AS to be "*a leading provider of data and consulting services in the European energy market*" (Wattsight-AS, 2019).

The production and consumption of electricity varies a lot intraday. Since the spot price is set at a supply and demand basis, the price varies a lot as well. The production and consumption changes throughout the day as the most people sleep at nighttime and the heavy electricity–consuming industries are shut down. In the morning, people wake up and start using electricity. The industry starts its production and the demand for electricity increases rapidly. As shown by Figure 6 in the appendix, hour 9 and hour 19 have a maximum price of 200 EUR/MWh. According to Figure 7 in the appendix, hour 9 has a minimum price of approximately 2 EUR/MWh and during hour 19 has a minimum price of 6–7 EUR/MWh. This extreme hourly volatility would not be captured by a daily average of price.

3.1 Variables

We will now go more in depth in describing the variables day–ahead spot price, hydrology, residual load, PVs, wind, coal, and gas.

Figure 4. The graphs present the development of the variables from January 2014 to December 2018. The data is at level form with an hourly frequency for hydrology, PV, residual load, and wind. Coal and gas are at daily frequencies. Coal and gas are the short–run marginal costs (SRMC) of the two with the price of CO_2 emissions included. Hydrology is the hydrological balance in water dams, lakes and snow in the mountain. Residual load is consumption subtracted from renewable energy production. Wind and PVs represent the power productions of these sources.



The electricity price is the hourly *day–ahead spot price* at the Nord Pool exchange. The development of the spot price has been further analyzed over Figure 1 on page 6.

Hydrology refers to the hydrological balance, also called the water balance. This balance represents the potential GWh amount of power stored within water dams, lakes, and snow in the mountains. Changes in this balance happen mainly because of precipitation and evaporation. The potential outflow is simply the inflow plus the change in storage levels (Goldscheider, 2010, pp. 305-338). The hydrology then represents the potential production from hydro power plants. Therefore, it also reflects the production capacity of hydro power plants when excluding the constraints of facilities. Figure 4 above indicates that hydrology shows some seasonal behavior. In spring, we experience snowmelt and substantial rainfall. During summertime, the values are decreasing. This is because rainfall usually is at its minimum and the water built up during winter has been used. In autumn, we experience increasing precipitation. This is continuous in wintertime. The reservoir levels are then increasing, and there is an accumulation of snow. This is the common behavior of hydrology over a year (Anghileri, Pianosi, & Soncini-Sessa, 2014). We also see that each year has large differences in the amount of GWh stored.

We left hydro power production out of the model because the production from hydropower plants can be regulated according to the market unless there is a run–of–river power production. This means that hydropower production has the option to adjust its production quickly according to market demand and prices (Nunez, 2019). Hence, the production of hydropower plants will almost mechanically follow historical changes in price in the short run. This would then create a synthetically high R^2, and we might have issues with collinearity in our model. Even though the production from hydropower plants would be lagged one day behind price, we expect the correlation between historical changes in hydropower production and the price to be high.

Residual load is the electricity consumption subtracted for the production from renewable energy sources. This load is then the MWh amount of electricity produced by conventional thermal power production using fuel such as coal, gas, and nuclear sources of energy (Seier & Schebek, 2017). These are sources of power production with significantly higher marginal costs of production compared to renewable sources (Appunn, 2015). Since residual load represents the consumption of electricity, it is the variable that represents the demand in the market. Thus, the residual load is also largely driven by social factors and temperature changes. The social factors of when people need electricity throughout the day is driven by their daily schedules of waking up, turning the lights on, using kitchen appliances, going to work, utilizing industry machinery and so on. The temperature is an important factor, as heating is a large source of electricity consumption in households (Pöyry, 2018). According to Figure 4 on page 19, residual load shows seasonality with a replicating pattern for every year. The expected increase in wintertime happens mainly due to the increased need for heating. Conversely, summertime shows low values because the outside temperature is higher (Group, 2014). The graph does not display any trending effect, so the consumption was been mean–reverting in this period.

Photovoltaics (PV), also known as solar power, is the production of electricity in MWh from solar panels. This power production happens through the conversion of photons from sunlight into electricity (Z. Zhang et al., 2019). The production of PVs has a strong seasonal pattern, and as expected the production is increasing during summertime (Figure 4 on page 19). PV also shows an increasing MWh of production throughout the years. This indicates the focus on the development of PV capacity in the Nordic countries.

Wind is the MWh amount of electricity produced from windmills. The production from both PVs and wind are highly dependent on weather. As we can see from Figure 4 on page 19, wind power production shows a seasonal pattern that is the opposite of PVs. Wind production increases during wintertime and decreases during summertime. Wind, like PVs, also shows increasing production throughout the years because of the increasing focus on renewable power production.

Coal represents the short–run marginal cost (SRMC) of using coal as a fuel for thermal power production. The base price of the coal is the API2 spot price, which is a benchmark for high quality coal. It has a power delivery of 6,000 kcal/kg and is delivered in northwest Europe in the Amsterdam, Rotterdam, and Antwerp (ARA) hubs (Konstantine & Konstantine, 2018). The production output from coal is corrected for a fuel efficiency of 40%, as mentioned by Wattsight AS in a phone call 07/05/2019. This indicates the ratio of electricity production to the input of fuel. Losses in fuel efficiency happen because of the production of waste heating.

SRMC is the cost of producing one extra MWh of power with coal as fuel. SRMC captures the true change in the cost of the fuel and provides a more correct effect of coal prices on power production (Biskas, Bakirtzis, & Chatziathanasiou, 2015). The coal SRMC also includes the price of CO_2 emissions, which represent the price in EUR per ton of CO_2 emitted. The SRMC of coal show steady development from the beginning of 2014 until a small drop in 2016, and then steadily increases up to 2018 (Figure 4 on page 19).

Gas represents the SRMC of using gas as fuel for thermal energy production. The base price is the Dutch Title Transfer Facility (TTF) natural gas spot price that is traded on the Intercontinental Exchange (ICE). This is the price that European end–consumer contracts are pegged to (Xunpeng, 2016). The SRMC of gas, like coal, includes the CO_2 emission cost and is corrected for a fuel efficiency of 50%, as mentioned by Wattsight AS in a phone call 07/05/2019. Natural gas emits 50–60% less carbon dioxide compared with coal, and is therefore less affected by changes in CO_2 prices than coal (Laboratory, 2010). Gas and coal will also be referred to together as fuel. The SRMC of gas has shown relatively drastic price changes. The lowest price recorded in 2016 was below 30 EUR. Two years later in 2018 it had more than doubled, and it peaked at about 70 EUR (Figure 4 on page 19).

Table 2. *Cross—correlations between the variables. Price is the day—ahead spot price. Coal and gas are the short—run marginal costs (SRMC) of the two. Hydro is the hydrological balance in water dams, lakes, and snow in the mountain. Residual load (load) is consumption subtracted for renewable energy production, and PVs and wind are the power productions of these sources. The variables are the first difference in the logarithm at hourly frequency of the full sample from January 2014—December 2018. *, **, and *** represent the significance of the variable at the 10%, 5% and 1% levels respectively.*

	Price	Coal	Gas	Hydro	Load	PV	Wind
Price	1						
Coal	0.0039	1					
Gas	0.0267 ***	0.0612 ***	1				
Hydro	-0.0910 ***	0.0114 **	-0.0216 ***	1			
Load	0.5869 ***	0.0078	-0.0077 ***	-0.1247 ***	1		
PV	0.0194 ***	-0.0113 **	0.0112	0.0404 ***	0.0044	1	
Wind	-0.3551 ***	0.0038	-0.0048	0.1079 ***	-0.5140 ***	-0.0686 ***	1

The main correlations we are addressing are between the variables and price. Coal has a positive correlation with price, but the coefficient is insignificant both economically and statistically. Gas and load have, positive correlation with price and are significant. The positive correlation is expected as an increase in the SRMC of gas and a higher consumption presented by load will lead to an increase in prices. Gas has a weak correlation, while load has the strongest correlation of the variables. We can also see that the correlation between wind power production and price has a significant and strong negative coefficient. Hydrology also has a negative correlation with price, but it is weaker than the correlation of wind to price. The negative correlations for hydrology and wind were expected as both variables will lead to higher supplies in the market and that will drive the price down. PV power production is significant, but it is a bit surprising that it has a weak positive correlation.

A noticeable anomaly is the low correlations for gas and coal. Since they both are fossil fuels that include the CO_2 price, one might expect their relationship to show higher correlation.

***Table* 3**. *Descriptive statistics for the day–ahead spot price at an hourly frequency for 1,828 observations for the full sample period of January 2014–December 2018. The prices are reported in Euro per MWh. The mean is the average price for each hour. The median is the middle value found when the series is arranged in ascending order. The maximum and minimum values are simply the maximum and minimum values of price observed within the respective hour. Standard deviation is a measure for the dispersion of the observations. The higher the standard deviation is, the larger the distance between the data observations and the mean value. Skewness defines the shape of the distribution. A normal distribution is symmetric when the skewness is zero. Kurtosis is a measure of the fatness of the tails and how peaked the mean is. Normal distribution has a kurtosis of 3 and any value above this is viewed as excess kurtosis (Brooks, 2014). We have the hours 8–11 (07:00–11:00 CET) and 17–19 (16:00–19:00 CET) in bold since we refer to them as the peak hours of the day where we experience the highest daytime volatility.*

Hour	Mean	Median	Maximum	Minimum	Std. Deviation	Skewness	Kurtosis
1	27.38	26.59	57.36	2.17	9.57	0.50	3.84
2	26.50	25.94	55.91	1.72	9.56	0.42	3.74
3	25.98	25.48	55.32	1.14	9.55	0.37	3.68
4	25.77	25.32	54.27	1.27	9.54	0.33	3.60
5	26.06	25.77	53.99	1.18	9.50	0.27	3.56
6	27.37	26.73	56.67	1.15	9.65	0.37	3.59
7	29.41	28.30	63.08	1.39	10.06	0.48	3.64
8	**32.22**	**30.21**	**160.00**	**1.93**	**12.16**	**1.92**	**17.01**
9	**33.71**	**31.18**	**199.97**	**2.58**	**13.72**	**3.47**	**37.69**
10	**33.32**	**30.99**	**168.64**	**2.71**	**12.28**	**2.29**	**20.59**
11	**32.71**	**30.74**	**120.05**	**2.86**	**10.99**	**1.21**	**7.81**
12	32.14	30.42	78.79	2.92	10.40	0.79	4.17
13	31.55	29.98	76.62	2.77	10.24	0.74	3.95
14	31.17	29.73	76.62	2.32	10.24	0.74	3.99
15	30.90	29.46	77.14	2.11	10.32	0.74	4.03
16	31.02	29.40	95.01	2.96	10.81	1.00	5.38
17	**31.64**	**29.66**	**149.95**	**3.99**	**12.08**	**2.08**	**15.90**
18	**32.78**	**30.34**	**199.94**	**5.02**	**13.47**	**3.38**	**34.58**
19	**32.78**	**30.51**	**150.08**	**6.84**	**12.07**	**1.87**	**14.14**
20	31.80	30.11	81.61	6.57	10.44	0.81	4.27
21	30.77	29.38	64.68	6.07	9.81	0.68	3.86
22	30.17	28.84	62.73	5.71	9.55	0.69	3.96
23	29.34	28.12	59.64	5.46	9.37	0.68	3.95
24	27.98	27.06	56.84	3.27	9.31	0.57	3.93
Daily avg.	30.19	28.76	94.79	3.17	10.61	1.10	8.95

Hours of high volatility are shown in the increase of standard deviation, skewness and kurtosis. These are referred to as *higher moments* of the series and are characteristics used to describe observations that are not perfectly normally distributed (Brooks, 2014, p. 66).

We can see that the price experiences higher standard deviation, skewness and kurtosis in the periods between hour 8–11 (00:07–11:00 CET) and 17–19 (16:00–19:00 CET). These are therefore the hours with highest volatility in prices.

These hours will henceforth be referred to in this paper as the peak hours of the day. We can also see that the extreme values of the maximum price (Figure 6, the appendix) and minimum price (Figure 7, the appendix) are present in those periods. This is expected, since these are the hours of the day where there is a lot of consumption (Ward et al., 2019). Standard deviation shows an increase in daytime compared to nighttime and has its peaks in the periods mentioned. Skewness and kurtosis are relatively stable except for strong peaks in the hours mentioned. A positive skewness, as we experience in Table 3 on page 23, means that the distribution has long tails to the right and most observations are more to the left. Economically, this means that we are more likely to experience the observations on the far right, which means high values of the price. The distribution shows excess kurtosis, which means kurtosis in excess of 3. This leptokurtic distribution is what we experience in the hours when kurtosis increases in the peak volatility hours. This means that we can experience higher peak values in the mean and more extreme values of price in the tails of the distribution (Brooks, 2014, pp. 66-67).

4. Methodology

In this section, we will go through the VAR model used, generalized impulse response function (GIRF), the lag length chosen based on Akaike information criterium (AIC), the hypothesis, the regression and the stationarity test provided by the augmented Dickey–Fuller (ADF) test.

The prices for the 24 hours were calculated based on the information in the market today. This means that the hourly continuous day–ahead market data does not follow a times series process, but is a panel of 24 cross sectional hours that vary from day to day (Huisman et al., 2006). Since this hourly data does not follow a time series process one cannot use regular time series regressions such as least squares regressions, without merging or cleansing the data. This could lead to a loss of important information in the data set (Lee & Kim, 2018). Research on the topic of electricity pricing often uses daily average prices such as Würzburg et al. (2013) and Clò et al. (2015). The daily average price of electricity is a key reference price in the electricity market and is used in financial contracts for price hedging and risk management (Raviv, Bouwman, & Dijk, 2015). However, the electricity market has substantial volatility intraday and Raviv et al. (2015) suggest that a lot of valuable information would be forgone by averaging out the intraday behavior of electricity prices.

Paschen (2016) looked at wind power production, PV power production, total load (demand) and conventional power production (thermal energy production by coal, gas and nuclear sources of power), and the European Power Exchange (EPEX) spot prices for electricity. The main aim of his paper was to get a better understanding of the dynamic interrelationship between the spot price and the independent variables over time. He approached this by using a structural vector autoregressive (SVAR) model and the related structural impulse response function (SIRF). The raw data he used was at an hourly frequency, but he divided the data into nighttime and daytime. This is because he expects the presence of PV power production to be prominent during daytime and wind power during nighttime. We approached our analysis with similar variables, but we include the price of CO_2 in the SRMC of coal and gas, and we also added the variable for hydrology to represent the longer–term effects of hydropower which are more prominent in the Nordic region. Unlike Paschen (2016), we used hourly data to avoid the elimination of any relevant and valuable intraday information. We did so by addressing the issue of overlapping data by looking at the data as 24 individual matrixes of data where there is one matrix for every hour of the day. This way, the matrix contained information about all the variables in hour 1 (00:00–01:00 CET) of every day of the entire sample. The same was true for hour 2 (01:00–02:00 CET), the hour 3 (02:00–03:00 CET), and so on. We then looked at the difference's day–by–day for every hour separately. This approach let us look further into the behavior of the variables for each hour, which means that we could look at the changes in explanatory power and coefficients throughout hours of high and low volatility and see if some variables are changing throughout the day.

4.1 Vector Autoregressive Model

With this setup, we used a vector autoregressive (VAR) model. The study of Raviv et al. (2015) also show that a multivariate model for the full panel of hourly prices outperformed univariate models using daily average prices. They found a reduction in root mean squared errors of 16%, implying increased precision using a multivariate model with hourly data. In a VAR model, all variables are endogenous, and it captures interdependencies in multivariate systems. It is therefore a natural generalization of the univariate autoregressive (AR) model. In a VAR model, each variable is explained by its own lagged values, the lagged values of the other variables in the model, and the error term. By resolving this setup with one regression for every hour of the day we could also have used a least squared model. Unlike the VAR model, a least squared model does not allow for the variables to depend on its own lags and the lags of other variables. This allows the VAR to capture more features of the data. Another advantage of VAR is that it performs well with large–scale datasets (Brooks, 2014, pp. 326-338).

In their study of the performance of different models in different electricity markets, Ziel and Weron (2018) found that the VAR performed best at the Nord Pool exchange compared to the other European electricity markets. It was also found by Raviv et al. (2015) that the VAR model outperformed the regular AR models with an improvement of mean absolute error (MAE) of 12% when forecasting day–ahead spot price listed on Nord Pool.

The lag lengths for the VAR models were chosen by the lag length criteria of the AIC which is supported by both Ziel et al. (2015) and Raviv et al. (2015). The AIC information criteria adds a penalty term to the R^2 when the model increases its parameters in order to correct for possible overfitting (Brooks, 2014, p. 275). The lag length is dynamic in the sense that we tested the AIC for each hour of the day and changed the lag length afterwards.

Next the R^2, adjusted R^2 and the standard error of the regression were noted. To see how precisely the model describes variations in the dependent variable. To inspect the variables and their coefficients, generalized impulse response functions (GIRFs) were provided. The GIRFs map out the reactions of the price by describing the dynamics in the series conditional on both history and a shock of one standard deviation to the variables. We chose accumulated impulse responses in order to include the effect of previous lags of the variables. The number of periods included were equal to the lag length given by AIC. Then we can see whether the variations in the dependent variable have a positive or negative relation with the variables and the strength of this relation. The reason for the suitability of GIRFs for this setup is that they are invariant to the ordering of the variables (Koop, Pesaran, & Potter, 1996). A shock of one standard deviation also allows for proportional comparisons of effect with other markets, as a shock of a fixed size might have different effects in markets of different sizes (Würzburg et al. 2013). The GIRF was introduced by Koop et al. (1996), who argued its suitability for multivariate models in econometrics. Later on, Pen and Sévi (2010) proved its relevance in the commodity and electricity markets.

To see how these variables affect variations in the day–ahead spot prices, we test the following hypotheses

Ho: There is no relation between the variables X and the dependent Y.

Ha: There is a relation between the variables X and the dependent Y.

for each variable by running the regression

$$\Delta Spot_t = \beta_0 + \beta_{1\Delta hydro_{t-1}} + \beta_{2\Delta load_{t-1}} + \beta_{3\Delta coal_{t-1}} + \beta_{4\Delta gas_{t-1}} + \beta_{5\Delta PV_{t-1}} + \beta_{6\Delta Wind_{t-1}} + \varepsilon_t$$

for every hour of the day.

The null hypothesis is the statement being tested and if we can statistically reject the null hypothesis, we can conclude that the alternative hypothesis is true and the variable being tested does have a relation to the price (Brooks, 2014, p. 99).

Since we want to see if changes in the explanatory variables can describe the variations in the day–ahead spot price, we looked at the first difference of the natural logarithm of the variables.

$$\Delta X_{i,t} = LN\left(x_t\right) - LN\left(x_{t+1}\right)$$

This was done to the raw data of the dependent and independent variables. The data then represents a percentage change in the variables and also addresses that the variables are stated in different units, (table 1 page 18) to facilitate comparison (Graff, 2014). Since the day–ahead spot price quoted today is the price of buying electricity for tomorrow, the day–ahead spot price is one day ahead of the explanatory variables. In other words, all explanatory variables lag one day behind the price. This way, we can see how changes in the variables at time X_t describe changes in the prices at time Y_{t+1}.

No weekend dummies were included in the modelling as there are few practical differences between weekends and weekdays in the power market suggested by Nord Pool in a phone call 28/05/2019.

The VAR require stationary data, and the stationarity of the data set is presented by the ADF test for unit roots presented in Table 5 in the appendix.

5. Results and analysis

Table 4. *The rows show the coefficients that represents the generalized impulse response function (GIRF) in price by one standard deviation shock to the respective variable and their significance, lag length (lags) and R^2 for every hour of the day. Price is the day–ahead spot price. Coal and gas are the short–run marginal costs (SRMC) of the two with the price of CO_2 included. Hydrology is the hydrological balance in water dams, lakes, and snow in the mountain. Load is consumption subtracted for renewable energy production. Wind and PVs are the power production of these sources. *, **, and *** represent the significance of the variables at 10%, 5%, and 1% levels respectively. The hour represents the hour up to the noted value, e.g. hour 1 represents (00:00–01:00 CET). X noted in hour four for PVs is due to collinearity issues in this hour. Extended version including adjusted R^2 and the standard error of each regression (hour) and each variable are presented in Table 6 in the appendix.*

Hour	Price	Hydrology	Load	PV	Wind	Coal	Gas	lags	R-2
1	0.0608***	-0.0156***	0.0290***	-0.0080	-0.0197***	0.0013	0.0073	7	0.1746
2	0.0655***	-0.0200***	0.0313***	-0.0031	-0.0219***	-0.0008	0.0071	7	0.1973
3	0.0754***	-0.0194***	0.0339***	0.0015	-0.0224***	-0.0017	0.0082	7	0.2150
4	0.0783***	-0.0185**	0.0359***	X	-0.0249***	-0.0014	0.0084	7	0.2338
5	0.0713***	-0.0192***	0.0307***	-0.0147**	-0.0222***	-0.0021	0.0078	7	0.2469
6	0.0738***	-0.0082	0.0449***	-0.0092*	-0.0157***	0.0062	0.0083	8	0.3439
7	0.0810***	-0.0060	0.0506***	0.0082*	-0.0116**	0.0026	0.0079	8	0.4748
8	0.0920***	-0.0041	0.0627***	0.0039	-0.0140***	-0.0028	0.0124**	8	0.5144
9	0.0930***	-0.0041	0.0631***	-0.0033	-0.0138***	-0.0057	0.0183***	8	0.4918
10	0.0816***	-0.0046	0.0558***	0.0026	-0.0144***	-0.0046	0.0144***	8	0.4429
11	0.0690***	-0.0052	0.0487***	0.0011	-0.0128***	-0.0021	0.0117**	8	0.3998
12	0.0637***	-0.0063	0.0444***	0.0030	-0.0126***	-0.0005	0.0117***	8	0.3736
13	0.0649***	-0.0060	0.0425***	0.0034	-0.0125***	0.0004	0.0095**	8	0.3803
14	0.0681***	-0.0066	0.0428***	0.0032	-0.0124***	0.0009	0.0088**	8	0.3925
15	0.0706***	-0.0076*	0.0437***	0.0023	-0.0123***	0.0012	0.0077*	8	0.4017
16	0.0728***	-0.0076*	0.0437***	-0.0010	-0.0120***	0.0016	0.0077*	8	0.3771
17	0.0768***	-0.0075	0.0430***	-0.0037	-0.0116***	0.0024	0.0102**	8	0.3204
18	0.0501***	-0.0074	0.0206***	-0.0007	-0.0148***	-0.0019	0.0122*	7	0.2720
19	0.0704***	-0.0075	0.0382***	0.0012	-0.0128***	0.0017	0.0149***	8	0.2582
20	0.0555***	-0.0092**	0.0327***	0.0041	-0.0141***	0.0030	0.0136***	8	0.2231
21	0.0506***	-0.0103***	0.0291***	0.0002	-0.0143***	0.0032	0.0088**	8	0.1851
22	0.0490***	-0.0101***	0.0272***	0.0036	-0.0139***	0.0029	0.0078**	8	0.1889
23	0.0476***	-0.0102***	0.0263***	0.0113***	-0.0154***	0.0043	0.0073**	8	0.1655
24	0.0537***	-0.0140***	0.0334***	-0.0044	-0.0228***	0.0033	0.0083*	8	0.2205

5.1 Analysis

In this section we will analyze coefficients of the variables and their effects from Table 4 on page 29. Price, wind, and residual load all rejects the null hypothesis throughout the day. This means that these variables have a relation with price for all hours of the day. PV, gas and hydrology only rejects the null hypothesis for various hours of the day, while coal fails to reject the null hypothesis for every hour of the day.

5.1.1 Price

As expected, the price coefficients are strong, positive and significant at the 1% level for all hours, proving that the price are an important variable in describing price variations. The coefficients show their peaks in the morning hours of hours 7–10 (06:00–10:00 CET) and this is also when the R^2 is at its highest (Figure 5, page 36). Since we have not found any research that looks at the autoregressive effect on day–ahead spot prices on the prices itself, there is no relevant sources to compare this to.

5.1.2 Hydrology

The hydrology, as expected, has negative coefficients for every hour of the day, but the statistical significance varies within the day and the economic impact on price is weak. The negative coefficients imply that an increase in the hydrology would lead to a decrease in the day–ahead electricity price. This makes sense because a higher potential of electricity production can drive up the supply in the market and therefore drive prices down. Vice versa, lower potential production would lead to an increase in price. Hydrology seems to show significant coefficients during the hours of the day when the market shows the low volatility. They are significant from hours 1–5 (00:00–05:00 CET), and then the market volatility increases from hour 6 (table 3 on page 21) and hydrology loses its significance. When the volatility calms a bit down, hydrology becomes significant again during hours 15 and 16 before it stays insignificant until hour 20, from whereon it is significant for the rest of the day. This reaction is reasonable considering that the changes in hydrology happens slowly and steadily whereas the day–ahead prices have extreme volatility and spikes in peak hours. It looks as if the changes in hydrology is simply not keeping up with the changes in prices in peak hours and is therefore insignificant in volatile hours. To our knowledge, there is no research available on the effect of hydrology on the day ahead spot price in the Nordic power market that we can compare our results to.

5.1.3 Residual load

The residual load has positive coefficients, as previous research has shown as well (Bublitz et al., 2017; Clò et al., 2015; Gürtler & Paulsen, 2018; Hirth, 2018; Lagarde & Lantz, 2018; Mosquera-López & Nursimulu, 2019; Paraschiv et al., 2014; Paschen, 2016). The coefficients are significant at the 1% level for every hour of day and shows strong positive economic impact on the price. This is as expected, as the load represents the consumption in the market – in other words, the demand. Therefore, the positive coefficients mean that higher demand leads to higher prices, as supported by the classical economic theory. Residual load also has strong coefficients and is an important driver of the variance in prices throughout the day. The impact of residual load shows stronger coefficients in the hours of high volatility (Table 3, page 23). This is rather obvious because changes in residual load, which again represents changes in electricity demand, lead to variations in price, and not the other way around. The underlying factors of demand such as changes in temperature, social behavior, lifestyle, and the goods and services we acquire, all affect variations in electricity prices. Thus, the volatility in prices shown by Table 3 on page 23 is largely driven by residual load. Only beaten by price itself, residual load is the variable with the highest significance and strongest coefficients and is therefore the second strongest driver of variations in the day–ahead spot price.

5.1.4 PV

PV showed some significant coefficients early in the morning and for one hour in the evening, but the strength of the coefficients was of little economic impact. PV first becomes significant in hour 5, which is reasonable since it is around this time of day that the sun rises. As expected, the coefficient is negative, since an increase in the supply of electricity from renewable sources drives supply up and prices down. The same goes for hour 6, but for hour 7 the coefficient, slightly surprisingly, turn positive. This result is supported by Mosquera-Lopez et al. (2017), who found a positive relationship between price and PV production in the morning. They rationalized this behavior because in the morning the sun comes up and PV production increases. At the same time the demand for electricity in the market is rapidly increasing. The increase in consumption alone increases the price, but also, high demand leads to more production from sources of high marginal costs like coal and gas, which will further increase the price. Therefore, in the hour 7 the increase in production from PVs and the increase in price have a positive relationship. It is also probable that the positive relationship in hour 23 has a similar, yet opposite, explanation. In the evening the supply from PVs is reduced since the sun goes down. The consumption of electricity also goes down as people tend to go to sleep around hour 23. This would lead to the effect of reduced consumption and reduced production from PVs happening at the same time. Therefore, they have a positive relationship.

One might think that PVs would have more significant coefficients during daytime, as this is when the sun is shining. A reason for the insignificance of PV might be that even though the development of production facilities for PV production in the Nordic region has been increasing a lot in recent years. The production is still low compared to hydropower, wind, and fossil fuel. In comparison, according to our data from 2014 to 2018, the highest production for a single hour in the Nordic power market from PVs was 715 MWh, while the lowest production from total thermal generation, represented by residual load, was 21,178 MWh. In other words, PVs maximum production in one hour equals just above 3% of the lowest production from thermal power. The low amount of electricity produced by PVs might be why a lack of impact is showing during the daytime.

PV shows collinearity in the GIRF in hour 4 of the sample and did not receive a coefficient for this hour. However, this is during nighttime and we do not expect a significant coefficient that would have implications for our analysis.

5.1.5 Wind

Wind has negative significant coefficients for every hour of the day and shows the third strongest economic impact. It was also found by Mosquera-Lopez et al. (2017) when they were looking at wind speeds that the effects of wind speeds were always negative. However, it is a bit surprising that wind is significant at the 1% level throughout the day with the only exception of hour 7, at which it is significant at the 5% level. The strong significance of wind throughout the day was surprising since the production of electricity from wind has a high dependence on exogenous weather factors (Mosquera-Lopez et al., 2017). Since the wind speeds tend to vary a lot, we were expecting wind power production to have some hours of weak or insignificant coefficients. The significance of electricity production from wind is not affected by whether it is daytime or nighttime or by the changing volatility in the market. There is a noticeably stronger impact of wind during the nighttime compared to the daytime. In their study of the drivers of daily average prices in Germany Mosquera-López and Nursimulu (2019) also found that wind is a good short–run indicator of price variations which supports our results. Paraschiv et al. (2014) found in their study on the German market that the impact of wind is stronger than the impact of PV, and that the impact on the price is stronger during nighttime. Paraschiv et al. (2014) expected that the impact of wind would increase during nighttime because wind speeds tends to increase in the evening and stay stronger during nighttime compared to daytime. This is supported by Paschen (2016), who also found a stronger negative impact from wind during the nighttime.

5.1.6 Coal

The results from coal shows positive insignificant coefficients for all hours of the day. This is supported by Mosquera-Lopez et al. (2017), who also presented positive statically insignificant coefficients of coal for almost all the percentiles that they were looking at. A reason for this lack of significant estimates could be the fact that coal is not a good hourly driver of variations in the day–ahead spot price but is more suitable in the longer term. This is because the price development of coal is strongly interrelated to the global market and coal supplies a third of all energy used worldwide (I. E. Agency, 2018). Coal is also regulated through climate policies due to its high emission levels (Krzemien, Fernandez, Sanchez, & Lasheras, 2015). We interpreted that since coal is affected by global and regulatory factors, the coal price is more stable than the electricity price. Therefore, the coal price cannot describe the more volatile short run changes in electricity spot price. This interpretation coincides with the findings of (Mosquera-López & Nursimulu, 2019). They used data on daily frequency and found poor performance from coal prices in the short–run but that coal was one of the main drivers of pricing in the future market.

The study of Hirth (2018) found that coal was an economically important driver in the German market, but not for the Swedish market, where it was close to zero from 2008 to 2015. Sweden is a big participant in the Nordic market and has a more similar production mix to the Nordic power market overall than the German market has (Appunn, Bieler, Haas, & Wettengel, 2019; Pöyry, 2018; Research, 2018)**.** Therefore, the very low impact of coal in Sweden found by Hirth (2018) supports our results of a weak economic and insignificant impact of coal in the Nordic power market. While we have included the cost of CO_2 emissions in the SRMC of coal, Hirth (2018) included CO_2 as a separate variable and he found that the impact of the cost of CO_2 emissions was rather weak – approximately 8%. This is a result that can neither confirm nor contradict the weak impact of coal with CO_2 costs included that we found. On the other hand, a strong effect of the CO_2 price in Sweden could have indicated that our results are somewhat opposing.

Since coal is the energy source that pollutes the most, it is a natural place to start reducing production when the object is to reduce emissions. From the period of 2010 to 2014, Gianfreda et al. (2016) found that the increase of renewable energy sources significantly reduced the production from coal in Great Britain and Spain. Therefore, the influence of coal prices on the electricity price was decreasing. The insignificant results we found in the Nordic power market could be an extension of the results of Gianfreda et al. (2016), considering that the coal production in the Nordic region is even lower than in the rest of Europe (Energiewende & Sandbag, 2019; Pöyry, 2018).

5.1.7 Gas

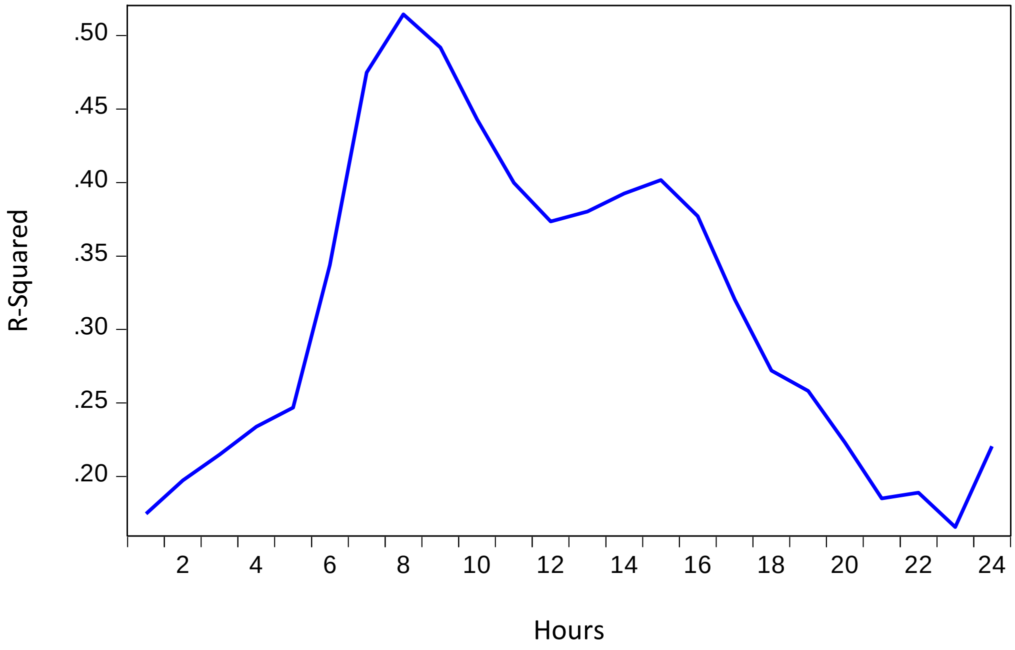
Gas is not significant during nighttime from hours 1–8 (00:00–08:00 CET) but stays significant throughout the rest of the day and the strongest impact is noted in the peak hours. Gas seems to show a stronger impact during the peak hours in the morning and evening as the coefficients are stronger in these periods. The coefficient of gas stays positive throughout the entire day, which means that an increase in the SRMC of gas leads to higher electricity prices. We can see that the significance levels show signs of clustering as the highest significance levels are during the peak hours of the day. As shown in the Table 3 on page 23, these are also the hours of the day with the highest kurtosis, skewness, and standard error. This shows that gas is a significant driver of the price through volatile periods and is insignificant during the calm night period. This is supported by the findings of (Würzburg et al., 2013) in their study of Germany and Austria. They also found that gas prices are short–term determinants for spot prices, especially during times of high demand. This is also supported by Paraschiv et al. (2014), who found evidence of gas to be decreasing over time due to higher amounts of renewable energy, which again supports the MOE as gas, with the highest marginal costs, after oil, is the first source to be squeezed out of the market.

5.2. Summary

Price, wind, and residual load all rejects the null hypothesis throughout the day. PV, gas and hydrology rejects the null hypothesis for various hours of the day, while coal fails to reject the null hypothesis for every hour of the day.

Our results are mostly as expected, but the strong significance of wind was slightly surprising. The strongest variables in describing the variations in the day–ahead spot price was the price itself followed by the residual load due to its strong coefficient. Both had strong significance and positive coefficients throughout the day. Wind showed significant coefficients throughout the day but had noticeable weaker negative coefficients. While coal was insignificant, PVs, hydro, and gas showed varying significance throughout the day. This goes to show that the variables are not performing equally in different hours of the day. PV showed significant coefficients in the early morning hours and for one hour in the late evening, but the economically significance was low. Gas became significant in the morning and stayed significant from there on out with strongest impact during peak hours. Hydrology, on the other hand, stayed significant during the calm nighttime, midday and evening. It was during these significant hours that hydrology showed economically impact on price. The changing significance of the variables intraday tells us that they are affecting volatility differently. Price, gas, and load showed the strongest coefficients during the peak hours of the day. Hydrology showed the weakest coefficients in those hours. This means that price, gas, and load are better at describing the intraday price variation during hours of high price volatility and hydrology is better during hours of low price volatility. What is noticeable is that the explanatory power of the model (Figure 5, page 36), performs best during the hours of the day when the volatility is highest (Table 3 page 21. This shows that the model captures rapid changes in price well. The model provides an R^2 of around 50% for hours 8 and 9, which are noted as the most volatile hours of the day (Figure 5, page 36). It is during these hours that we experienced the highest prices (Figure 6, the appendix) and the lowest prices (Figure 7, the appendix). This strongly supports the notion from Raviv et al. (2015) that valuable and important information about price development will be lost when you average out hourly prices to daily prices.

Figure 5. *The explanatory power of the model represented by the* R^2 *for every hour of the day.*



6. Concluding remarks

Our thesis addressed the volatile Nordic power market with a model setup that has not been done by previous research. This is to provide better insights about the drivers of variations in the day-ahead spot price on the Nord Pool power exchange, and intraday changes in these drivers from 2014 to 2018.

The VAR model was used because of its rich structure and suitability to large-scale simultaneous equations, and the supplementary GIRF was provided to analyze the variables. We had 24 individual matrixes, one for each hour of the day, containing all the variables. The variables we approached were residual load, production from wind and PVs, the hydrological balance, and the SRMCs of coal and gas with the price of included.

Our findings are largely as expected, but the strong significance of wind throughout the day was slightly surprising. Price and residual load were the main drivers due to its strong coefficients. Price itself, as expected, was the most important driver. The coefficients were strongest during the peak hours of the day and they were positive and significant for every hour. Like price, the residual load showed significant and positive coefficients throughout the day and had the second strongest coefficients. Residual load also showed its strongest impact during peak hours and a weaker impact during calm hours. Wind had negative and significant coefficients for every hour of the day, but showed noticeably weaker coefficients than price and residual load. The negative coefficients for wind were strongest during nighttime. The variables gas, PV, and hydrology were significant in different hours of the day and showed far weaker coefficients than the main drivers. Gas had positive and significant coefficients during the daytime hours of high and medium volatility in the spot price but were insignificant during the calm night hours. On the other hand, the hydrology showed the opposite pattern, as it was significant during the hours of low volatility and always showed negative coefficients. This is expected as the changes in hydrology are slower than the extreme behavior of price during volatile hours, and therefore hydrology does not significantly explain the price variations in those hours. PV mostly showed significant coefficients during the less volatile hours in the morning, but the weak coefficients imply little economic impact. Coal had insignificant coefficients throughout the day, this is slightly as expected because coal is unable to capture the volatility in the power market. The setup of the VAR model performs better during hours of high volatility as this is when the explanatory power is highest (Figure 5, page 36).

We addressed the hourly effect of hydrology. This has not been done by previous research in the Nordic power market. The changing strength of the coefficients and significance of the variables throughout the day, reveal that there is valuable information intraday that many researchers have forgone by averaging out hourly data, such as Clò et al. (2015) and Würzburg et al. (2013). Our results provide information about the intraday changes in the variables that affects the day–ahead spot price. This can help investors better understand which variables and exogenous effects are driving the variations in price hour by hour. This is essential for investors who are to inform Nord Pool about the amount and price of the electricity they are supplying or buying, especially in hours of high volatility and extreme spikes in prices intraday.

The findings should be interpreted with caution as there is little previous research and literature to compare our approach and the variables with. Further research should be done within the area to eventually replicate the study. An appealing supplementation of our research would be to address the dataset with periodical breaks. We have delineated and focused our data on a continuous sample hour by hour, but it would be interesting to see how periodical breaks based on seasonal changes between summer and wintertime affect the variables, especially for the renewable sources. The renewables, PV and wind, show large seasonal changes in production, see figure 4 on page 19, therefore their impact on the price might also change.

7. Appendix

Table 5. *Augmented Dickey Fuller (ADF) test for stationarity at hourly frequency. The lags in this test are chosen by the Akaike information criterion (AIC). The coefficients noted are the probabilities.*

Null: Unit root present in the variable

	Levels	1st difference
Price	0.000	0.000
Coal	0.874	0.000
Gas	0.009	0.000
Hydro	0.256	0.000
PV	0.000	0.000
Hydro	0.000	0.000
Wind	0.000	0.000

Figure 6. *The maximum prices at level achieved for each hour of the day through 2014-2018. There are two spikes intraday and they are a clear indicator of higher consumption and demand during the hours when people wake up around hour 7, and when they get back from work and daily activities around hour 16.*

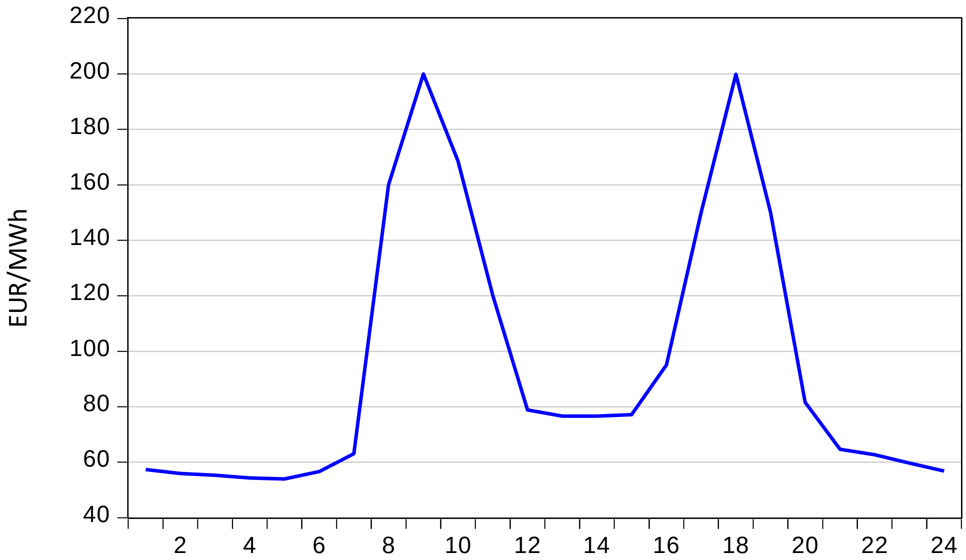


Figure 7. *The minimum price at level achieved for each hour of the day through 2014-2018. There is one spike that gradually starts around hour 15 (14:00-15:00 CET) and peaks around hour 19 (18:00-19:00 CET). During these hours we do not experience the low prices as we are during nighttime and until hour 15.*

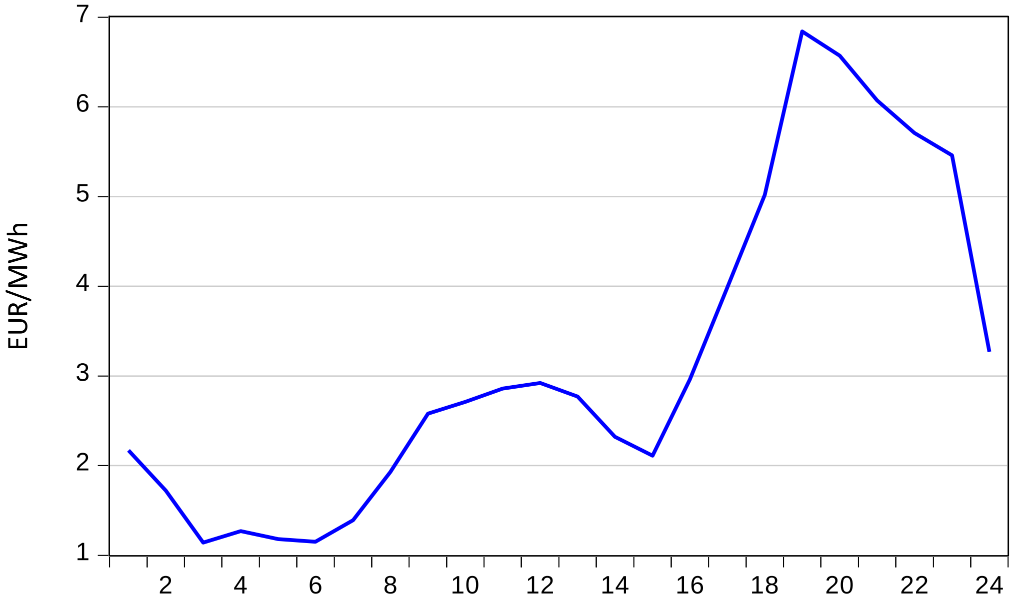


Figure 8. *Shows the average price for each hour from 2014-2018. Here we can see that spikes shown in figure 4 and 5 are smoothed, but still shows two peak hours, hour 9 and 19.*

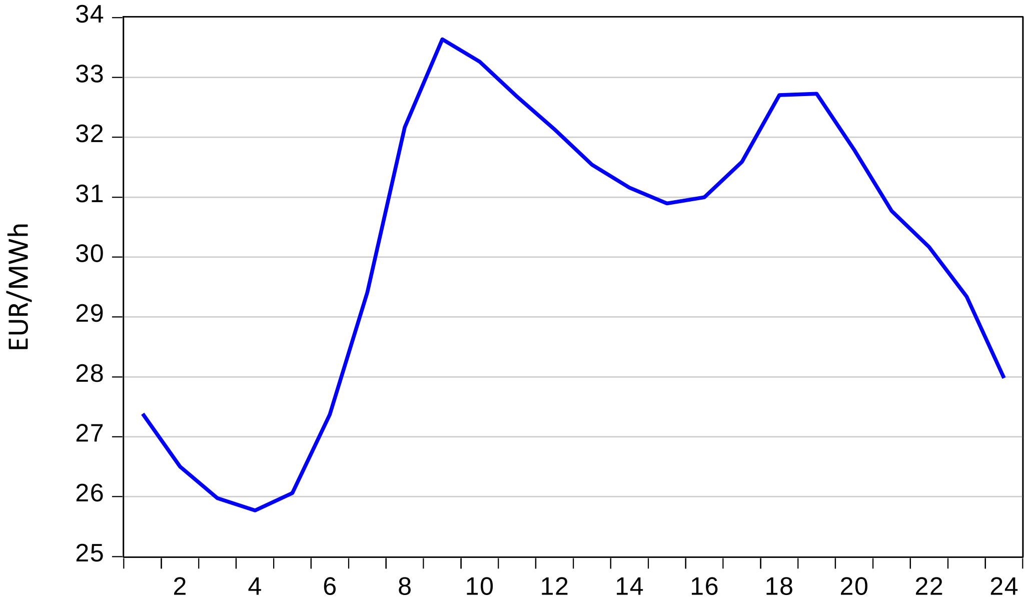


Table 6. *The table presents the lags, R^2 (R-2), the adjusted R^2 (adj. R-2) and the standard error (SE) from the Vector Autoregressive model (VAR). Also, the coefficients, Standard deviation (SE) and their significance of the Generalized Impulse Response Function (GIRF) for each variable with a shock of one standard deviation. *, **, *** represent the significance of the variables respectively, 10%, 5% and 1% level. The results are based on hourly data from January 2014 – December 2018. The lags of the VAR are chosen based on the Akaike Information Criteria (AIC).*

Hour	Price	Coal	Gas	Hydro	Load	PV	Wind	lags	R-2	adj. R-2	SE
1	0.0608 (0.0055) ***	0.0013 (0.0061)	0.0073 (0.0060)	-0.0156 (0.0061) ***	0.0290 (0.0056) ***	-0.0080 (0.0061)	-0.0197 (0.0054) ***	7	0.17	0.15	0.17
2	0.0655 (0.0061) ***	-0.0008 (0.0068)	0.0071 (0.0066)	-0.0200 (0.0067) ***	0.0313 (0.0063) ***	-0.0031 (0.0068)	-0.0219 (0.0060) ***	7	0.20	0.18	0.20
3	0.0754 (0.0068) ***	-0.0017 (0.0075)	0.0082 (0.0073)	-0.0194 (0.0074) ***	0.0339 (0.0069) ***	0.0015 (0.0072)	-0.0224 (0.0066) ***	7	0.21	0.19	0.21
4	0.0783 (0.0069) ***	-0.0014 (0.0075)	0.0084 (0.0073)	-0.0185 (0.0074) **	0.0359 (0.0069) ***	X X	-0.0249 (0.0066) ***	7	0.23	0.22	0.22
5	0.0713 (0.0063) ***	-0.0021 (0.0070)	0.0078 (0.0068)	-0.0192 (0.0069) ***	0.0307 (0.0064) ***	-0.0147 (0.0067) **	-0.0222 (0.0062) ***	7	0.25	0.23	0.21
6	0.0738 (0.0050) ***	0.0062 (0.0058)	0.0083 (0.0056)	-0.0082 (0.0057)	0.0449 (0.0052) ***	-0.0092 (0.0054) *	-0.0157 (0.0052) ***	8	0.34	0.32	0.18
7	0.0810 (0.0043) ***	0.0026 (0.0052)	0.0079 (0.0050)	-0.0060 (0.0050)	0.0506 (0.0044) ***	0.0082 (0.0049) *	-0.0116 (0.0046) **	8	0.47	0.46	0.16
8	0.0920 (0.0048) ***	-0.0028 (0.0056)	0.0124 (0.0054) **	-0.0041 (0.0055)	0.0627 (0.0045) ***	0.0039 (0.0054)	-0.0140 (0.0050) ***	8	0.51	0.50	0.16
9	0.0930 (0.0050) ***	-0.0057 (0.0059)	0.0183 (0.0056) ***	-0.0041 (0.0057)	0.0631 (0.0047) ***	-0.0034 (0.0055)	-0.0138 (0.0052) ***	8	0.49	0.48	0.16
10	0.0816 (0.0046) ***	-0.0046 (0.0054)	0.01444 (0.0051) ***	-0.0046 (0.0052)	0.0558 (0.0044) ***	0.0026 (0.0047)	-0.0145 (0.0047) ***	8	0.44	0.43	0.14
11	0.0690 (0.0042) ***	-0.0021 (0.0048)	0.0117 (0.0046) **	-0.0052 (0.0047)	0.0487 (0.0039) ***	0.0011 (0.0041)	-0.0128 (0.0042) ***	8	0.40	0.38	0.13
12	0.0637 (0.0039) ***	-0.0005 (0.0045)	0.0117 (0.0043) ***	-0.0063 (0.0044)	0.0444 (0.0037) ***	0.0030 (0.0038)	-0.0126 (0.0039) ***	8	0.37	0.35	0.12
13	0.0649 (0.0039) ***	0.0004 (0.0044)	0.0095 (0.0042) **	-0.0060 (0.0042)	0.0425 (0.0037) ***	0.0034 (0.0037)	-0.0125 (0.0038) ***	8	0.38	0.36	0.12
14	0.0681 (0.0039) ***	0.0009 (0.0044)	0.0088 (0.0042) **	-0.0066 (0.0043)	0.0428 (0.0037) ***	0.0032 (0.0038)	-0.0124 (0.0039) ***	8	0.39	0.37	0.12
15	0.0706 (0.0039) ***	0.0012 (0.0045)	0.0077 (0.0043) *	-0.0076 (0.0044) *	0.0437 (0.0038) ***	0.0023 (0.0039)	-0.0123 (0.0040) ***	8	0.40	0.38	0.12
16	0.0728 (0.0041) ***	0.0016 (0.0046)	0.0077 (0.0045) *	-0.0076 (0.0046) *	0.0437 (0.0039) ***	-0.0010 (0.0043)	-0.0120 (0.0041) ***	8	0.38	0.36	0.13
17	0.0768 (0.0044) ***	0.0024 (0.0050)	0.0102 (0.0048) **	-0.0075 (0.0049)	0.0430 (0.0043) ***	-0.0037 (0.0048)	-0.0116 (0.0044) ***	8	0.32	0.30	0.13
18	0.0501 (0.0044) ***	-0.0019 (0.0049)	0.0122 (0.0048) *	-0.0074 (0.0048)	0.0206 (0.0041) ***	-0.0007 (0.0046)	-0.0148 (0.0043) ***	7	0.27	0.25	0.14
19	0.0704 (0.0044) ***	0.0017 (0.0049)	0.0149 (0.0047) ***	-0.0075 (0.0048)	0.0382 (0.0043) ***	0.0012 (0.0048)	-0.0128 (0.0043) ***	8	0.26	0.23	0.12
20	0.0555 (0.0036) ***	0.0030 (0.0039)	0.0136 (0.0038) ***	-0.0092 (0.0039) **	0.0327 (0.0035) ***	0.0041 (0.0037)	-0.0141 (0.0034) ***	8	0.22	0.20	0.10
21	0.0506 (0.0033) ***	0.0032 (0.0035)	0.0088 (0.0034) **	-0.0103 (0.0035) ***	0.0291 (0.0031) ***	0.0002 (0.0034)	-0.0143 (0.0031) ***	8	0.19	0.16	0.08
22	0.0490 (0.0031) ***	0.0029 (0.0033)	0.0078 (0.0032) **	-0.0101 (0.0033) ***	0.0272 (0.0030) ***	0.0036 (0.0031)	-0.0140 (0.0029) ***	8	0.19	0.16	0.07
23	0.0476 (0.0032) ***	0.0043 (0.0034)	0.0073 (0.0033) **	-0.0102 (0.0034) ***	0.0263 (0.0032) ***	0.0113 (0.0034) ***	-0.0154 (0.0030) ***	8	0.17	0.14	0.08
24	0.0537 (0.0045) ***	0.0033 (0.0049)	0.0083 (0.0047) *	-0.0140 (0.0049) ***	0.0334 (0.0045) ***	-0.0044 (0.0049)	-0.0228 (0.0043) ***	8	0.22	0.20	0.14

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