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Analyzing Drivers of Day Ahead Electricity Prices in Norway NO2: Is there an impact of Cross-Zonal Connections?

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Abstract

This thesis investigates the various factors influencing the day-ahead electricity prices in the NO2 bidding zone of Norway, with a special focus on the effect of cross-zonal connections.

Utilizing a Ordinary Least Squares regression model, the study analyzes an extensive dataset from 2015 to 2023, including variables such as production data, load, precipitation, wind, temperature, gas prices, CO_2 prices, coal prices, transmission levels to other regions and geopolitical and economic uncertainty indexes.

A significant discovery of this thesis is the pronounced effect of natural gas prices on electricity costs in the NO2 zone. This correlation highlights the deep interconnection between global commodity markets and regional energy prices, illustrating how international market fluctuations and geopolitical events can directly impact local electricity prices. Conversely, other anticipated influencers, such as coal and CO_2 prices, did not show significant effects, possibly indicating a shift in energy market dynamics due to evolving policies, technological advancements, and the growing penetration of renewable energy sources.

The research further explores the nuanced role of electricity transmission and its complex interplay with price formations, revealing that while transmissions have a notable impact, they account for only a small portion of price variation. This finding underscores the importance of understanding cross-border electricity flows within market frameworks to understand price driving dynamics.

Contents

List of Figures

List of Tables

Abbreviations

ADF	Augmented Dickey-Fuller Test
ANN	Artificial Neural Network
ARIMA	Auto-Regressive Integrated Moving Average
CD	Cooling Degrees
CO2	European Union Allowances
DAM	Day Ahead Market
EEX	European Energy Exchange
EPF	Electricity Price Forcasting
EUPHEMIA	Pan-European Hybrid Electricity Market Integration Algorithm
GWh	Gigawatt Hour
HD	Heating Degrees
HEnEX	Hellenic Energy Exchange
ICE	Intercontinental Exchange
ICSS	Iterative Cumulative Sums of Squares
LEAR	Local Expansion and Reduction
LMP	Locational Marginal Price
LSGP	Local Search Genetic Programming
MCP	Market Clearing Price
MET	Norwegian Meteorological Institute
MWh	Megawatt Hour
NB	Norges Bank
NEMO	Nominated Electricity Market Operator
NVE	The Norwegian Water Resource and Energy Directorate
OLS	Ordinary Least Square
OMIE	Spanish and Portugese power exchange
OPCOM	Romanian power exchange
OTE	Czech power exchange
PCR	Price Coupling of Regions
RES	Renewable Energy Sources
SD	Standard Deviation
SDAC	Single Day-Ahead Coupling
SIDC	Single Intraday Coupling
TGE	Polish power exchange
TSO	Transmission System Operator
TVP	Time Varying Parameter
TWh	Terrawatt Hour
VRE	Variable renewable energy source

1 Introduction

Electricity distribution originally functioned as a monopolistic utility system, where distinct regional utilities were responsible for the generation, transmission, and distribution of electricity. Governed by rate-of-return regulation, these utilities managed all aspects of electricity provision centrally. Over recent decades, global electricity markets have increasingly deregulated, leading to the establishment of competitive trading systems (Mayer & Trück, 2018).

In Norway, the 1990 Energy Act catalyzed reforms inspired by early adopters like the UK and New Zealand, introducing competitive markets like Nord Pool and its spot market (Bye & Hope, 2005).

Simultaneously, the work for a single pan European cross zonal day-ahead electricity market has progressed, launching the North Western Europe Price Coupling in 2014 ("ENTSO-E - Single Day-ahead Coupling (SDAC)", n.d.). Norway's interconnections to the European continent are all localized in the Norway South/South West, or NO2, bidding area. This study focuses on the NO2 electricity prices in the period 2015 to 2023. The first 6 years have been characterized by low prices, with some peaks and fluctuations as seen in Figure 13.

However, In the second half of 2021, an unprecedented situation emerged. Norway, traditionally insulated from significant volatility by its hydro-powered self-sufficiency and comparative low electricity prices, found itself in uncharted territory seeing electricity prices on historic highs. In the same period an energy shortage arose across Europe, further catalyzed by the geopolitical unrest stemming from the invasion of Ukraine in 2022 and the subsequent sabotage of the Nord Stream pipeline, drove electricity prices to unprecedented levels. Combined with Europe's dependency on Russian gas, this triggered a widespread energy crisis across the continent, reverberating through the industrial sectors and household economies alike. In the middle of this crisis, Norway opened two new interconnections to both Germany/Luxembourg (2021) and Great Britain (2022).

These interconnections have come under great scrutiny by the media, and have by several been pointed out as one of the main reason for the soaring electricity prices in parts of Norway (Rognsvåg, 2022; Solli, 2022; Stavrum, 2021). This has fueled further debate as strong differences within Norway's five bidding areas have emerged in the later years, leading to cases of daily average price differences up to 21 000% between NO2 and its more northern counterparts (Ertesvåg, 2022). In 2023 the Norwegian Ministry of Energy established an expert panel to assess the current market situation. The expert panel investigated the current market structure and, among other, the potential effects of removing the foreign cross-zonal connections. They concluded that the current market structure was the best option. However even this report contributed to differing views on the drivers of electricity prices and especially the role of the interconnections ("Har vurdert en rekke strømpris-forslag", 2023).

Despite the abundance of opinions and speculations, there exists a gap in the literature addressing the quantitative impact of cross zonal connections on electricity prices. This thesis aims to help bridge this gap by providing a comprehensive analysis of the drivers affecting electricity prices in NO2, with a particular focus on the role of these cross-zonal connections. This empirical investigation serves both as a tool for policy makers and has practical usage for market operators, such as electricity producers.

We have assembled a comprehensive dataset, which after reviewing existing literature, we believe to be unique due to its wide range of variables. To analyze the quantitative impact of these variables we have used an OLS-regression model. We've chosen an OLS-regression model to analyze the quantitative impact of these variables due to its robustness, simplicity, and interpretability. OLS-regression allows us to estimate the relationship between our independent variables and the dependent variable, providing a clear understanding of how changes in the predictors are associated with changes in the response. By capitalizing on the advantages of OLS-regression, we aim to evaluate the influence of various variables in our dataset, particularly those associated with the transmission of electricity in and out of NO2.

This thesis is structured to first lay the groundwork with an overview of the electricity market, followed by a literature review to frame the research within the context of existing studies. It then outlines the research methodology employed to investigate the research question, proceeding to analyze the data and present findings. Ultimately, it aims to shed light on the intricate dynamics of electricity pricing, offering evidence-based insights that could inform policy decisions and market strategies moving forward.

2 Electricity Market

In this chapter we will go through how the European and the Norwegian electricity market are connected, going from state driven monopolies to liberalized markets. Today's Nordic market structure will be described with focus on price setting mechanisms as well as how market integration is made possible through different market operations. Finally, we will delve into the merit order and the concept of water value to understand the price driving dynamics of electricity prices in NO2.

The European electricity market is characterized by a diverse energy mix and ambitious sustainability goals, but are still heavily reliant on non-renewable energy sources such as coal, nuclear and gas - as seen in Figure 1.

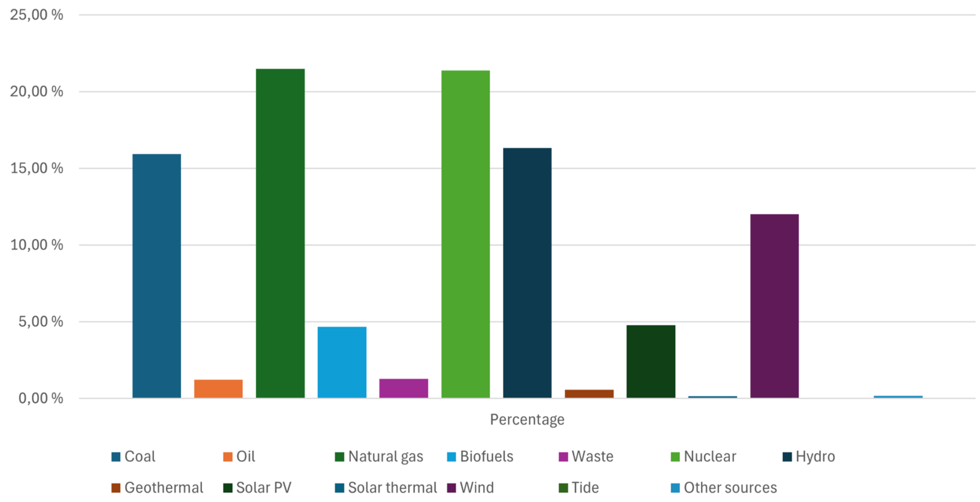

Figure 1: Electricity generation by source, Europe 2021 ("IEA - Energy Mix", n.d.)

However, over the last years Europe have seen a rapid development in introducing more wind and renewables to its energy mix, illustrated in Figure 2.

This development is expected to continue with the EU's binding renewable targets of a minimum of 42.5% of the total energy mix by 2030 ("European Commission - 2030 Targets", n.d.). The introduction of intermittent renewable energy such as wind and solar introduces some challenges for the market. The inability to store electricity coupled with the unpredictable production from renewable sources complicates forecasting, increasing the probability for price spikes.

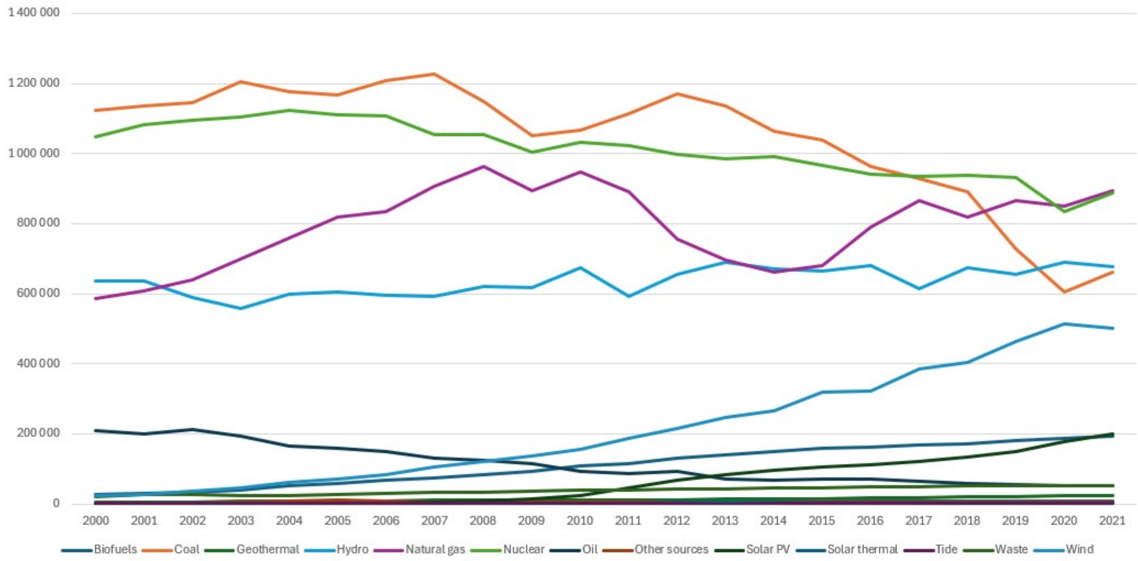

Figure 2: Evolution of electricity generation by source in GWh, Europe 2000-2021 ("IEA - Energy Mix", n.d.)

Within the context of renewables, the Nordic countries, and Norway in particular, emerge as pivotal players due to their unique position in hydropower - a position often referred to in Norway as 'Europe's battery' ("How Norway can become Europe's battery", n.d.) due to the ability to store water in reservoirs and regulate production - meaning that when solar and wind production is low, Norway can export electricity and import when it is the other way around - consequently flattening the price curve.

Roughly 90% of Norway's total production stems from hydro-power ("Om magasinstatistikken - NVE", n.d.). The hydro-production is spread throughout Norway, but majority of it resides in the south of Norway, also known as the NO2 price area. In 2023 NO2 produced 50TWh, or 33% of the total production, while only 35TWh consumption 26% of the total of 136TWh ("Statnett - Report 2023", 2024). This excess of electricity is why most of the interconnections to the European markets are localized in NO2, as seen in Figure 3.

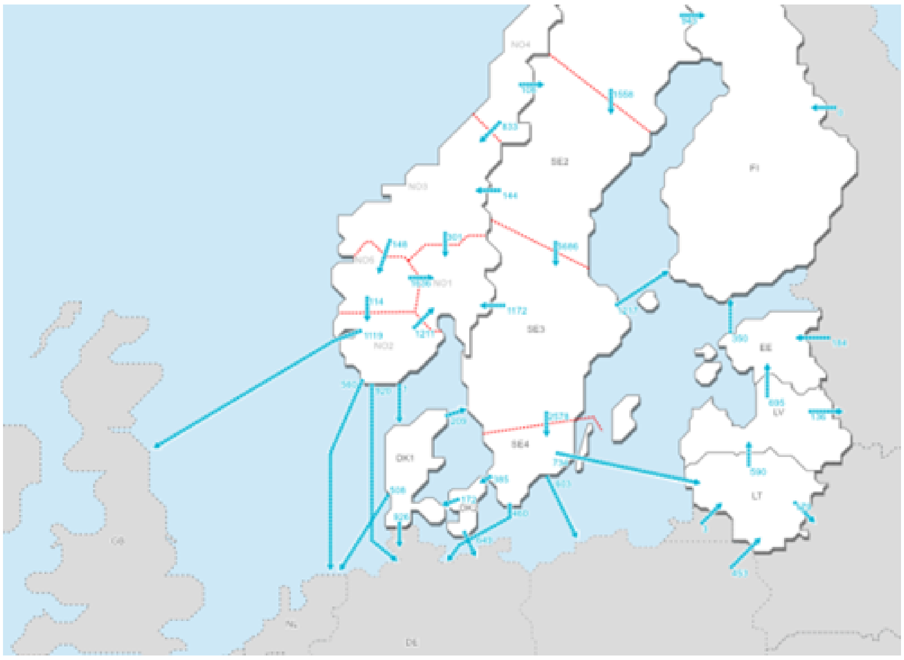

Figure 3: Interconnections NO2 (“Tall og data fra kraftsystemet”, 2024)

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2.1 Nord Pool and an Integrated European Market

In Norway the new Energy Act of 1990 laid the legal foundation for Norway’s electricity reform. This was a consequence of generation capacity considerably exceeding electricity demand. Pioneering countries as the UK and New Zealand fueled inspiration for the market reform, laying ground for the introduction of Nord Pool and its spot market (Bye & Hope, 2005).

In 1996 the Nord Pool was established as a Norwegian-Swedish power exchange. In the following years both Finland and Denmark joined the exchange making it a fully integrated Nordic market. As of 2023, 370 companies from 20 countries trade on the Nord Pool markets, and Nord Pool is appointed as Nominated Electricity Market Operator (NEMO) in 16 European countries, including the Baltics, Netherlands and Germany. This liberalization of energy markets set the standards for the rest of Europe, and as of 2023 all European countries are using Power exchanges. In 2023 a total of 1 104 TWh was traded through Nord Pool’s platforms making it Europe’s leading power exchange (Mayer & Trück, 2018; “Next - Power Exchanges”, n.d.; “Nord Pool - Figures 2023”, n.d.; “Nord Pool - History”, n.d.; “Nord Pool - Our business”, n.d.).

2.2 The Day-Ahead Market

The Day-Ahead Market (DAM), as the primary venue for power trading in the Nordic region, sees the highest volumes traded on Nord Pool. This market involves hourly contracts for next-day physical power delivery. Orders must be submitted between 08:00 and 12:00 CET daily, with Transmission System Operators (TSOs) required to publish capacities for each bidding area by 10:00 CET, which are defined based on electrical grid constraints ("Nord Pool - System price and Area price calculations", n.d.).

After the auction closes at 12:00 CET, an aggregated supply curve for each hour and bidding area is created from all anonymous block orders. Prices for each hour of the next day are then calculated based on these orders and the available transmission capacity, and are then published at 13:00 CET ("Norwegian Ministry of Energy - Power Markets", n.d.) ("Nord Pool - System price and Area price calculations", n.d.). Nord Pool calculates two prices in the day-ahead market: the System Price and Area Prices.

2.2.1 The System Price

The System Price within the Nordic electricity market represents a benchmark, serving as an unconstrained market-clearing reference price across Norway, Sweden, Denmark, and Finland. Defined by Nord Pool, this price is calculated under the theoretical condition of infinite transmission capacity, effectively ignoring any congestion within the Nordic transmission grid ("Nord Pool - System price and Area price calculations", n.d.) This approach facilitates a unified price across the Nordic region and serves as a reference price in standard financial contracts within the region. This aspect helps align financial transactions with the underlying physical market dynamics.

The calculation of the System Price takes into account electricity flows between the Nordic countries and their European neighbors, including the Netherlands, Germany, Poland, and the Baltic states, based on the outcomes of area price calculations ("Nord Pool - System price and Area price calculations", n.d.).

The day-ahead calculation of the System Price by Nord Pool is predicated on the equilibrium between supply and demand, where bids from producers and consumers are matched to determine the marginal cost of electricity production. This equilibrium pricing mechanism ensures that the cheapest available energy resources are deployed to meet the demand, optimizing the cost-efficiency of electricity supply within the Nordic market.

External factors, such as Norway's significant trading capacity and the prices of global energy commodities, exert a pronounced influence on the System Price. Additionally, the high proportion of hydropower in the Nordic energy mix introduces variability to the System Price, with fluctuations in hydrological conditions directly affecting electricity prices. Similarly, the integration of wind power and temperature-driven demand variations further compound the price sensitivity to renewable energy production and consumption patterns ("Norwegian Ministry of Energy - Power Markets", n.d.).

2.2.2 Area Prices

In the Nordic and Baltic electricity markets, Area Prices address grid congestion and ensure efficient electricity distribution across regions. TSO-defined bidding areas are delineated based on the grid's capacity and congestion issues, stemming from supply-demand imbalances ("Nord Pool - System price and Area price calculations", n.d.).

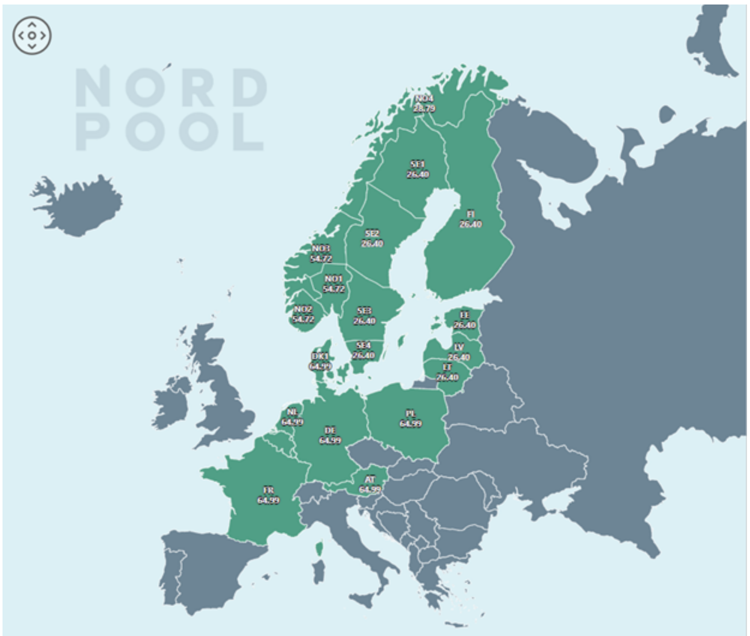

Figure 4: Overview of bidding areas NordPool ("Nord Pool | Day-ahead map", n.d.)

Electricity flows from areas with lower prices or surplus supply to areas with higher demand and prices, influenced by the transmission capacity between these regions. Insufficient capacity leads to different area prices, reflecting local electricity values based on supply and demand dynamics ("Nord Pool - System price and Area price calculations", n.d.). For instance, high demand and prices in foreign areas incentivize exports from regions like NO2, while the reverse occurs during low-price, high-production periods. This is an interesting dynamic and is why we have included transferred electricity to adjacent bidding areas as variables in our model.

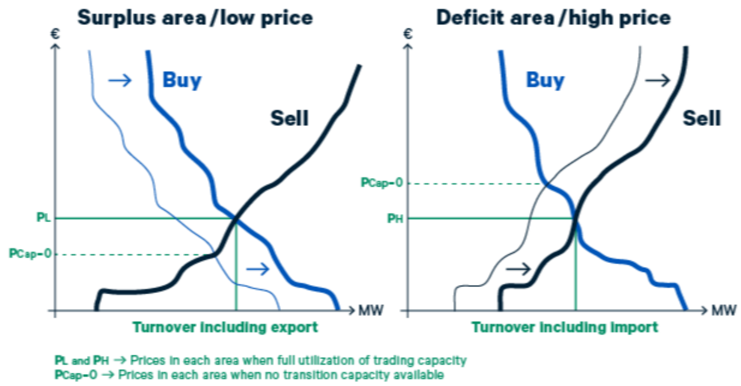

Figure 5: Price determination in Bidding areas ("Nord Pool - System price and Area price calculations", n.d.)

Area Prices, determined by aggregated supply and demand curves intersecting with net flow dynamics, serve as the payment standard for all transactions within the bidding zone. This mechanism aligns electricity generation and consumption financially according to market conditions ("Nord Pool - System price and Area price calculations", n.d.).

Furthermore, bidding zones and Area Prices signal power deficits and surpluses, guiding optimal adjustments in generation and consumption. This influences long-term infrastructure planning by indicating where new capacities or consumption sites might be needed. However, without capacity constraints in the Nordic grid, Area Prices tend to harmonize across regions, aligning with the System Price and indicating a unified market free from congestion ("Norwegian Ministry of Energy - Power Markets", n.d.).

In our study we operate with one price-variable. This is the sum of the Area Price of NO2 and the System Price, which is the wholesale electricity price paid within the NO2 area.

2.2.3 The Single Day-Ahead Coupling (SDAC)

The SDAC aims to integrate day-ahead markets across the continent into a unified, efficient trading platform. This integration optimizes electricity trading by facilitating effective competition, enhancing market liquidity, and ensuring the efficient use of generation resources across Europe ("ENTSO-E - Single Day-ahead Coupling (SDAC)", n.d.). By incorporating cross-border transmission capacities into the trading algorithm PCR EUPHEMIA, SDAC efficiently allocates these resources, thereby maximizing social welfare and contributing to the creation of a cohesive pan-European electricity market.

Figure 6: Participating countries in the Single Day-Ahead Coupling ("ENTSO-E - Single Day-ahead Coupling (SDAC)", n.d.)

The Price Coupling of Regions (PCR) algorithm, known as the Pan-European Hybrid Electricity Market Integration Algorithm (EUPHEMIA) is the operational backbone of SDAC. It plays a pivotal role in calculating electricity prices across Europe and implicitly allocating cross-border capacities through auction mechanisms. PCR EUPHEMIA considers a wide array of inputs including network capacities and constraints from TSOs and bids and offers from NEMOs, it then executes a calculation that addresses the matching problem ("ENTSO-E - Single Day-ahead Coupling (SDAC)", n.d.) - ensuring an optimal match between demand and supply while maximizing social welfare.

Market statistics highlight the substantial impact of SDAC, with 98.6% of EU consumption now coupled through this mechanism, facilitating 1 530 TWh/year in a unified market solution and handling an average daily value of matched trades amounting to 200 million euros. ("ENTSO-E - Single Day-ahead Coupling (SDAC)", n.d.).

PCR EUPHEMIA is the foundation for the market integration in NO2, by managing transmission constraints and enhancing market liquidity. This in principle could lead to converging prices across borders, and highlights the importance of data on transmission to neighbouring bidding areas in our model.

2.2.4 The Price Coupling of Regions (PCR)

The PCR initiative underpins the SDAC through the PCR EUPHEMIA algorithm, emphasizing three core principles: employing a unified algorithm, ensuring robust operations, and maintaining individual power exchange accountability ("Nord Pool - What is Price Coupling of Regions?", n.d.).

PCR facilitates the anonymized sharing of orders and network constraints via the PCR Matcher and Broker service, enabling precise calculations of bidding zone prices, reference prices, and net positions. This ensures a balance between collective efficiency and the accountability of individual exchanges within the European electricity market.

Operated collaboratively by eight power exchanges - EPEX, GME, HEnEx, Nord Pool, OMIE, OPCOM, OTE, and TGE - the initiative's significant contribution is the development of the EUPHEMIA, enhancing market integration ("Nord Pool - What is Price Coupling of Regions?", n.d.).

2.2.5 Flow based capacity calculation

The Nordic region plans to switch from Available Transfer Capacity (ATC) to Flow-Based (FB) capacity calculation starting in early 2024 ("Nord Pool - Flow Based", n.d.). While the fundamental principles for calculating the Nordic System Price, such as incorporating hourly electricity import and export values from neighboring areas, will remain unchanged, the shift to FB could alter electricity flows across the nine Nordic borders with the SDAC (Core/Baltic). This change stems from FB's enhanced ability to reflect actual physical constraints and transmission capabilities, which may affect cross-border electricity flows and the dynamics of the System Price in the Nordic market ("Nord Pool - Flow Based", n.d.). As the efficiency of managing transmission constraints increases through the FB capacity calculation, a plausible outcome is that of further price convergence between bidding areas.

2.3 The Merit Order

The merit order is a principal that guides the dispatch of electricity generation in a manner that prioritizes cost efficiency. By ranking available generation units by their marginal costs, the cost of producing one additional unit of electricity, in a supply stack. The merit order curve ensures that the lowest-cost sources are utilized first to meet demand, and where the two curves cross the Market Clearing Price (MCP) is formed. This system not only promotes economic efficiency, but also has profound implications for the integration of renewable energy sources and the overall dynamics of electricity pricing (Next Kraftwerke, n.d.).

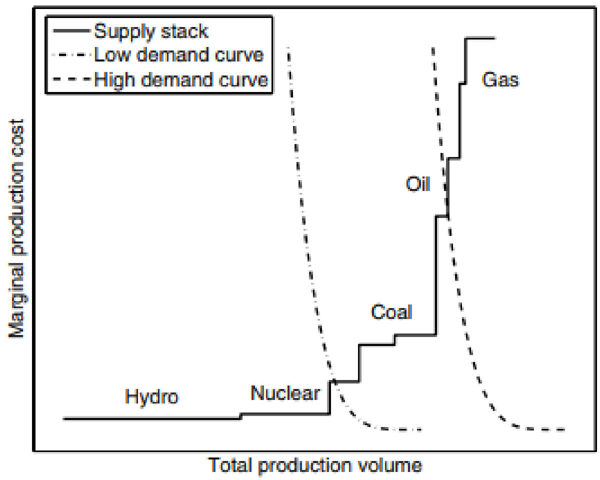

Figure 7: Supply stack as illustrated by Weron, 2007

Renewable energy sources such as wind and solar power, which have negligible marginal costs, reside at the bottom of the merit order curve due to free "fuel" sources like sunlight and wind, reducing operational expenses. Nuclear energy also occupies a favorable position on this curve because of its low running costs. This cost-effectiveness hierarchy is evident in the Nord Pool electricity market, where a diverse array of generation technologies with varying costs is organized into a step wise marginal cost curve. This configuration facilitates optimized electricity dispatch that meets demand efficiently, reflecting the economic rationale of the merit order in energy markets (Huisman et al., 2014; “Next - Merit Order”, n.d.). The merit order in combination with the interconnections to other countries highlights the need for price data on energy sources such as coal, oil, gas and CO2 - making them a natural inclusion in our model.

Price spikes, common in deregulated electricity markets, result from the volatile supply-demand interplay, often precipitated by sudden demand increases or operational constraints in generation assets. These spikes highlight the merit order's role in stabilizing the market during fluctuations caused by seasonal variations, unexpected weather events, and the operational traits of generation technologies (Weron, 2007).

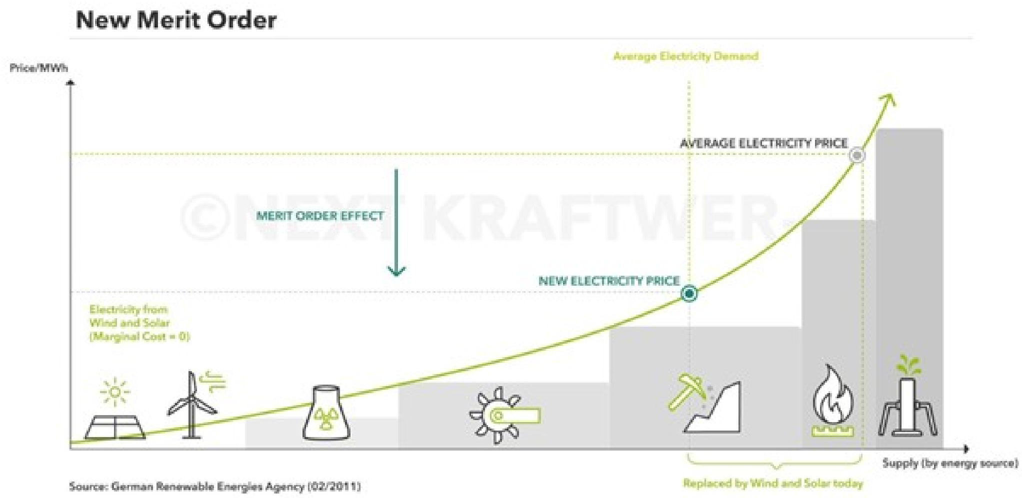

Figure 8: Introduction of renewables, "Next - Merit Order", n.d.

The integration of renewable energy significantly affects the merit order, lowering wholesale electricity prices as seen in markets like Germany and Belgium. However, the reduction in wholesale prices does not fully translate to lower consumer costs due to taxes, levies, and tariffs embedded in electricity bills, illustrating the complexity of converting market efficiencies into consumer benefits ("Next - Merit Order", n.d.).

Additionally, the merit order influences operational strategies by dictating the flexibility and response capabilities of different generation technologies. For instance, gas-fired plants, despite higher costs, provide essential flexibility for peak demand, whereas nuclear and hydroelectric plants offer consistent base-load power due to their lower costs but limited flexibility. This demand for flexibility highlights the importance of Norway's position as "Europe's battery" ("How Norway can become Europe's battery", n.d.). This ordering ensures a strategic, reliable deployment of resources to match demand (Weron, 2007).

2.3.1 Water Value

The concept of water value emerged from the liberalization of the Norwegian electricity market, reflecting the alternative value of using water for hydropower today versus its future utility. This dynamic valuation requires sophisticated approaches for managing hydropower reservoirs (Førsund et al., 2005).

The establishment of the Nord Pool spot market ended state monopolies on electricity export/import, integrating various power sources like thermal, nuclear, and wind into the market (Førsund et al., 2005). In this context, the inherently low marginal costs of wind and hydropower highlight the cost-effectiveness of renewable resources. The variability of water availability introduces opportunity costs, affecting decisions on immediate power generation or reserving water for future use, thereby making hydropower's marginal cost dynamic (Huisman et al., 2014).

Norway, with nearly half of Europe's water reservoirs, holds a strategic position in the European energy landscape. The complex and uncertain task of calculating water value is crucial for producers navigating water availability and fluctuating electricity prices. This calculation involves factors like current reservoir levels, potential overflow, and expected future prices, requiring a decentralized approach where local knowledge is essential (Gran et al., 2023).

Overall, water value serves as both a marginal cost in the short term and a broader economic principle for optimizing the use of Norway's extensive hydropower resources, balancing immediate benefits against future water value in a sustainable, efficient manner. Since water value calculations are proprietary for the producers, it is not included in our model. However we have included reservoir levels for the NO2-area, as we see them as a possible driver of electricity prices.

2.4 The Intraday Market

In the real-time electricity market, Nord Pool facilitates intraday trading across 14 countries, complementing the day-ahead market to help market participants adjust their positions closer to the physical delivery time. This is crucial as the rise of intermittent renewable energies complicates post-day-ahead market balance ("Nord Pool Intraday", n.d.). Trading is available continuously, with transactions possible up to one hour before delivery, allowing for dynamic capacity adjustments by TSOs based on day-ahead market outcomes and intraday trade volumes ("Nord Pool Intraday", n.d.).

Despite these mechanisms, unforeseen events can still disrupt market balance. As the system operator in the Nordics, Statnett ensures stability by leveraging balance markets to adjust production and consumption levels as needed ("Norwegian Ministry of Energy - Power Markets", n.d.).

2.4.1 The Single Intraday Coupling (SIDC)

The SIDC initiative represents an advancement in the European electricity market, facilitating a unified cross-zonal intraday electricity market across the European Union. This framework enables market participants to engage in electricity trading up to the day of delivery, enhancing the overall efficiency of intraday trading ("ENTSO-E - Single Intraday Coupling (SIDC)", n.d.). The integration of intraday markets across Europe serves multiple objectives, including the promotion of competition, augmentation of market liquidity, and facilitation of shared energy generation resources. Moreover, it provides a mechanism for market participants to adjust for unforeseen changes in consumption and outages effectively. ("ENTSO-E - Single Intraday Coupling (SIDC)", n.d.).

3 Literature review

3.1 Drivers of Electricity Prices

Understanding the drivers of electricity prices is crucial for stakeholders across the energy sector, including policymakers, energy companies, and consumers. The aim of our study is to investigate the effect of electricity transmission between regions in the NO2 bidding area, however electricity prices are influenced by a complex interplay of factors ranging from the fundamental dynamics of supply and demand, weather and hydrology, to regulatory policies and market prices. In recent years, the integration of renewable energy sources has added another layer of complexity to this dynamic. With this in mind, we review the existing literature focusing on electricity price drivers in the following sections.

Burger et al., 2014 introduced the following framework to illustrate the interplay of fundamental drivers for both the demand- and supply side.

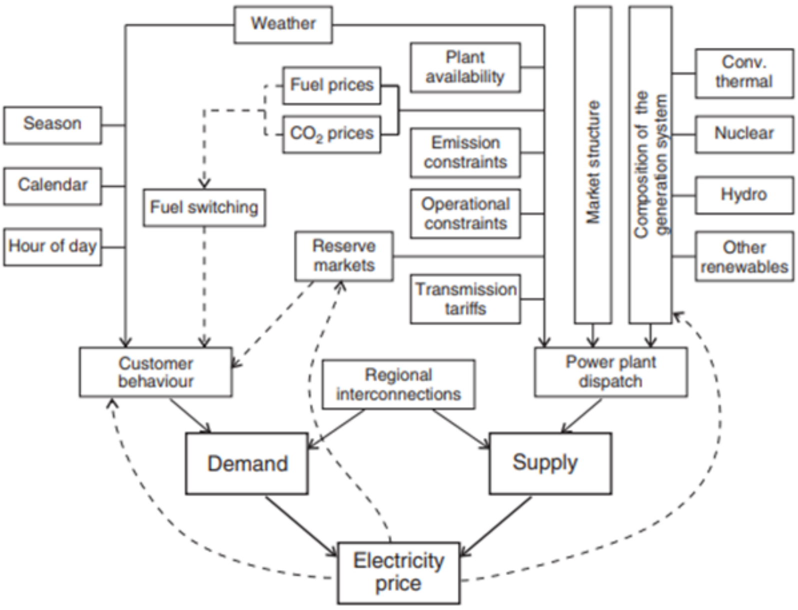

Figure 9: Electricity price drivers Burger et al., 2014

The demand side is subject to seasonality and its different weather conditions. Escribano et al., 2011 highlights that electricity demand is heavily influenced by seasonality in both business activities and weather conditions. Voronin et al., 2014 argues that "electricity demand is higher when the atmospheric temperature rises or falls from a base 'comfortable level'". This is relevant for the NO2 price area which, as the rest of the

Nordic, experiences significant drops in temperature during winter - and the demand for heating increases. However, in the model proposed by Voronin et al., 2014, the effect of temperature and other weather related variables were incorporated in the electricity demand. In Norway, households accounts for 32% of the total electricity consumption, where as industry accounts for 46% ("Statistisk Sentralbyrå", n.d.). As difficult weather conditions are typical for the Nordic region, extreme weather conditions may cause an increase in the electricity demand, this in turn can lead to higher electricity prices because more expensive production sources must be activated (Voronin et al., 2014). In addition to seasonality, Burger et al., 2014 found that electricity consumption varies significantly depending on the day of the week, with heightened industrial and service activities on weekdays and reduced demand on weekends. Public holidays and school holidays, as well as days adjacent to weekends or holidays, typically see decreased industrial and service demand but increased household consumption.

Daily electricity usage patterns also shift based on the type of day, such as working days, weekends, or holidays, mirroring the typical daily routines and activities of those periods. Weather conditions further affect electricity use, especially for heating and cooling, depending on temperature and, to a lesser extent, wind speeds. Buildings' thermal inertia can delay the electrical demand response to temperature changes, while lighting needs across sectors generally follow global daylight levels (Burger et al., 2014).

Supply, on the other hand, based on the framework of Burger et al., 2014 depends on the availability and cost of fuels (such as natural gas, coal, and oil), the operational status of power plants (maintenance, outages), and the capacity to generate electricity, including from renewable sources like wind and solar, which are inherently variable.

Howison and Coulon, 2009 introduced a foundational model for spot electricity prices, which is grounded in stochastic processes governing key factors such as fuel prices, power demand, and generation capacity availability. Through analysis of observed bid data, they identify significant correlations between bid fluctuations and the associated variations in fuel prices.

Huisman et al., 2014 discuss the nuanced relationship between fuel and emission prices and their impact on electricity prices within markets heavily influenced by hydro power, which is the case for NO2. This research stands as a significant contribution to the understanding of how hydroelectric supply dynamics, emanating from hydro producers' actions, affect competitive electricity markets.

The study reveals that a supply curve incorporating reservoir levels, CO2 emission permit prices, and natural gas prices can explain a significant portion of the variation in hourly spot prices. Notably, hydro supply is found to exert a dampening effect on day-ahead electricity prices, whereas fuel and emission prices contribute to price increases.

Through a detailed subsample analysis, the study highlights the necessity for time-varying parameters in the supply curve, indicating that the influence of these parameters on electricity prices shifts with the changing availability of hydro supply. This finding suggests that market agents' competitive behaviors vary across different reservoir levels, altering the competitive landscape of the power market. This is also highlighted by Førsund et al., 2005, and Gran et al., 2023, as hydro producers determines the water value based on its future value. The analysis also demonstrates that emission permits and natural gas prices significantly influence day-ahead electricity prices, especially when reservoir levels are low, underpinning the increased reliance on thermal power production under such conditions.

Hirth, 2018 highlights the nuanced impact of Germany's Energiewende, a policy framework aimed at transitioning to renewable energy sources while simultaneously phasing out nuclear power. The findings suggest that these two foundational strategies of the Energiewende essentially counterbalanced each other with respect to their effects on power prices.

Zakeri et al., 2023 investigates the role of fossil-fuelled versus low-carbon electricity generation in each EU-27 country plus Great Britain and Norway during 2015-2021, and their findings reveal a paradoxical situation where, despite a decrease in fossil-fuel generated electricity to 34% of total electricity generation, with natural gas comprising 18%, fossil fuel based (notably those powered by natural gas) power plants set the wholesale electricity prices approximately 58% of the time. This dependency of natural gas highlights the European vulnerability to price volatility, as well as (or induced by) geopolitical risks, exchange rate fluctuations. The gap left by coal's decline has been predominantly filled by natural gas, exacerbating Europe's exposure to external energy market shocks and price volatility. The study notes a shift towards higher electricity import dependency in countries like Ireland and Denmark, further intensifying the interconnection between European electricity prices and broader market dynamics.

Deane et al., 2015 highlights a significant transformation in the dynamics of electricity markets across Europe is examined over the preceding decade. The integration of Renewable Energy Sources (RES) into the grid leads to a rightward shift in the merit order curve, thereby lowering the spot market price for electricity, a phenomenon known as the merit order effect. This effect is also found by Spodniak et al., 2021 but in addition he notes that the stochastic nature of wind generation introduces greater variability between the actual power generated in real-time and the day-ahead forecasts. This discrepancy necessitates an increased reliance on balancing services to maintain grid stability (the ability to maintain correct frequency, transport and deliver electricity, and minimize outages), potentially escalating the costs associated with these services. The merit order effect is pronounced in the German market, yet Deane et al., 2015 notes that similar outcomes are observable in other market designs.

The view of renewables lowering electricity prices is supported by Hosius et al., 2023 who studied the impacts of wind energy, distinguished between onshore and offshore, on the wholesale electricity prices in Germany, Western Denmark, and Great Britain between 2015 and 2018. Central to their findings was a reduction in electricity prices. The magnitude of this effect, as highlighted by the study, is contingent upon the steepness of the supply curve at the juncture of supply and demand, varying significantly across different regions and times of the day. Notably, the research underscores that offshore wind energy generally exerts a more pronounced positive impact on wholesale electricity prices than onshore wind, primarily due to its more stable feed-in patterns and lower correlation with overall wind feed-in. This stability contributes to reduced price levels and volatility, underscoring the value of diversifying wind energy sources.

Although several studies highlights the introduction of renewables and the "merit order effect" Bublitz et al., 2017 dissects the fundamental price drivers that have contributed to the observed price reduction in the observed years 2011-2015. The findings presented by Bublitz et al., 2017. challenge the prevailing narrative in the energy economics field. Through their analysis, they ascertain that the significant fluctuations in wholesale electricity prices can be attributed to the variations in fuel and carbon prices, rather than the expansion of RES like photovoltaics. Specifically, they identify a substantial decline in coal and carbon emission allowance prices as the primary catalysts for the reduction in electricity spot prices during the period under review.

Karakatsani and Bunn, 2008 emphasize that the structure and design of the market are fundamental to the formation of prices, a sentiment echoed by Wolak, 2001 and Bower and Bunn, 2001. They assert that the specific characteristics of the market must be accurately represented in models to generate precise predictions and understandings of market behaviors. They also argue that electricity markets are volatile, subject to various shocks including fuel prices, demand and supply fluctuations, and regulatory changes, such as the imposition of carbon dioxide prices in Europe.

The research by Lago et al., 2018b shows that market integration significantly affects electricity price dynamics, highlighted by the interactions between Belgium and France, proving the efficacy of EU market integration policies. Meanwhile, Uribe et al., 2020 finds that an integrated market framework allows for better risk sharing across borders, attributing more price variability to intermarket shocks rather than isolated ones. This enhances market stability, efficient energy distribution, and resilience against energy crises, reinforcing the benefits of ongoing market integration efforts.

Market integration and interconnections to neighboring countries is highlighted by several (Burger et al., 2014, Lago et al., 2018b and Uribe et al., 2020) as having effects on electricity prices. As we've already concluded that the inherent European and Nordic market design is designed for this very interconnectivity - we find it surprising given the last years political discussion that there, to our knowledge, exists almost no literature on its effects on the NO2 bidding zone.

3.2 Electricity Price Modeling

Electricity price modeling plays a pivotal role in the energy sector, guiding decision-making processes for utility companies, regulators, investors, and consumers. Different modeling and prediction methods have long been employed to predict electricity prices, leveraging historical data and statistical techniques to estimate future price movements. This section will delve into different studies on predicting methods, providing insights into how they have been applied to anticipate electricity price trends and their relevance in today's rapidly changing energy landscape. The literature on modeling and predicting electricity prices is interesting to us as the literature showcases not only different methods for modeling electricity prices, but importantly also different sets of predictors, which is also related to the purpose of our study.

There is no consensus in the literature to define what is the short-, medium- and long-term electricity, but short-term EPP (Electricity Price Prediction) generally forecasts from a few minutes up to a few days ahead (Weron, 2014), which will be the focus for studies included in this literature review - as the thesis focuses on the day ahead electricity price modeling. We did not want to limit the included studies to solely focus on the Nordics or NO2, first and foremost because of gaps in the literature, but also as we've touched upon earlier, markets across the world, and especially Europe, is getting liberalized and increasingly integrated.

3.2.1 Proposed Taxonomies

Aggarwal et al. (2009) proposed a categorization of forecasting methodologies into three main categories; Game theory models, Time series models, and Simulation models:

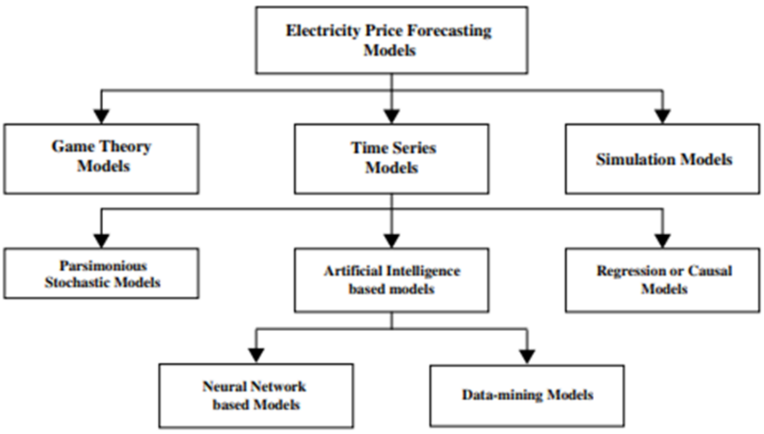

Figure 10: Classification of price-forecasting models as illustrated by Aggarwal et al., 2009.

This categorization faced some criticism by Weron, 2014, especially as to the statistical models included both time series and artificial intelligence models. In the same article Weron, 2014 proposed the following taxonomy for electricity price models which will be the basis for the following literature review.

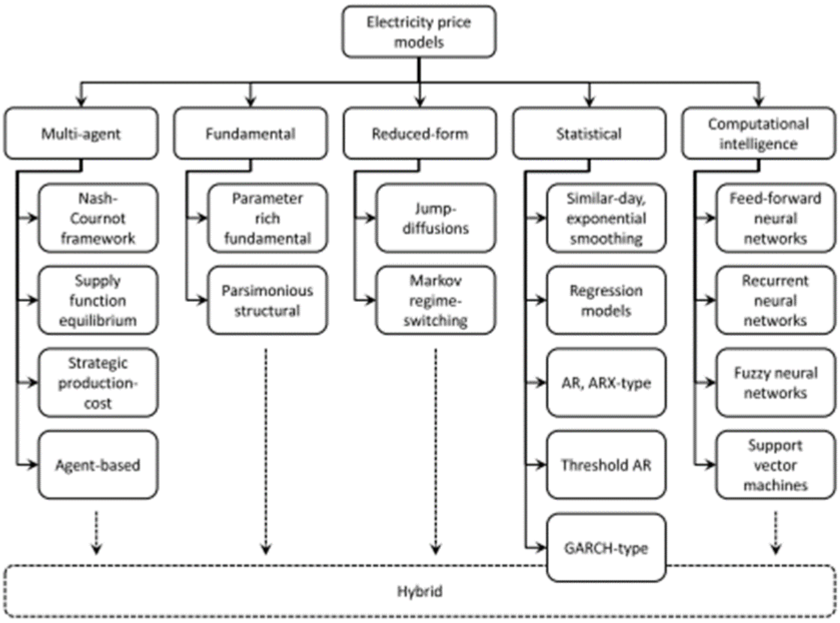

Figure 11: The taxonomy proposed by Weron, 2014.

The main categories is defined by Weron, 2014 as follows:

- **Multi-agent models:** Simulate the operation of a system of heterogeneous agents (e.g., generating units, companies) interacting within a market, building the price process by balancing demand and supply.

- **Fundamental models:** Describe the dynamics of electricity prices by modeling the impacts of key physical and economic factors.

- **Reduced-form models:** Characterize the statistical properties of electricity prices over time, focusing on derivatives evaluation and risk management.

- **Statistical approaches:** Apply statistical techniques directly for load and price forecasting or implement econometric models tailored to power markets.

- **Computational intelligence techniques:** Integrate learning, evolution, and fuzziness to adapt to complex dynamic systems, often considered as 'intelligent' approaches.

In our thesis we will use a standard regression-based technique that falls into the 'statistical' category and to which we refer to as 'Traditional forecasting'. However, we will also follow the 'computational intelligence' literature as they represent the recent trends in predicting electricity prices and we will refer to that category as 'Machine Learning'.

3.2.2 Traditional Forecasting

Based on econometric models traditional forecasting methods encompass approaches such, as time series analysis, regression models and Auto-Regressive Integrated Moving Average (ARIMA) models. These techniques, refined over the years, play a role in understanding the complexities and fluctuations of electricity prices. This section aims to discuss the strengths and limitations of forecasting techniques shedding light on their evolution and relevance amidst advancements in capabilities and emerging forecasting strategies.

Weron and Misiorek, 2008 conducted a study to assess the effectiveness of 12 different time series forecasting methods designed for predicting short term (day ahead) spot prices, in auction based-electricity markets. Their analysis covered two markets; California, where they used spot prices and system wide load data as well as their day-ahead forecasts and the Nordic market, where they utilized hourly spot prices along with air temperature data. Their findings showed that models that incorporate system load as a factor generally outperform models based on price in terms of predictive accuracy particularly in the California market. The impact of air temperature as an exogenous variable on forecasting performance is not as distinct, underscoring the variable's lower predictive strength for electricity prices compared to system load.

In their study, Karakatsani and Bunn, 2008 investigates the effectiveness of price models, in predicting day ahead electricity spot prices in the British market. They utilize two modeling techniques; a time varying parameter (TVP) regression model that adapts to changing pricing structures due to factors like agent behavior and shifts in regulations and market frameworks and a regime switching regression model that addresses pricing inconsistencies stemming from variations and scarcity events. Fuel prices were omitted from the model due to their slow evolution over the 10-month sample period. Karakatsani and Bunn, 2008 also includes 'demand volatility' in their model, acting as an expression of temporal weather and consumption patterns - similar to Weron and Misiorek, 2008. The study demonstrates that models incorporating market fundamentals with time varying coefficients outperform other forecasting methods, including models with similar coefficient dynamics. Kristiansen, 2012 presents an approach to predicting the day ahead electricity prices in the Nord Pool market building upon the foundation laid out by Weron and Misiorek, 2008. This model distinguishes itself by streamlining the complexity of the model consolidating 24 parameter sets into one and incorporating Nordic demand and Danish wind power generation as key external factors. Rather than implementing a dependence on the minimum price on the previous day as proposed by Weron and Misiorek, 2008, Kristiansen, 2012 introduced a dependence on the maximum price from the previous day. The modifications introduced by Kristiansen, 2012 by emphasizing the maximum price from the previous day as a predictor diverging from Weron and Misiorek, 2008 reliance on the minimum price, significantly improves the model's accuracy, in an out-of -sample forecasting framework. As Kristiansen, 2012 sees the Nordics as one, his inclusion of wind generation and demand is similar to what we are doing in our thesis with regards to NO2. However, as the European electricity markets get increasingly more integrated one can argue that the lack of interconnections to other regions makes Kristiansen's study outdated. We solve this by including all interconnections to other price regions as well as the actual flow of electricity on these interconnections.

In the study by Kristiansen, 2014, the focus is on developing and evaluating spot price forecasting models for the Nord Pool market, contrasting with the commonly utilized Electricity Market Planning and Simulation (EMPS), or 'Samkjøringsmodellen' and stochastic dual dynamic programming (SDDP) models, which are complex, proprietary, and often considered 'black box' due to their inaccessibility. Kristiansen, 2014 introduces three models that are more transparent and straightforward, leveraging historical spot prices, futures prices, and hydrological data (inflows and reservoir levels) to predict future prices with high precision. These models include a regression model that utilizes historical data to forecast prices with a high degree of accuracy. The effect of hydro reservoir levels is also discussed by Huisman et al., 2014 who suggests that market agents' competitive behavior changes with different levels influencing the price, making it a natural inclusion in our model.

Voronin et al., 2014 present a hybrid model designed to predict electricity prices in the Finnish spot market. What sets this model apart is its focus on both price fluctuations and sudden spikes in prices. The methodology involves analyzing the electricity price data in layers to separate price trends from spike behaviors using different data processing methods for each to adjust for trends and seasonal patterns.

The effectiveness of the model was compared to eight forecasting techniques showing better accuracy in forecasting regular market prices and a satisfactory level of accuracy in predicting spikes. This progress is credited to the models' capacity to blend non-linear predictive skills, as well as its innovative method, for forecasting spikes.

Karabiber and Xydis, 2019 conducted an examination of predicting day electricity prices in Denmark West, utilizing various methods over a 212-day period beginning in early 2017 with data from 2016 for training. Variables included in the model and their correlation coefficient is presented in Table 1.

While our study includes historical data on the same variables, we hope to add to the list of explanatory variables that should be included in similar models in the future by including variables such as interconnections to neighbouring bidding areas and geopolitical uncertainty.

Table 1: Explanatory Variables, (Karabiber & Xydis, 2019)

Explanatory Variable	Correlation with price
Temperature	0.057
Consumption Prognosis	0.430
Production Prognosis	0.005
Wind Prognosis	0.368
Oil Prices	0.259
Natural Gas Prices	0.293
Hydro Reservoir Levels	0.313

Sirin and Yilmaz, 2020 delve into the dynamics within the Turkish electricity market between May 2016 and May 2019. They investigate the rise of variable renewable energy sources (VRE) and their interplay with market prices and remuneration mechanisms. As the share of renewable energy sources like wind and run-of-river hydro has climbed, the conventional wisdom surrounding electricity market economics and pricing mechanisms has been challenged. The study employs a quantile regression model to dissect the merit-order effect - a phenomenon where increased renewable energy supply leads to lower average day-ahead market prices.

The research uncovers a significant, albeit variable, negative merit-order effect attributable to wind and hydro technologies. This variability is closely tied to fluctuating demand, differing price levels, and the specific technology in question.

In their analysis, Sirin and Yilmaz, 2020 consider an array of factors influencing wholesale electricity prices, including forecasted demand, renewable production, and fuel prices, alongside variables such as interconnection capacities and international energy trade. They meticulously account for the exogenous nature of demand and the negligible short-term price elasticity, using day-ahead demand forecasts and projected VRE generation as critical variables. Notably, the study sidesteps distributed generation and conventional energy sources that might skew market price responses due to endogeneity concerns.

The analysis incorporates natural gas prices and temporal variables like weekly and seasonal patterns to comprehensively capture price determinants. The approach also respects the integrity of electricity price spikes as vital market signals, rejecting any data manipulation that might obscure the underlying market dynamics.

Biber et al., 2022 conducted an analysis using logistic regression models to explore the impact of various factors on the occurrence of low and negative electricity price events. These factors included the generation mix, fuel and emission allowance prices, and temporal variables, with the models being finely tuned and validated against data spanning from 2019 to 2021. The findings underscore the role of fluctuating renewable energies, such as wind and solar, in increasing the probability of these price phenomena. The presence of flexible generation sources like gas-fired power plants, coupled with high grid demand and traditional energy production, was associated with higher and more stable market prices.

The study also observed that an increase in CO2 allowance prices tends to mitigate the frequency of negative prices, attributing this effect to the operational flexibility of gas power stations - which emit less CO2 compared to their coal-based counterparts. Notably, the COVID-19 pandemic exerted a significant influence by reducing grid load in 2020 and 2021, thereby exerting downward pressure on electricity market prices.

The study identified key independent variables influencing electricity price formation, including the generation source, fuel prices, CO2 emission allowances, grid load, and temporal factors. The analysis leveraged dummy variables to capture temporal dependencies, distinguishing price events across day/night, weekdays/weekends, and seasonal transitions, thereby illustrating the dynamic nature of electricity pricing.

While the inclusion of variables is similar to our own model, Norway and the NO2 bidding zone is highly hydro-dominated in terms of electricity production and does not display the same range of generation sources as the German market. However, considering the connection between the German market and NO2, we expect to see an influence of gas prices due to Germany's dependence on gas-fired plants.

Tselika, 2022 delves into the effects that intermittent RES exert on electricity price distributions and their volatility in Denmark and Germany. Harnessing hourly data spanning from 2015 to 2020, this investigation uses the innovative Quantiles via Moments (MMQR) methodology for a panel quantile analysis. This approach marks a departure from prior studies that predominantly relied on aggregated daily data within a time-series framework. The rationale behind employing a panel method that integrates both temporal and cross-sectional dimensions of electricity prices is underscored by the significant intra-day fluctuations in electricity price formation and renewable energy output. Such a methodology enables the isolation of time-invariant characteristics specific to each hour, thereby uncovering market dynamics that unfold throughout the day.

By analyzing the effect of RES, particularly wind and solar power, on different price quantiles while factoring in market dynamics, this research sheds light on the diverse impacts these energy sources have on electricity price distributions. The study underscores the occurrence of the merit-order effect in both countries, with wind and solar generation influencing the price distribution differently. Additionally, the paper explores the interaction between RES and demand levels, revealing how wind generation amplifies price volatility under low demand conditions yet mitigates it when demand is high, particularly in Germany where solar power plays a stabilizing role for high demand levels.

3.2.3 Machine Learning

Machine learning (ML), with its ability to learn from and make predictions on data, offers a promising alternative to conventional statistical methods. It excels in handling large datasets, recognizing patterns, and adapting to new information without explicit programming for each change in market conditions. This subsection reviews seminal and recent studies that have applied various ML algorithms, including neural networks, decision trees, and support vector machines, to predict electricity prices. It examines the methodologies employed, compares their performance, and discusses their practical implications for the energy sector.

Tan et al., 2010 presents a technique for predicting electricity prices that combines wavelet transform with ARIMA and Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) models. This approach excels at handling the non-stationarity, nonlinearity and volatility commonly found in electricity market data - aspects that traditional forecasting methods often struggle with. By breaking down the price series into components this combination method achieves higher accuracy in predicting MCPs for Spain and locational marginal prices (LMP) for the Pensylvania, New Jersey and Maryland (PJM) market surpassing several contemporary forecasting approaches. This study demonstrates how blending machine learning principles with time series analysis can enhance accuracy in volatile markets, like the electricity sector.

Keles et al., 2016 set out to develop an artificial neural network model (ANN), for forecasting hourly electricity prices in the EPEX day ahead market. Their approach involved selecting and preparing input data using algorithms and optimizing various aspects of the ANN configuration, such as the activation function, training algorithm, learning rate and momentum. This preparation ended up in including parameters such as time lagged hourly electricity prices, gas price of previous day, different data on residual demand among others. This resulted in the validation of their ANN model against prices demonstrating its superior forecasting accuracy compared to traditional models like seasonal ARIMA and other ANN applications in electricity price prediction studies.

Panapakidis and Dagoumas, 2016 also explore the field of predicting electricity prices for the day using ANN models. They investigate both models and hybrid systems that combine ANNs with algorithms. This study is notable for its examination of data sets with price trends and many outliers posing a challenge to the reliability of forecasting models. The hybrid models show flexibility by dividing the training data into groups each analyzed by a customized ANN predictor. The comparison of model performances suggests a preference for cascading networks underlining the significance of having an input dataset that extends beyond historical price information to encompass variables like natural gas costs renewable energy generation capacities and cross market energy prices.

Lago et al., 2018a explore the emerging field of deep learning (DL) in predicting electricity prices by introducing four DL models designed to improve prediction accuracy. Their study fills a gap in research literature as the use of deep learning for electricity price forecasting was still limited despite its success in other areas. The research conducts a benchmark analysis comparing these DL models with 27 used methods in electricity price forecasting to assess the effectiveness and positioning of DL techniques in predictive modeling for electricity prices. Key findings from the study include the Deep Neural Network (DNN) model excelling in accuracy, demonstrating the effectiveness of deep learning in electricity price prediction. Compared to traditional statistical forecasting, machine learning techniques provide more accurate results, indicating their potential to shape future price prediction methods. Additionally, the study finds that models incorporating moving average components and hybrid models do not consistently outperform simpler models, prompting a reassessment of the effectiveness of these components in models.

Lago et al., 2018b present an exploration into the future by exploring how market integration can boost the accuracy of electricity price predictions. They introduce two models that use data from connected markets to enhance local market forecasting, using data from the Belgian market. The first model is a network that incorporates external features from neighboring markets while the second model predicts prices for two markets simultaneously to take advantage of their combined effect on forecasting accuracy.

A key aspect of their research is the development of a unique feature selection algorithm. This algorithm, which combines optimization and functional analysis of variance carefully evaluates how different features impact the model's performance helping differentiate between irrelevant variables. Integrating features from connected electricity markets into the Belgium forecasting model lead to an improvement in predictive accuracy. The progress made not only emphasizes how well the models work, but also showcases the role that incorporating markets play in influencing changes in electricity prices. Furthermore, the research emphasizes the significance of precise price forecasting in enhancing grid stability. By pinpointing the value of accurate predictions, it reveals the critical role they play for energy companies, enabling more effective grid imbalance management by operators. The increased integration of renewable energy sources into the grid amplifies electricity price volatility, which in turn makes the behavior of market agents less predictable. This dynamic leads to a higher likelihood of abrupt changes in power generation and consumption, intensifying the discrepancies between production and consumption which elevates the risk of instability in the electrical grid.

Castelli et al., 2020 venture into improving the forecasting of electricity prices by utilizing an approach in machine learning known as Local Search Genetic Programming (LSGP). This method stands out for its awareness in the search process and the inclusion of a local search optimizer to speed up the learning phases convergence. By analyzing real world data from energy markets in the EU they compare the LSGP model with established techniques for forecasting tasks.

The LSGP model considers various factors affecting electricity prices, such as weather conditions, and prices of oil and CO2 emission quotas to predict prices 24 hours in advance. The findings show progress over existing prediction methods demonstrating that the LSGP model offers greater accuracy in predicting future electricity prices.

Heijden et al., 2021 explore how the integration of markets impacts the DAM price predictions, specifically focusing on the Dutch market. Their research indicates that incorporating factors can result in overfitting leading to a decline in model performance. To address this issue, they introduce an algorithm that carefully selects relevant European features from potential countries to enhance the accuracy of DAM price prediction models. This approach can be adapted for regression and machine learning frameworks. The study applies this algorithm to develop prediction models for the Netherlands by analyzing data on the electricity market to choose suitable candidate countries. The addition of these elements greatly improves the accuracy of forecasting for the Dutch market. Through further analysis it is confirmed that European features significantly enhance the accuracy of predictions.

Tschora et al., 2022 delve into the realm of machine learning methods to improve the accuracy of electricity price predictions. Their approach involves integrating elements, such as the historical prices of neighboring countries, which significantly enhances forecast precision. This study highlights the importance of these features during periods of market changes.

Tschora et al., 2022 also discuss areas for research such as incorporating additional electricity price forecasting (EPF) features like coal, oil, carbon prices and data from additional countries. They also explore different machine learning models such as Gaussian processes, nearest neighbors, multi kernel support vector regressions (SVR) to enhance the forecasting accuracy. Tschora et al., 2022 highlight the importance of including real time price data and transfer capabilities to improve the understanding of energy movements across borders. Additionally, they propose investigating time series machine learning models and Graph Neural Networks (GNN) to effectively handle the complexities of forecasting multiple countries simultaneously.

Trebbien et al., 2023 explore the possibility of predicting electricity costs, in Germanys day-ahead-market using a machine learning method that goes beyond the traditional merit order approach. This unique blend allows for an understanding of the ever-changing factors that influence electricity prices bypassing the constraints of conventional market models based on the merit order principle.

While the merit order principle serves as a foundation for understanding market dynamics in perfect market conditions, it oversimplifies how dispatchable power plants marginal costs interact with residual load overlooking the complexities of real-world market fluctuations.

The methodology of Trebbien et al., 2023 avoids these simplifications by integrating a range of variables into their model to capture the diverse drivers behind price shifts. Their analysis sheds light on how factors like load, wind power and solar energy play roles in shaping prices with wind power having a significant impact compared to solar energy. Additionally fuel prices and generation ramps from sources such as nuclear and lignite are identified as crucial elements that influence prices, in intricate and nonlinear ways.

The use of SHapley Additive exPlanations (SHAP) values in their model analysis signifies progress in enhancing the interpretability of machine learning models. By measuring the impact of each feature on price predictions, SHAP values provide insights into how market factors and circumstances influence price dynamics going beyond just relying on the merit order principle for explanations. This approach not only improves the transparency of the model but also fosters a deeper comprehension of the cause-and-effect relationships within the market although its recognized that conducting a more explicit causal analysis would require additional assumptions and methodologies.

3.2.4 The Future of Electricity Price Forecasting

Jedrzejewski et al., 2022, studies the inconsistencies found in predicting electricity prices shedding light on the lack of evaluation methods that often lead to biased outcomes and conclusions. They raise concerns about the absence of tests to determine accuracy differences between models casting doubt on the reliability of analyses. The study also highlights issues with how data is divided for training, validation and testing purposes well as determining optimal input features and model settings crucial for reproducibility. Additionally, it emphasizes the oversight of computational linked to implementing forecasting techniques, which is a critical aspect for real time electricity price forecasting applications.

Furthermore, Jedrzejewski et al., 2022 underscore the inconsistency in model recalibration practices, especially in benchmark comparisons, where new models are recalibrated frequently, whereas benchmarks may not be, skewing accuracy metrics in favor of newer models. To mitigate these issues, they propose a series of best practices aimed at enhancing reproducibility and enabling meaningful comparisons within the electricity price forecasting community. These include utilizing a diverse and extensive test dataset, employing multiple evaluation metrics including the relative mean absolute error (MAE), applying statistical testing for performance differences, and ensuring transparent reporting of data splits, model inputs, and computational costs.

Lago et al., 2021 identified a gap in the research on predicting electricity prices. They propose a standardized approach to evaluating new predictive algorithms. The authors point out shortcomings in the field such as relying on non-public and unique datasets, limited testing in specific markets and overlooking comparisons with simpler, yet effective, benchmark models. They argue that these practices have made it challenging to determine which methods excel in predicting electricity prices and what should be considered best practices.

To address these issues, Lago et al., 2021 conducted a comparison of deep learning methods over multiple years and markets. Their contribution involves establishing practices for research on predicting electricity prices emphasizing the importance of sizes, accuracy metrics and statistical testing to validate differences in model performance.

Their analysis shows that deep neural networks generally outperform Local Expansion and Reduction (LEAR) methods, in accuracy though LEAR models are preferred for time decisions. Ensemble methods, which combine models often produce much better results compared to individual models. The study questions the reliability of Mean Absolute Percentage Error (MAPE) as an accuracy measure and emphasizes the importance of statistical testing to draw meaningful conclusions in EPF research. This is important as MAPE is used as an accuracy measure in several of the studies in the field.

Maciejowska et al., 2022 provide an analysis of the changing landscape of predicting electricity prices emphasizing the obstacles and methodological trends influencing this area. They highlight the emphasis on short term predictions, driven by the need for power systems to maintain a balance between generating and consuming electricity. External factors like weather conditions impacting both supply (due to fluctuations in energy sources) and demand, as well as shifts in business activities affecting demand further complicate this requirement.

The research emphasizes the difficulties posed by the integration of renewable energy sources, which are not adequately addressed by advancements in storing electricity or updating grids. These market dynamics call for forecasting methods to adapt to the unpredictable nature of electricity prices. In terms of methodology, Maciejowska et al., 2022 pinpoint three trends in studies on predicting electricity prices:

1. Expansion of Forecasting Methods; There is a shift towards not only single point forecasts but also probabilistic ones (including interval and density forecasts) and path forecasts. This shift reflects an increasing acknowledgment of the importance of capturing uncertainties in predicting electricity prices offering detailed insights for decision makers.

2. Advancement towards Machine Learning; The field is gradually shifting from models to more complex statistical and machine learning approaches. This change is driven by the need for models that despite being intricate provide flexibility and accuracy in predicting outcomes.

3. Moving Beyond Standard Error Metrics; While traditional error measures are still crucial for evaluating models there is a growing recognition of the importance of considering the consequences of forecasting errors. Recent studies are increasingly incorporating real world case studies to assess the profitability of strategies developed from forecasting models indicating a shift towards practical research approaches.

In addition to the advancements and direction of future research highlighted by Maciejowska et al., 2022, we believe that adding new types of price-drivers is needed in the field of electricity price forecasting and that our study contributes to this advancement.

3.3 Contribution to Existing Literature

In this study, we aim to add to the existing body of academic literature by specifically examining the NO2 bidding area. This region is distinct due to its strategic interconnections with adjacent countries and other domestic bidding zones, coupled with its significant hydro-resource endowment. Our review of the literature has not revealed any prior studies that simultaneously consider the same range and combination of variables that our thesis proposes to explore. Accordingly, we believe our research provides a novel contribution to the field, addressing a gap in the current understanding of the price-dynamics within the NO2 bidding area and especially the possible impact of cross-zonal connections.

4 Research Methodology

In this section, we provide a fundamental overview of the dataset, highlighting the data collection process and the sources from which the data was gathered. Additionally, we will delineate the statistical tests and models that have been utilized in the course of our research.

4.1 Data

In our thesis we are examining the drivers of the electricity price in the Norwegian NO2 Market. The original dataset used in this thesis include 109 variables each containing 72.768 observations. The dataset has an hourly resolution and stretches from 01.01.2015 to 20.04.2023, thus equaling 3032 observations for each hour.

Some of the variables in the dataset has a daily resolution. For those variables we have used the last known observation to consolidate the dataset. In such instances, the daily observation is attributed to every hour of that day. Given our setup (to be described later) and the market price creation, this procedure will not lead to a look-ahead bias in our predictive regression.

An overview of the variables in the dataset is presented in Appendix A.

4.1.1 Data Selection

Nord Pool Power Price

In line with the research questions we aim to address, price data represents one of the most significant variables in our dataset. Nord Pool has provided price data for NO2 from 01.01.2015 to 20.04.2023 for this thesis. The data is presented in an hourly resolution and denoted in Norwegian Krone (NOK).

For this thesis the price variable will be denoted as $P_{t,h}$.

Production

Our dataset incorporates seven production variables, all of which have been sourced from ENTSO-E for the period 01.01.2015 to 20.04.2023. These variables encompass production from various sources including fossil gas, hydro, waste, onshore wind, and others. All variables are presented on an hourly basis and illustrate the actual aggregated amount, and we use only aggregated amounts of production in our analysis.

The European Network of TSOs for Electricity (ENTSO-E) is the association for the cooperation of the European transmission system operators, bringing together the unique expertise of the interconnected power system ("Entso-E - Mission Statement", n.d.). The organization works on "ensuring the security of the interconnected power system in all time frames at pan-European level and the optimal functioning and development of the European interconnected electricity markets" ("Entso-E - Mission Statement", n.d.).

To simplify the analysis we chose to sum up all production variables into one variable. By consolidating the production variables, we were able to retain important information for the analysis, while simultaneously making the data easier to handle.

For this thesis the aggregated production variable will be denoted as $PROD_{t,h}$.

Load

From ENTSO-E we have also procured hourly data that exhibits both the load and forecasted load for the period 01.01.2015 to 20.04.2023. Load refers to the consumption of electricity, and reflects the demand side of the electricity market.

For this thesis the load and forecasted load will be denoted as $LOAD_{t,h}$ and $FORC_{t,h}$, respectively.

Electricity Transmission NO2

The Norwegian NO2 zone is equipped with six cables that have the capacity to transport electricity to or from other zones, as depicted in Figure 3. It has four international cables, extending to Great Britain, Denmark, the Netherlands, and Germany, along with two national cables that connect to the Norwegian NO1 and NO5 zones. These cables are capable of bi-directional electricity transport, albeit not simultaneously. For our dataset, we have procured data for both import and export across all these cables, presented in an hourly time resolution, from ENTSO-E for the period 01.01.2015 to 20.04.2023.

In addition to retaining these original variables, we have also calculated several new variables: international import, international export, national import, national export, total import, total export, and net flow. The net flow is calculated by subtracting the total import from the total export. These additional variables provide an overview of the electricity transmission dynamics, both within and between countries and zones, while also offering a measure of the net electricity flow.

The denotations for electricity transmissions are specified in Table 2. We have not denoted the net electricity transmission as we will not use this in our model fit.

Table 2: Denotation Electricity Transmissions

Connection	Import	Export
Denmark	$IDK_{t,h}$	$EDK_{t,h}$
The Netherlands	$INL_{t,h}$	$ENL_{t,h}$
Great Britain	$IGB_{t,h}$	$EGB_{t,h}$
Germany/Luxembourg	$IDE_{t,h}$	$EDE_{t,h}$
Norway Zone 1	$INO1_{t,h}$	$ENO1_{t,h}$
Norway Zone 2	$INO5_{t,h}$	$ENO5_{t,h}$
National	$NATI_{t,h}$	$NATE_{t,h}$
International	$INTI_{t,h}$	$INTE_{t,h}$

Weather and climate

Weather data is an important factor when trying to understand or predict the electricity market (Burger et al., 2014). We have downloaded data on wind, precipitation and temperature for the period 01.01.2015 to 20.04.2023 from the Frost-Api driven by The Norwegian Meteorological Institute (MET). The MET was established in 1866 and forecasts weather, monitors the climate and conducts research ("MET - About Us", n.d.).

The observations have been gathered from a total of 36 weather stations in different parts of the NO2 zone, with 16 of those weather stations providing data for precipitation, 10 weather stations providing data for wind and 10 stations providing data on temperature.

To simplify the analysis and reduce the dimensionality of the dataset, we decided to consolidate each category into a single variable. This resulted in the creation of three new variables, each representing the average value of its respective category: temperature, precipitation and wind. This aggregation process not only streamlined the dataset, but also maintained the essential information from each category for further analysis.

For this thesis wind and precipitation will be denoted as $WND_{t,h}$ and $PRC_{t,h}$, respectively.

Pardo et al., 2002 analyzed the non-linear relationship between temperature and electricity demand. They utilized a population-weighted temperature index and introduced heating degree days (HDD) and cooling degree days (CDD) to distinguish between the effects of cold and heat on electricity usage.

The relationship between electricity demand and temperature is non-linear, with demand increasing for both decreasing and increasing temperatures, due to the use of heating appliances in winter and air conditioners in summer. A neutral zone around 18°C was identified where demand should be inelastic to temperature changes.

To better analyze this non-linear relationship, two temperature-derived functions, HDDs and CDDs, were introduced. These functions measure the intensity of cold or heat in winter and summer days, respectively, and help to separate the winter and summer data, with a potential for more accurate linear model estimations.

We have also split our temperature data accordingly into heating degrees (HD) and cooling degrees (CD), as these variables, when inserted into a linear regression model, have the potential to capture the non-linear dependency between electricity demand and outside temperature.

For calculating Cooling Degrees we have used this equation:

$$CD_t = \begin{cases} C_t, & \text{if } C_t \geq 18\,[°C] \\ 0, & \text{if } C_t < 18\,[°C] \end{cases} \tag{1}$$

Similarly for the Heating Degrees:

$$HD_t = \begin{cases} H_t, & \text{if } H_t < 18\,[°C] \\ 0, & \text{if } H_t \geq 18\,[°C] \end{cases} \tag{2}$$

For this thesis the heating degrees and cooling degrees will be denoted as $HD_{t,h}$ and $CD_{t,h}$, respectively.

Hydropower constitutes the majority of Norway's power supply, accounting for roughly 90% of the total capacity. Of the approximately 1400 lakes in Norway regulated for power production, around 490 are utilized to compute the reservoir statistics ("Electricity production", n.d.; "Om magasinstatistikken - NVE", n.d.). This statistic is also computed for all five distinct price zones. We have downloaded the statistics specific to the NO2 from The Norwegian Water Resources and Energy Directorate (NVE) for the period 01.01.2015 to 20.04.2023. The NVE is a directorate under the Ministry of Petroleum and Energy. NVE's mandate is to ensure that the development of Norwegian hydropower is environmentally friendly and beneficial to the Norwegian society ("NVE - About Us", n.d.).

We have incorporated the reservoir statistic into our dataset; however, we have chosen to exclude it from our analysis due to its unsuitability for our regression model. This decision was influenced by the high autocorrelation within the data and the challenges associated with differentiation. Given the long-term nature of the changes in this statistic, it is not expected to have a short-term impact on prices.[1]

Market Variables

The analysis of commodity prices plays a significant role in the examination of power prices, given the interconnected nature of these markets (Burger et al., 2014; Huisman et al., 2014). Commodity prices affect the cost of electricity generation as they directly influence the operational costs of power plants and the competitiveness of various energy sources. In our research, we have incorporated the closing prices of natural gas, oil, and coal, as these are deemed to be critical variables in the literature on electricity markets (Bublitz et al., 2017; Burger et al., 2014; Gran et al., 2023; Huisman et al., 2014). In addition, we have included the spot prices for European Union Allowances, which we refer to as CO2 or CO2 prices.

For the period 01.01.2015 to 20.04.2023 data for gas, oil and coal have been provided by the Intercontinental Exchange (ICE), while data for CO2 has been procured from European Energy Exchange (EEX).

We've denoted these market variables as follows:

- Gas Price - GAS_t
- Oil Price - OIL_t
- CO2 Price - $CO2_t$
- Coal Price - $COAL_t$

[1] We executed the model, adding the reservoir statistic as an independent variable. However, no significant results were observed across any observations.

Foreign exchange markets

The dataset in use contains variables expressed in multiple currencies: Norwegian Krone (NOK), US Dollar (USD), and Euro (EUR). However, the dependent variable for the regression model is configured in NOK. Instead of recalculating the USD and EUR variables into NOK, the exchange rates for NOK/USD and NOK/EUR have been included as independent variables in the model.

This approach holds significance for several reasons. Firstly, it enables the model to naturally accommodate fluctuations in exchange rates, which may impact the relationships between the variables. Secondly, it maintains the original monetary units of the variables, which is crucial for interpretation and understanding the economic context in which the data were gathered. Additionally, it allows the model to capture potential interactions between the exchange rates and other variables, which might be overlooked if all variables were simply converted to NOK. Moreover, this approach facilitates the separation of the effect of commodity price changes from exchange rate changes.

The data for the Foreign exchange markets has been downloaded from the Central Bank of Norway (NB) for the period 01.01.2015 to 20.04.2023.

For this thesis the NOK/USD and NOK/EUR exchange rates will be denoted as USD_t and EUR_t, respectively.

Economic Uncertainty

Economic uncertainty mirrors the economic conditions, investor sentiment and likely also electricity markets. For example, in periods of heightened geopolitical risk the demand for commodities and energy commodities might increase, which in-turn might also increase marginal costs for some power plants that run on gas and oil - perhaps not in Norway directly, but in interconnected areas. If that is the case, the increased price in those areas will lead cheaper electricity producers from Norway to supply more electricity to those areas which in turn might also increase, albeit in smaller manner, the electricity price in Norway. To this end, we have incorporated data on political uncertainty from various indexes, providing a broad perspective on global political uncertainty and its potential effects on power markets.

- Geopolitical Risk and Geopolitical Uncertainty

  The inclusion of the Geopolitical Risk Index, constructed by Caldara and Iacoviello, 2022, and the Global Economic Uncertainty Index, constructed by Baker et al., 2016, allows us to capture the general political and economic uncertainties that can influence power markets. These indexes are widely recognized and used in economic research, providing a reliable measure of global uncertainties.

- Twitter-based Uncertainty

  The Twitter-based Uncertainty Indexes as used in this thesis were constructed by Baker et al., 2021. They constructed four different indexes, all of which are included in the dataset for our thesis. The indexes are calculated and weighted differently to incorporate different aspects of the Twitter-verse.

- VIX-index

  The VIX index, often referred to as the fear index, was presented in 1993 to provide a benchmark of expected short-term market volatility and provide an index upon which futures an options contracts on volatility could be written (Whaley, 2009). When the VIX Index is high, it implies that there's significant uncertainty and fear among market participants, often due to expected major market moves. Conversely, a low VIX Index suggests a period of relative calm and confidence in the market. It is important to note that the VIX is forward looking, as it measures volatility that investors expect to see (Whaley, 2009).

For the variables covered under Economic Uncertainty we have chosen to summarize Geopolitical Risk Index, Global Economic Uncertainty Index and the Twitter-base Uncertainty indexes. By consolidating these diverse measures of uncertainty into a single variable, our goal is to create a comprehensive indicator of global political and economic uncertainty. This consolidation simplifies the modeling process and reduces the potential for multicollinearity, a common issue when multiple correlated variables are included in a regression model (Hanck et al., 2024). We will refer to this variable as GEPU-indicator going forward. Data for these indexes have been downloaded from "GPR", n.d. and "EPU", n.d. for the period 01.01.2015 to 20.04.2023.

For this thesis the GEPU-indicator and VIX-index will be denoted as GPU_t and VIX_t, respectively.

Calendar Effects

Finally, we have included variables for weekday, month, holiday, daylight hours and trend. These variables serve to capture temporal and contextual influences and patterns in the data. It will enable us to account for daily and monthly patterns, the impact of holiday effects, the variation in energy demand related to daylight hours and the long-term economical trend.

The weekday variables are denoted as $MON_t, TUE_t, ..., SUN_t$, and the month variables are denoted as $JAN_t, FEB_t, ..., DEC_t$.

The data for the holiday variable in the model is derived from "Norsk Kalender", n.d. and encompasses both hard and soft holidays. Hard holidays are typically public holidays, which are officially recognized and often involve a complete shutdown of work and school activities. On the other hand, soft holidays refer to less formal holiday periods such as summer, winter, and fall breaks, which may not involve a complete stoppage of activities but can still influence daily routines and consequently, energy consumption patterns.

For this thesis holiday effects will be denoted as HDE_t.

The methodology adopted for calculating daylight hours in the model is derived from Do et al., 2021. Their paper presents a robust and empirically tested approach to quantifying daylight hours, a variable that can significantly influence electricity demand patterns. According to Do et al., 2021, daylight hours represents a deterministic function, dependent on both the latitude of a specific location and a particular day of the year, as indicated by the Julian calendar. Let J_t denote the day of a Julian calendar, the angle of the sun is calculated as follows:

$$\lambda_t = 0.4102 \sin\left(\frac{2\pi(J_t - 80.25)}{365}\right) \tag{3}$$

Then, based on the angle of the sun, the following equation is calculates daylight hours:

$$DL_t = 7.72 \arccos\left[-\tan\left(\frac{2\pi\delta}{360}\right)\tan(\lambda_t)\right] \tag{4}$$

For our thesis we have use latitude 58.5, which is an average of the latitude for the north and south part of NO2.

The inclusion of this daylight hours calculation in the model highlights the importance of considering natural light availability in power demand forecasting, particularly in regions where daylight variation can significantly impact energy consumption behaviors. The daylight hours variable will be denoted as DL_t for this thesis. Finally, we added a time trend variable denoted as TR_t.

4.2 Models and statistics

In this section we will explain our research design and delineate the specifications of the models intended for addressing our research inquiries. We will also give a brief explanation of the different statistical measures used in this thesis.

4.2.1 Multiple Regression Model

Multiple regression model is a fundamental statistical method used for estimating the unknown parameters in a linear regression model. The equation for the model is:

$$Y_t = \beta_0 + \beta_1 X_{t,1} + \beta_2 X_{t,2} + ... + \beta_p X_{t,p} + \epsilon_t \tag{5}$$

The Ordinary Least Squares (OLS) regression model makes several key assumptions, including linearity, independence, homoscedasticity, and normality. If these assumptions are violated, the OLS-estimates may be inefficient, biased, or inconsistent. Despite these potential issues, OLS-regression remains a popular method due to its simplicity, interpretability, and the extensive theory developed around it. It is widely used in econometrics, finance, and other fields where causal relationships between variables are of interest. It provides a foundation for understanding more complex regression techniques and serves as a key tool in empirical research.

We have decided to use OLS-regression for our models and to address the assumptions inherent in OLS-regression, we will test for the presence of serial correlation and heteroscedasticity in residuals. If one of those is present, we will estimate standard errors of regression coefficients via the Newey and West, 1986 variance-covariance estimator with automatic bandwidth selection procedure of Newey and West, 1994 and quadratic spectral kernel weighting scheme as introduced by Andrews, 1991.

Our interpretation of OLS-results will focus on the coefficient of determination, R^2, and the regression coefficients. R^2 is a fundamental statistical measure used in regression analysis. It quantifies the proportion of the variance in the dependent variable that can be attributed to the independent variables (Hanck et al., 2024). R^2 provides an indication of the goodness of fit of a statistical model and is expressed as a value between 0 and 1. A value close to 1 suggests that the model accounts for a large proportion of the variance in the outcome variable. Conversely, a value near 0 suggests that the model explains very little of the variability.

Regression coefficients provide valuable insights into the relationships between the predictor and response variables. In the context of OLS-regression, these coefficients are estimated such that they minimize the sum of the squared residuals, thus providing the best linear unbiased estimates (Hanck et al., 2024). Each coefficient represents the expected change in the response variable per unit change in the corresponding predictor variable, assuming all other predictors are held constant. The sign of the coefficient indicates the direction of the relationship; a positive sign denotes a direct relationship, while a negative sign indicates an inverse relationship. The magnitude of the coefficient illustrates the strength of the relationship. The interpretation of these coefficients is contingent upon the scale of the variables and the assumptions of the regression model being met.

4.2.2 Research Design

In the preceding chapter, we conducted a comprehensive examination of our dataset. To address our research inquiries, we have devised specific methodological approaches. Recall from Section 2.2 that prices for every hour of day $t+1$ are set at 12:00am at the previous day t. It follows, that in order not to subject our analysis to a look-ahead bias, our predictive regressions need to model the electricity price two-days ahead, i.e. using information from day t to predict prices at day $t+2$ instead of $t+1$. The reason is, that when data (e.g. daily temperature, production, market prices) at day t are revealed on afternoon, electricity prices for next day are already set, i.e. publicly known, as illustrated in Figure 12.

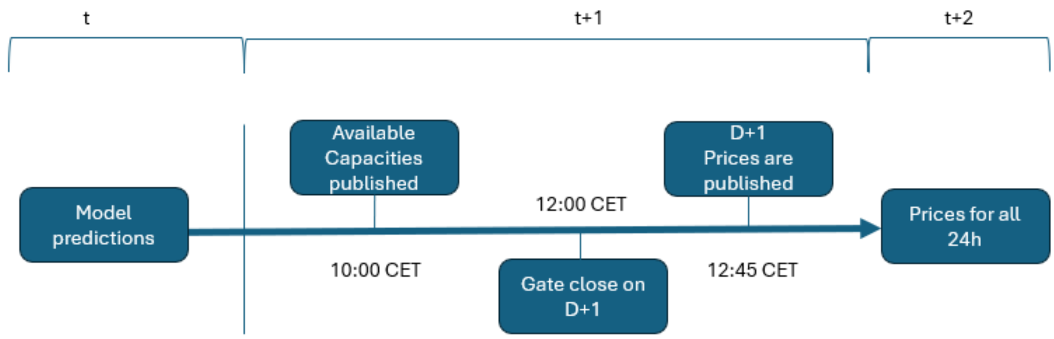

Figure 12: Timeline of model predictions and price setting mechanisms

We fit two regression models with different inclusion of the electricity transmission variables. If we let h denote a specific hour and t a specific day, the first specification is as follows:

$$
\begin{aligned}
\mathrm{P}_{t+2,h} \quad &= \quad \alpha + \boldsymbol{\phi}_h^{\mathrm{T}} \boldsymbol{P}_{t,h} + \boldsymbol{\beta}^{\mathrm{T}} \boldsymbol{C}_t + \boldsymbol{\gamma}_h^{\mathrm{T}} \boldsymbol{L}_{t,h} + \boldsymbol{\delta}_h^{\mathrm{T}} \boldsymbol{M}_t + \\
&\quad\ \zeta_h^{\mathrm{T}} \boldsymbol{W}_{t,h} + \boldsymbol{\eta}_h^{\mathrm{T}} \boldsymbol{G}_t + \boldsymbol{\kappa}_h^{\mathrm{T}} \boldsymbol{F}_{h,1} + \epsilon_{h,t} \qquad (6)
\end{aligned}
$$

The column vectors $\boldsymbol{\phi}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\delta}, \boldsymbol{\zeta}, \boldsymbol{\eta}, \boldsymbol{\kappa}$ contain regression coefficients, and following column vectors control potential price drivers. Specifically, prices are stacked into the following vector:

$$
\boldsymbol{P}_{t,h}^{\mathrm{T}} = [P_{t,h}, P_{t-5,h}, P_{t-12,h}, P_{t-19,h}, P_{t-26,h}] \qquad (7)
$$

The lags we employ utilize the fact, that electricity prices have weekly seasonality. Therefore using lag $P_{t-5,h}$ to predict $P_{t+2,h}$ means that we are predicting electricity price using price from the same hour, but seven days ago.

Calendar effects are stacked into the following vector:

$$
\boldsymbol{C}_t^{\mathrm{T}} = [MON_t, TUE_t, ..., SUN_t, JAN_t, FEB_t, ..., DEC_t, DL_t, HDE_t, TR_t] \qquad (8)
$$

Production, load and forecasted load are stacked into the following vector:

$$
\boldsymbol{L}_{t,h}^{\mathrm{T}} = [PROD_{t,h}, LOAD_{t,h}, FORC_{t,h}] \qquad (9)
$$

Market variables are stacked into the following vector:

$$
\boldsymbol{M}_t^{\mathrm{T}} = [OIL_t, GAS_t, COAL_t, CO2_t, USD_t, EUR_t] \qquad (10)
$$

Weather and climate variables are stacked into the following vector:

$$\boldsymbol{W}_{t,h}^{\mathrm{T}} = [HD_{t,h}, CD_{t,h}, WND_{t,h}, PRC_{t,h}] \tag{11}$$

Economic Uncertainty are stacked into the following vector:

$$\boldsymbol{G}_{t}^{\mathrm{T}} = [GPU_{t}, VIX_{t}] \tag{12}$$

Electricity transmissions are stacked into the following vector:

$$\begin{aligned}\boldsymbol{F}_{h,1}^{\mathrm{T}} = [&IDK_{t,h}, EDK_{t,h}, INL_{t,h}, ENL_{t,h}, IGB_{t,h}, EGB_{t,h},\\ &IDE_{t,h}, EDE_{t,h}, INO1_{t,h}, ENO1_{t,h}, INO5_{t,h}, ENO5_{t,h}]\end{aligned} \tag{13}$$

Our second specification closely mirrors the first, albeit with modifications to the vector encapsulating electricity transmission, denoted as $\boldsymbol{F}_{h,1}^{\mathrm{T}}$. In this revised specification, the variables are arranged within the vector as follows:

$$\boldsymbol{F}_{h,1}^{\mathrm{T}} = [INTI_{t,h}, INTE_{t,h}, NATI_{t,h}, NATE_{t,h}] \tag{14}$$

The purpose of the revised specification is to examine electricity transmissions at an aggregated level, which are divided into national and international segments. The aim is to identify any significant effects that might not be immediately noticeable when analyzed at a more detailed level.

Given the extensive nature of our dataset, which comprises hourly observations, we have opted to implement separate models for each hour. This approach is specifically tailored to our task of predicting electricity prices, as it aligns with the market's hourly mechanisms and enables us to capture the nuanced variations in price dynamics within distinct time intervals.

4.2.3 Descriptive statistics

Minimum (Min)

The minimum value in a dataset represents the lower extremity or bound of the observations. It is a crucial measure in descriptive statistics as it provides insights into the range and potential limitations of the data. However, like the mean, the minimum can be influenced by outliers and may not always reflect typical data behavior.

Maximum (Max)

The maximum value, conversely, represents the upper bound of a dataset. It is as critical as the minimum in understanding the range of the data. The maximum value can highlight potential outliers or unusual observations within the dataset.

Mean

The arithmetic mean, commonly referred to as 'the average', is a fundamental concept in statistics and represents the central tendency of a dataset. It is calculated by summing all observations and dividing by the count of observations:

$$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{15}$$

While it is a useful measure, it is sensitive to extreme values or outliers, which can distort the mean and may not accurately reflect the central tendency.

Median

The median is a measure of central tendency that represents the middle value in a sorted dataset. Unlike the mean, the median is not affected by outliers or extreme values, making it a more robust measure of central tendency for skewed distributions. If the dataset has an even number of observations, the median is the average of the two middle numbers.

Skewness

Skewness quantifies the degree and direction of asymmetry in a probability distribution. A distribution with zero skewness is perfectly symmetrical. Positive skewness indicates a distribution with a longer or fatter right tail, while negative skewness signifies a longer or fatter left tail.

The equation for skewness as calculated in this thesis is as follows:

$$\text{Skewness} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^{\frac{3}{2}}} \tag{16}$$

Skewness is a crucial measure as it can influence statistical analyses and the selection of appropriate statistical models.

Kurtosis

Kurtosis measures the tailedness or extremity of outliers in a distribution. The following equation has been used for calculating kurtosis in this thesis:

$$\text{Kurtosis} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^{2}} - 3 \tag{17}$$

High kurtosis indicates a distribution with heavy tails and a sharper peak, suggestive of more extreme outliers. Conversely, low kurtosis indicates lighter tails and a flatter peak, suggestive of fewer or less extreme outliers. Kurtosis is a critical measure in assessing the risk of certain statistical models.

Autocorrelation

Autocorrelation, also known as serial correlation, is a statistical property where a given time series is linearly related to a lagged version of itself. The equation for autocorrelation is as follows:

$$\rho_k = \frac{\sum_{t=k+1}^{T}(Y_t - \mu)(Y_{t-k} - \mu)}{\sum_{t=1}^{T}(Y_t - \mu)^2} \tag{18}$$

Autocorrelation is a key characteristic in many time series models. It can indicate the presence of trend or seasonality in the data. To test the significance of the serial correlation we will us the test of Escanciano and Lobato, 2009.

Stationarity

Stationarity is a critical property for many time series models, implying that the statistical properties of the series (like mean and variance) do not change over time (source). Specifically, in time-series the assumption is less strict, expecting time-series to be co-variance stationary, having a constant mean, variance and auto co-variance only.

The Augmented Dickey-Fuller (ADF) test is a unit root test used to determine the stationarity of a time series. The ADF test uses an autoregressive model and optimizes an information criterion across multiple different lag lengths. The null hypothesis of the ADF test is that the time series possesses a unit root and is non-stationary. If the ADF test statistic is less than the critical value, the null hypothesis can be rejected and the time series can be considered stationary. This test is critical in the model selection process of time series analysis and helps ensure that the assumptions of chosen models are met. We employ the ADF-test on all variables to assess stationarity. If any variable is found to be non-stationary, we will differentiate it with an appropriate lag.

The first step when performing the unit root test was to categorize the variables into different groups based on their characteristics. The variables were divided into 'common' and 'hourly' based on whether they remained constant across hours or varied with each hour. The 'common' variables included days of the week, months, and certain economic indicators, while the 'hourly' variables included temperature, wind, precipitation, and energy metrics. Additionally, variables were identified as:

- Dummies
- Seasonal - not dummy variables, but seasonal
- Normal - not dummy variables and not seasonal

The proper classification helped simplify the process of doing appropriate statistical tests and analysis on each variable.

The ADF unit root test was performed at various lag lengths until a model devoid of serial correlation was identified. If a variable was found to have a unit root, implying it was non-stationary, a transformation was applied to make it stationary. This means differentiating the variable, a process that help stabilize the mean of a time series by removing changes in the level of a time series, and hence eliminating trend and seasonality.

Escanciano and Lobato Portmanteau test for serial correlation

The Escanciano and Lobatos automatic Portmanteau test is an advanced statistical tool used to identify the presence of serial correlation in a time series data set. The test was developed by Escanciano and Lobato, 2009, as an improvement over the traditional Ljung-Box Q test. Unlike the Ljung-Box test, which requires specification of a maximum lag length, the Escanciano and Lobatos test is automatic, meaning it determines the optimal lag length based on the data.

The test uses a consistent estimator of the long-run variance, making it robust to heteroskedasticity and applicable to a wider range of data sets. This feature allows for more accurate and reliable detection of serial correlation, particularly in financial and economic time series where variance can change over time.

Volatility break identification procedure

In an effort to further dissect the price series, we have made the decision to separate it into distinct price regimes. Rather than depending on arbitrary break dates, this method employs an endogenous algorithm that utilizes the data itself to pinpoint breaks.

The algorithm in question is the Iterative Cumulative Sums of Squares (ICSS) algorithm, developed by Inclan and Tiao, 1994. This algorithm is particularly effective in the identification of abrupt changes in the variance of a time series. The ICSS algorithm is not only sensitive to the presence of breaks, but also their timing and quantity.

Within the ICSS algorithm, we have chosen to apply the test proposed by Sanso et al., 2003, specifically the κ_2 test. This test provides a powerful tool for detecting multiple breaks in the variance of a time series. The κ_2 test is especially useful in situations where the break dates are unknown and need to be estimated from the data. The implementation of this method follows the procedure that is publicly available from Baumöhl et al., 2011. Baumöhl et al., 2011 provides a guide to the implementation of the ICSS algorithm and the κ_2 test.

5 Data Analysis and Findings

5.1 Preprocessing

The preprocessing phase is divided into three sub-sections, each focusing on a different group of variables.

5.1.1 Unit Root Test - Common Variables

The unit root test was performed at various lag lengths until a model devoid of serial correlation was identified. In the conducted unit root tests, a total of six variables were found to be non-stationary and hence needed differentiating. Variables that have been differentiated will be labeled with Δ in the preliminary analysis.

5.1.2 Unit Root Test - Seasonal Hourly Variables

The second stage of the analysis revolved around the 'hourly' variables that demonstrated seasonal patterns. Seasonality refers to periodic fluctuations in the variable that occur at regular intervals, such as daily, weekly, or annually. Analyzing seasonal variables can be challenging because their patterns repeat over time, which can complicate the modeling process.

Table 3: Highest Observed Values of Auto Correlation

Variable	Q3AC	Hour	Max AC	Hour	Transformation
Mean Temperature	0.373	12:00	0.864	04:00	NO
Mean Wind	0.364	11:00	0.905	12:00	NO
Mean Precipitation	0.299	06:00	0.862	03:00	NO
Heating Degrees	0.371	15:00	0.675	16:00	NO
Cooling Degrees	0.379	15:00	0.864	04:00	NO
Production	0.342	00:00	0.921	01:00	NO

One common approach to deal with seasonality is to examine the autocorrelation of the time series. Autocorrelation measures the relationship between a variable's current value and its past values. In the context of seasonal variables, a high autocorrelation might indicate a strong seasonal component.

Seasonal data are seasonal in several dimension. The higher-level is annual and the lower level is weekly seasonality that we account for in our model. We therefore examined the auto-correlation of the hourly data at a given day but for different years. This leads to many, but short-time series with only eight observations, which is not suitable for any unit-root test. However, we examined the auto-correlation coefficient as for non-stationary data, these tend to be close to 1 or -1. Apart from few cases (which can be random by nature) we have found that most of the first-order auto-correlation coefficient show limited persistence, as seen in Table 3, which led us to conclude that these variables cannot be considered co-variance non-stationary.

5.1.3 Unit Root Test - Non-seasonal Hourly Variables

The third segment of the analysis was dedicated to conducting unit-root tests on the 'hourly' variables that did not demonstrate seasonality. In the process of conducting this analysis the results showed no indications of non-stationarity. Based on this, all variables were kept in their original form.

5.2 Preliminary Analysis

In this section, we will present the descriptive statistics for various components of the dataset. This analysis aims to provide a comprehensive overview of the key quantitative characteristics and distributions within the dataset, serving as a foundational exploration of the data's central tendencies, variability, and distributional properties.

Despite the inclusion of the automatic portmanteau test from the study of Escanciano and Lobato, 2009 in the descriptive tables, this section will not provide a detailed discussion on it. It is worth noting that the test results are significant for nearly all variables, with only a few exceptions. Consequently, this leads to the dismissal of the null hypothesis, which implies the detection of serial correlation in these variables.

5.2.1 Price - $\boldsymbol{P}_{t,h}^{\mathbf{T}}$

In the following Figure spanning the period 01.01.2015 - 20.04.2023 we present the price path of the variable of interest, the electricity price in NO2 in NOK. The marked dates in Figure 13 correspond to significant events that could have potentially influenced electricity prices (see Appendix B). These events are categorized into five different groups: Environmental(M), Geopolitical(G), Political(P), Financial (F), and Energy-related(E). The resurgence of the COVID-19 pandemic, the war in Ukraine, and extremely low gas reserves are mentioned as examples. Particularly relevant to this study is the official opening of the overseas cable to Germany/Luxembourg on March 31^{st} 2021 (E5) and the cable to Great Britain on September 10^{th} 2022 (E7). The opening of these cables has linked the Norwegian energy market more closely with those in Germany, Luxembourg, and Great Britain, making it more susceptible to price fluctuations in these markets (Burger et al., 2014; Lago et al., 2018b; Uribe et al., 2020).

From the plot, it can be observed that the prices remain relatively stable during the years 2015-2020. However, from 2021 onwards, there is a noticeable increase in volatility, with extremely high peaks emerging from the fall of 2021. While there are fluctuations in the 2015-2020 period as well, these are comparatively insignificant when juxtaposed with the volatility displayed from 2021 onwards.

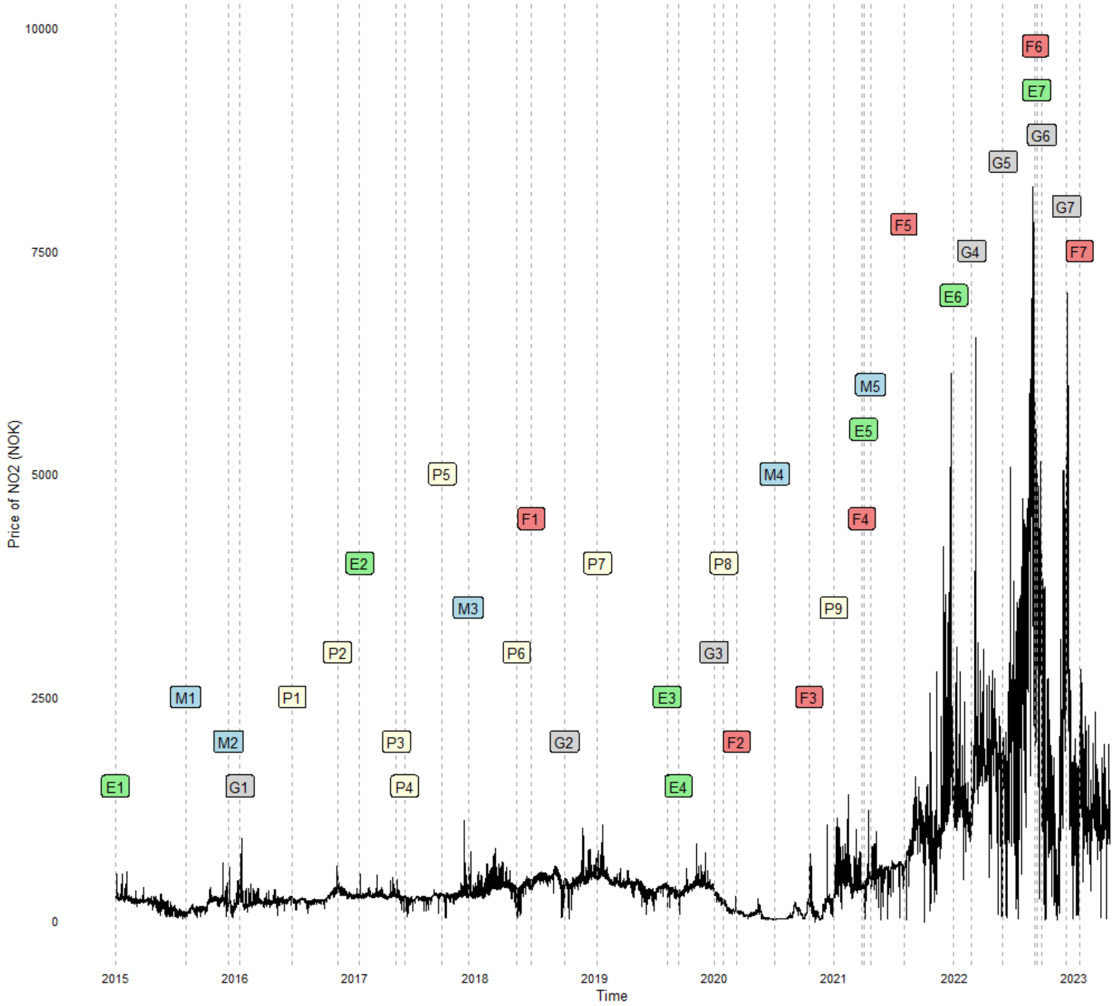

Figure 13: Time Series Plot - Price NO2

The ICSS algorithm, as delineated in section 4.2, identifies two volatility shifts, occurring on October 4, 2016, and August 8, 2021. Descriptive statistics for the NO2 price over these three periods are provided in Table 4. Notably, these periods exhibit significant disparities, particularly the final period spanning from August 8, 2021, to April 20, 2023, which displays a substantial increase in both range and standard deviation (SD). The first quartile (Q1) value from this last period surpasses the maximum value from the initial period. Moreover, the median value for the final period is nearly equivalent to the maximum value for the second period. Even when inflation is factored in, the significant surge in price levels cannot be attributed solely to this factor.

Table 4: Price NO2 Periodic Split

Period	Mean	SD	Min	Q1	Median	Q3	Max	Skew.	Kurt.	$\rho(1)$	$\rho(7)$
01.01.2015 - 03.10.2016	192	62.2	9.29	157	205	225	912	1.01	9.82	0.97	0.78
04.10.2016 - 07.08.2021	318	158	-19.2	246	313	418	1399	0.06	0.43	0.99	0.91
08.08.2021 - 20.04.2023	1731	1110	-19.7	1062	1383	1969	8225	1.81	3.65	0.98	0.86

Notes: SD denotes standard deviation; Q1 and Q3 are quartiles, 25% and 75% respectively; $\rho(.)$ is the autocorrelation of the given order, while Skew. and Kurt. are skewness and kurtosis, respectively. Statistics are computed over the whole sample of 72.768 observations, starting from January 1st, 2015, and ending on April 20th, 2023.

In summary, these statistics illustrate a significant change in price dynamics between the three periods. This highlights the evolving nature of the electricity market and underscores the importance of considering temporal changes in market behavior for accurate price analysis and forecasting. The marked increase in price volatility during the last period indicates a period of increased uncertainty and risk in the electricity market. Finding out which factor are the main drivers behind this change is something we will look more into in the following chapters.

Table 5 shows the descriptive statistics for Price NO2 per hour in the observed period. The highest observed mean value at hour 9 indicates a tendency for power prices to be elevated during this specific hour. This observation aligns with the findings of Burger et al., 2014, who attribute the surge in power consumption to the commencement of daily routines for businesses and individuals. Hour 9 also has the lowest autocorrelation suggesting that the price at this hour is less dependent on the price of the same hour from the previous day, compared to the other hours. This could indicate that the other factors influencing the price at this hour has a larger impact, making the price at this hour more difficult to predict. This is also reflected in the high SD at this hour.

Table 5: Descriptive Statistics Price NO2

Hour	Mean	SD	Min	Q1	Median	Q3	Max	Skew.	Kurt.	$\rho(1)$	$\rho(7)$	EL
00:00	555	740	1.40	208	295	497	6238	3.39	14.3	0.97	0.92	***
01:00	550	734	0.50	203	291	492	6475	3.40	14.5	0.96	0.90	***
02:00	528	692	-0.45	198	284	481	6037	3.30	13.8	0.96	0.90	***
03:00	515	674	-10.3	194	279	474	5967	3.31	14.0	0.96	0.89	***
04:00	505	657	-19.2	191	277	469	5718	3.27	13.6	0.95	0.89	***
05:00	508	658	-19.7	194	280	466	5816	3.28	13.9	0.95	0.89	***
06:00	530	695	-10.1	204	287	481	6441	3.40	15.0	0.95	0.90	***
07:00	563	745	0.10	213	305	508	6619	3.45	15.2	0.95	0.91	***
08:00	613	831	0.80	222	324	545	7280	3.44	14.7	0.94	0.90	***
09:00	645	883	4.11	227	342	583	7326	3.35	13.6	0.93	0.89	***
10:00	634	861	7.86	227	338	564	7036	3.33	13.4	0.94	0.89	***
11:00	615	820	9.04	225	333	547	6569	3.34	13.6	0.94	0.90	***
12:00	598	788	9.26	223	325	537	6927	3.38	14.2	0.94	0.89	***
13:00	579	750	9.41	220	319	526	6534	3.32	13.7	0.94	0.88	***
14:00	567	731	7.29	218	315	520	6323	3.35	14.1	0.94	0.88	***
15:00	560	727	3.05	216	309	515	5999	3.41	14.6	0.94	0.88	***
16:00	570	748	5.88	215	311	522	6208	3.43	14.8	0.94	0.88	***
17:00	592	788	6.59	217	322	533	6454	3.42	14.6	0.95	0.88	***
18:00	624	846	9.13	221	334	557	7028	3.44	14.6	0.96	0.88	***
19:00	639	879	10.4	223	335	559	7835	3.44	14.5	0.96	0.90	***
20:00	636	892	10.0	222	327	547	8225	3.55	15.5	0.97	0.91	***
21:00	620	871	8.81	221	320	527	8129	3.57	15.6	0.98	0.93	***
22:00	603	831	8.81	220	315	523	7554	3.50	15.0	0.98	0.93	***
23:00	585	793	4.15	217	307	516	6820	3.44	14.6	0.98	0.93	***

Notes: SD denotes standard deviation; Q1 and Q3 are quartiles, 25% and 75% respectively; $\rho(.)$ is the autocorrelation of the given order; EL represents the p-value of the (Escanciano & Lobato, 2009) automatic portmanteau test of serial correlation, while Skew. and Kurt. are skewness and kurtosis, respectively. Statistics are computed hourly with 3032 observations starting from January 1st, 2015, and ending on April 20th, 2023.

Next, the highest SD at hour 20 indicates that the variability in power prices is greatest at this time. A high SD suggests that prices are spread out over a larger range, meaning there are days when the price is significantly higher or lower than the average. This could be due to fluctuations in supply and demand effecting the equilibrium price as described in Escribano et al., 2011. For example, in the evening, people return home and start using electrical appliances more intensively, leading to a spike in demand. If the supply doesn't increase correspondingly, prices could surge, contributing to the high SD. The maximum price is also being observed at hour 20, which could be a result of this heightened demand outstripping supply.

The highest skewness at hour 21 suggests that the distribution of prices during this hour is positively skewed. This means that the tail on the right side of the distribution is longer or fatter than the left side. In other words, there are a few instances of exceptionally high prices during this hour, which pull the mean upwards. Similarly, the highest kurtosis at hour 21 suggests that the distribution has heavier tails and a sharper peak. High kurtosis indicates that data are subject to heavy tails or outliers, which means that there is tendency towards extreme values. This could be due to sudden surges in demand or supply constraints during this hour.

Time-series plots for Price NO2 for all hours can be found in Appendix B.

5.2.2 Production - $\boldsymbol{L}^{\mathbf{T}}_{t,h}$

The time series plot for power production in NO2, as shown in Figure 14, illustrates a noticeable seasonal pattern, with increased production during late autumn and winter months corresponding to higher power demand due to heating and reduced daylight hours. Conversely, lower production is observed during warmer months when demand decreases (Escribano et al., 2011). The load plot in Figure 15 mirrors this seasonal pattern, demonstrating the balance between supply and demand as we would expect according to Chapter 2.

This link between consumption and production is also apparent when looking at the hourly descriptives for the production variable as shown in Table 6. Firstly, there appears to be a clear pattern in power production, with a peak during the late morning and early afternoon hours, followed by a gradual decline towards the evening. This pattern aligns with the skewness values, which also show a slight right skew during the morning and early afternoon hours. This indicates that the majority of power production values are clustered towards the lower end, with a tail extending towards higher values. Conversely, a slight left skew during the evening and night hours suggests that most production values are concentrated towards the higher end, with a tail extending towards lower values. In simpler terms, right skewness implies that there are more lower production values with a few exceptionally high values, while left skewness indicates the opposite, with more high production values and a few exceptionally low values.

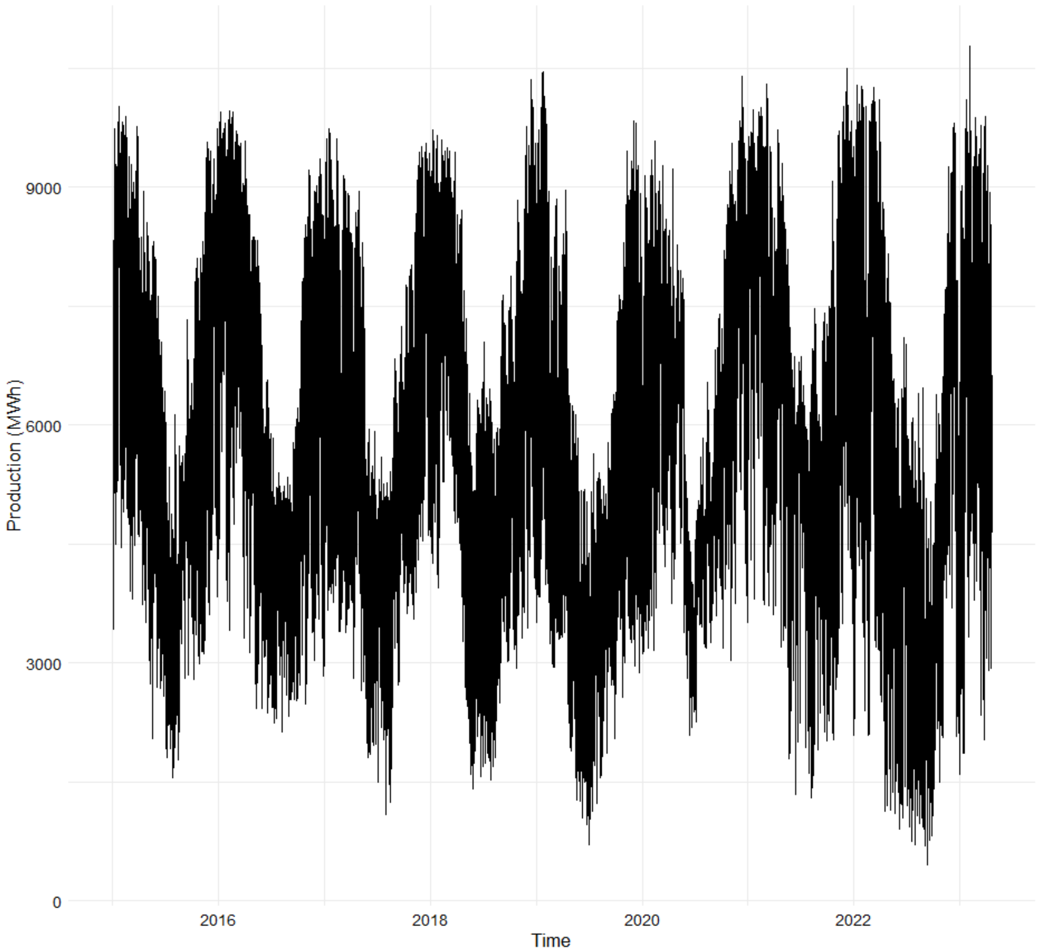

Figure 14: Time Series Plot - Production NO2

The rather low skewness values are also reflected in the relationship between the mean and median values. When the mean and the median follow each other closely like for this variable, it generally indicates that the data is symmetrically distributed with minimal skewness. In a symmetric distribution, the mean and median are close in value and may even be equal, suggesting that the central tendency of the data is consistent. This implies that there are minimal outliers or extreme values pulling the mean away from the center of the distribution.

An interesting observation regarding the research questions in our thesis is that the mean and median values for all hours are consistently higher for the production variable than for the load variable (Table 7). This suggests that, on average, the production of power in NO2 exceeds the load requirements throughout the observed period.

Table 6: Descriptive Statistics Production NO2

Hour	Mean	SD	Min	Q1	Median	Q3	Max	Skew.	Kurt.	$\rho(1)$	$\rho(7)$	EL
00:00	5267	1585	1039	4138	5075	6380	9562	0.26	-0.45	0.82	0.63	***
01:00	4889	1609	730	3776	4738	5960	9169	0.26	-0.42	0.83	0.63	***
02:00	4638	1626	698	3522	4472	5710	9198	0.30	-0.39	0.83	0.64	***
03:00	4501	1636	706	3370	4322	5557	9284	0.33	-0.40	0.82	0.64	***
04:00	4441	1653	714	3294	4274	5502	9274	0.34	-0.41	0.83	0.64	***
05:00	4526	1702	704	3328	4354	5656	9134	0.30	-0.48	0.83	0.66	***
06:00	4882	1787	707	3593	4770	6135	9413	0.20	-0.62	0.82	0.69	***
07:00	5574	1950	903	4119	5448	7095	9891	0.03	-0.78	0.76	0.74	***
08:00	6151	2058	932	4611	6066	7870	10259	-0.12	-0.83	0.73	0.78	***
09:00	6401	2023	999	4891	6345	8109	10439	-0.21	-0.74	0.73	0.78	***
10:00	6448	1982	975	4992	6440	8109	10386	-0.25	-0.63	0.76	0.76	***
11:00	6395	1983	925	4981	6378	8044	10455	-0.25	-0.59	0.78	0.76	***
12:00	6272	1993	853	4871	6228	7886	10429	-0.21	-0.58	0.79	0.76	***
13:00	6129	2005	751	4746	6054	7747	10499	-0.16	-0.60	0.80	0.76	***
14:00	6016	2026	460	4640	5926	7657	10440	-0.13	-0.63	0.80	0.76	***
15:00	5959	2045	451	4553	5846	7596	10327	-0.10	-0.67	0.81	0.77	***
16:00	6011	2066	466	4550	5934	7664	10370	-0.09	-0.73	0.83	0.78	***
17:00	6167	2058	530	4698	6108	7864	10516	-0.11	-0.78	0.84	0.79	***
18:00	6402	2002	1035	4891	6359	8110	10772	-0.16	-0.81	0.85	0.79	***
19:00	6512	1897	1092	5041	6492	8074	10610	-0.14	-0.83	0.85	0.77	***
20:00	6483	1782	1224	5067	6495	7906	10200	-0.07	-0.82	0.85	0.73	***
21:00	6289	1713	1273	4962	6206	7608	10247	0.01	-0.78	0.84	0.69	***
22:00	6087	1679	1166	4828	5957	7381	10029	0.07	-0.70	0.83	0.67	***
23:00	5737	1616	1162	4557	5568	6954	9880	0.16	-0.57	0.82	0.64	***

Notes: SD denotes standard deviation; Q1 and Q3 are quartiles, 25% and 75% respectively; ρ(.) is the autocorrelation of the given order; EL represents the p-value of the (Escanciano & Lobato, 2009) automatic portmanteau test of serial correlation, while Skew. and Kurt. are skewness and kurtosis, respectively. Statistics are computed hourly with 3032 observations starting from January 1st, 2015, and ending on April 20th, 2023.

The surplus in power production suggests that the trend of electricity transmission in NO2 is oriented more towards export than import, supporting the idea of Norway as "Europes Battery" ("How Norway can become Europe's battery", n.d.). We will examine this further when looking at the descriptive statistics for Electricity Transmission in Chapter 5.5.

In general, Table 6 offers a statistical examination of the NO2 production for every hour in a day. Looking at the statistical measures the mean NO2 production varies throughout the day, with the lowest average production observed at 03:00 and the highest at 19:00. The SD also fluctuates, with the smallest at 23:00 and the largest at 16:00.

The minimum and maximum values provide the range of the NO2 production, which spans from 451 to 10772. The 1st quartile (Q1), median, and 3rd quartile (Q3) values provide a snapshot of the data distribution at each hour. These values change throughout the day, reflecting the changing distribution of production in NO2.

The autocorrelation values at lag 1 and 7 ($\rho(1)$ and $\rho(7)$) are moderately high, indicating a significant positive correlation between the NO2 production values and their respective values at 1 and 7 days prior. This suggests a temporal dependency in the NO2 production data. The lowest observed autocorrelation appears at 08:00 and 09:00. This could mean that during these hours, other external factors exert a greater impact on NO2 production. This is also supported by the SD for those hours, which are close to the maximum observed values.

5.2.3 Load - $L^{\mathbf{T}}_{t,h}$

As mentioned in section 5.2.2 the load variable follows a clear, seasonal pattern closely mirroring the production variable as seen in Figure 15. In addition, this figure provides insights into the energy consumption habits of the Norwegian population. It shows that energy usage is not constant throughout the year, but varies in response to seasonal changes as highlighted by Burger et al., 2014.

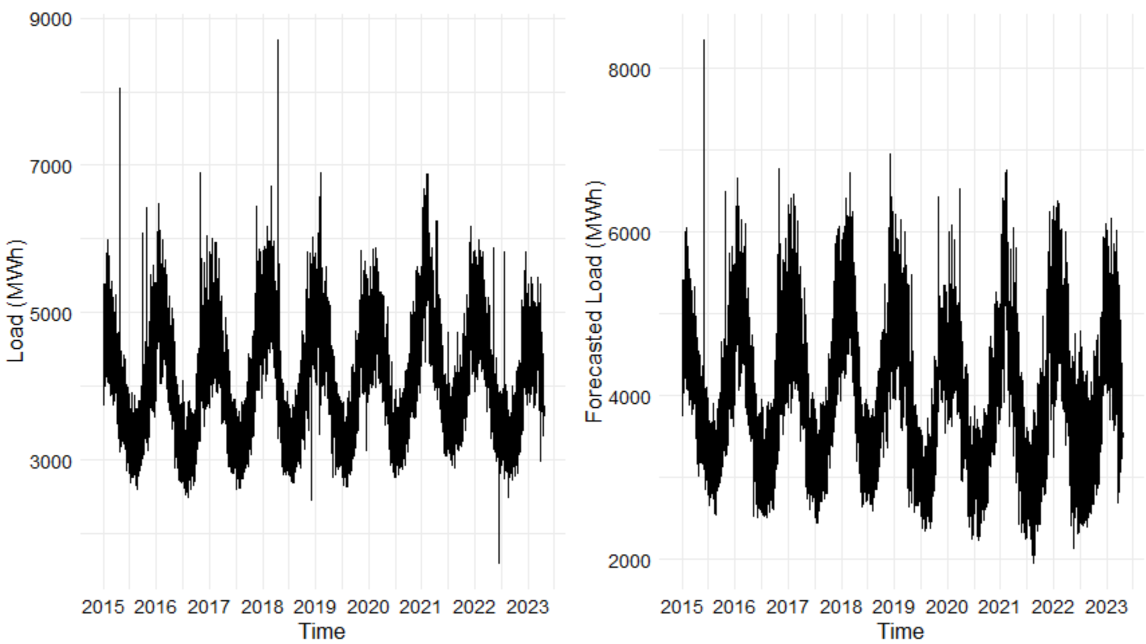

Figure 15: Time Series Plot - Load NO2

As indicated in the literature review, we anticipate observing correlations between electricity load and prices (Burger et al., 2014). The electricity market is intricate, and it will be interesting to investigate whether the impact of the load is substantial or if other factors have a greater influence on price trends in the day-ahead market.

Figure 15 also illustrates the pattern of the forecasted load. As anticipated, this pattern aligns with that of the load variable. Given the unique mechanisms of the electricity markets, as detailed in Chapter 2, it is expected that these variables will follow each other closely. Therefore, we will not conduct a more detailed investigation of this variable within this section.

Table 7 provides a statistical analysis of NO2 load for each hour of the day. The mean NO2 load fluctuates across the day, with the lowest average load observed at 03:00 and the highest at 10:00. The SD also sees fluctuations, with the lowest at 00:00 (630) and the highest at 07:00. As with the production variable, there is a clear link between high SD and low autocorrelation in the morning hours from 07:00 to 09:00. This confirms the strong connection between the production and load variables, and further underscores the heightened impact of external factors during these hours. The autocorrelation values at lag 1 and 7 in general are high, suggesting a strong positive correlation between the NO2 load values and their respective values at 1 and 7 days prior.

The minimum and maximum values, ranging from 1595 to 8700, indicate the range of the observed load in NO2. For example, at 03:00, 25% of the values are below 3124 (Q1), 50% are below 3664 (Median), and 75% are below 4218 (Q3). These quartile values shift throughout the day, reflecting the changing distribution of NO2 production.

The data distribution is mostly symmetrical with fewer outliers, indicated by positive skewness and negative kurtosis values. The positive skewness suggests higher production values, with a tail towards lower values. The negative kurtosis implies that extreme values are rarer, and data points are more clustered around the mean.

Table 7: Descriptive Statistics Load NO2

Hour	Mean	SD	Min	Q1	Median	Q3	Max	Skew.	Kurt.	$\rho(1)$	$\rho(7)$	EL
00:00	3813	630	2488	3247	3761	4318	5920	0.37	-0.74	0.97	0.90	***
01:00	3742	633	2630	3170	3698	4248	5735	0.36	-0.77	0.97	0.90	***
02:00	3712	641	2481	3132	3668	4214	6901	0.39	-0.56	0.95	0.89	***
03:00	3706	640	2156	3124	3664	4218	5733	0.32	-0.82	0.97	0.90	***
04:00	3726	656	2324	3122	3706	4252	5811	0.30	-0.84	0.97	0.89	***
05:00	3799	688	2376	3176	3775	4346	6039	0.29	-0.85	0.96	0.90	***
06:00	4013	751	2273	3353	3988	4606	7363	0.32	-0.60	0.93	0.89	***
07:00	4253	820	2142	3572	4198	4893	8515	0.34	-0.35	0.88	0.88	***
08:00	4347	813	1898	3663	4296	4974	8700	0.38	-0.25	0.89	0.88	***
09:00	4360	777	1860	3696	4322	4957	8674	0.43	-0.12	0.91	0.88	***
10:00	4364	757	1621	3695	4323	4944	8067	0.41	-0.32	0.93	0.88	***
11:00	4326	745	1753	3673	4261	4904	8106	0.47	-0.16	0.93	0.88	***
12:00	4291	729	1771	3649	4225	4866	7520	0.43	-0.42	0.94	0.89	***
13:00	4261	724	1595	3632	4180	4830	7435	0.41	-0.51	0.93	0.89	***
14:00	4247	722	1855	3628	4161	4820	7233	0.41	-0.60	0.94	0.89	***
15:00	4243	738	2203	3602	4143	4833	7085	0.41	-0.71	0.93	0.90	***
16:00	4267	764	2211	3600	4148	4888	7508	0.41	-0.71	0.94	0.90	***
17:00	4274	774	2242	3580	4154	4912	8076	0.43	-0.60	0.95	0.89	***
18:00	4274	769	2746	3574	4182	4917	8191	0.42	-0.55	0.95	0.89	***
19:00	4264	748	2940	3584	4194	4870	8130	0.42	-0.41	0.95	0.88	***
20:00	4225	724	2985	3572	4178	4798	8151	0.45	-0.15	0.94	0.87	***
21:00	4164	696	2918	3537	4128	4700	8044	0.46	-0.05	0.94	0.86	***
22:00	4064	661	2914	3467	4026	4579	7606	0.47	-0.18	0.95	0.86	***
23:00	3928	635	2760	3355	3884	4423	7000	0.45	-0.43	0.95	0.87	***

Notes: SD denotes standard deviation; Q1 and Q3 are quartiles, 25% and 75% respectively; $\rho(.)$ is the autocorrelation of the given order; EL represents the p-value of the (Escanciano & Lobato, 2009) automatic portmanteau test of serial correlation, while Skew. and Kurt. are skewness and kurtosis, respectively. Statistics are computed hourly with 3032 observations starting from January 1st, 2015, and ending on April 20th, 2023.

5.2.4 Weather and Climate - $W_{t,h}^{\mathbf{T}}$

Figure 16 presents a time series plot for three key meteorological variables: precipitation, wind speed, and temperature, as elaborated in Chapter 4.1.1.

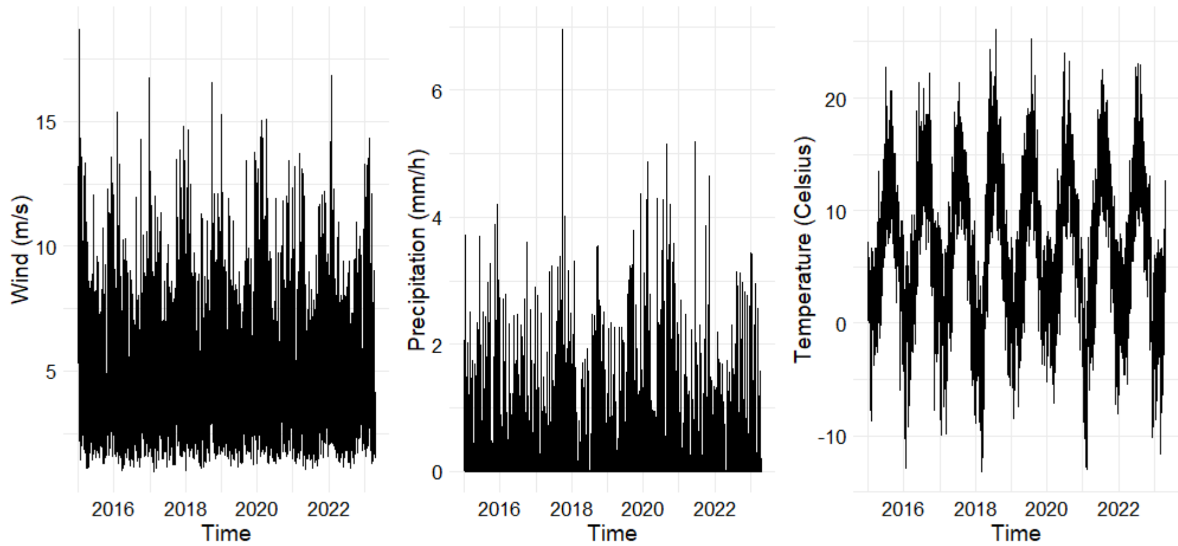

Figure 16: Time Series Plots - Weather NO2

As depicted in Figure 16, these variables behave as anticipated, exhibiting signs of seasonal fluctuations, particularly in the temperature plot. Both wind and precipitation demonstrate indications of outliers, potentially symbolizing extreme weather events.

For the sake of brevity, we have opted to present the descriptive statistics for selected hours only for these variables, as seen in Table 8. We have chosen hours 04:00, 09:00, 16:00, and 20:00 as they exhibit the most interesting characteristics from our analysis of Price, Production and Load, while also covering different periods of the day.

The temperature data shows a predictable daily fluctuation, with cooler temperatures at night and warmer temperatures during the day. The distribution appears symmetric, as indicated by low, negative skewness and kurtosis values. High autocorrelation is observed, as expected. Heating Degrees follows the average temperature's daily pattern but has fewer observations due to NO2's climate conditions, resulting in extreme skewness and kurtosis values. Cooling Degrees aligns with the Mean Temperature, with no significant deviations beyond what is expected.

Table 8: Descriptive Statistics Weather and Climate

Name	Mean	SD	Min	Q1	Median	Q3	Max	Skew.	Kurt.	$\rho(1)$	$\rho(7)$	EL
Panel A: Hour 03:00 - 04:00												
Mean Temperature	5.36	5.71	-13.0	1.44	5.21	10.1	20.9	-0.30	-0.39	0.91	0.74	***
Mean Wind	4.60	2.17	1.18	2.97	4.10	5.72	15.4	1.17	1.46	0.40	0.10	***
Mean Precipitation	0.17	0.40	0.00	0.00	0.01	0.16	6.72	5.20	43.5	0.16	-0.01	***
Cooling Degrees	0.02	0.61	0.00	0.00	0.00	0.00	20.9	31.9	1021	0.30	0.00	
Low Degrees	5.35	5.69	-13.0	1.42	5.20	10.0	17.8	-0.31	-0.40	0.90	0.73	***
Panel B: Hour 08:00 - 09:00												
Mean Temperature	6.45	6.32	-12.4	2.12	5.98	11.9	23.4	-0.18	-0.53	0.94	0.79	***
Mean Wind	4.74	2.08	1.02	3.20	4.37	5.85	14.4	1.05	1.22	0.38	0.07	***
Mean Precipitation	0.17	0.37	0.00	0.00	0.01	0.16	3.72	4.23	24.1	0.13	0.01	***
Cooling Degrees	0.26	2.22	0.00	0.00	0.00	0.00	23.4	8.60	72.3	0.47	0.11	***
Heating Degrees	6.19	6.18	-12.4	1.88	5.66	11.7	17.9	-0.21	-0.60	0.88	0.73	***
Panel C: Hour 15:00 - 16:00												
Mean Temperature	8.59	6.63	-9.93	3.53	8.17	14.3	25.9	-0.04	-0.75	0.96	0.84	***
Mean Wind	5.53	2.06	1.22	4.06	5.23	6.68	18.2	0.92	1.44	0.35	0.01	***
Mean Precipitation	0.16	0.33	0.00	0.00	0.01	0.16	3.28	3.45	15.1	0.10	0.01	***
Cooling Degrees	1.48	5.23	0.00	0.00	0.00	0.00	25.9	3.29	8.90	0.75	0.40	***
Heating Degrees	7.12	6.13	-9.93	2.26	6.58	12.7	18.0	-0.01	-0.96	0.82	0.59	***
Panel D: Hour 19:00 - 20:00												
Mean Temperature	7.36	6.59	-11.6	2.52	6.85	13.1	25.2	-0.09	-0.66	0.95	0.83	***
Mean Wind	5.13	2.14	1.24	3.56	4.76	6.28	18.2	1.09	1.80	0.34	0.03	***
Mean Precipitation	0.17	0.36	0.00	0.00	0.01	0.16	3.23	3.70	16.9	0.08	0.02	***
Cooling Degrees	0.82	3.92	0.00	0.00	0.00	0.00	25.2	4.61	19.4	0.65	0.31	***
Heating Degrees	6.54	6.23	-11.6	1.78	6.11	12.2	18.0	-0.10	-0.79	0.85	0.67	***

Notes: SD denotes standard deviation; Q1 and Q3 are quartiles, 25% and 75% respectively; $\rho(.)$ is the autocorrelation of the given order; EL represents the p-value of the (Escanciano & Lobato, 2009) automatic portmanteau test of serial correlation, while Skew. and Kurt. are skewness and kurtosis, respectively. Statistics are computed hourly with 3032 observations starting from January 1st, 2015, and ending on April 20th, 2023.

Wind patterns follow a similar cycle, but have positive values in skewness and kurtosis indicating a certain degree of asymmetry in the distribution. The autocorrelation is notably lower, which is logical considering the greater day-to-day variation we anticipate in wind patterns.

Unlike temperature and wind, precipitation does not exhibit a consistent daily pattern. The median value stands at 0.01, implying that approximately half of the days experience virtually no rainfall. Consequently, the high maximum values contribute to elevated skewness and kurtosis values. The autocorrelation, as anticipated, is low.

5.2.5 Market Variables - M_t^{T}

Figure 17 presents the time series for key financial variables oil, gas, coal, and CO2 prices. These variables have been identified as significant drivers of electricity prices in the existing literature (Bublitz et al., 2017; Gran et al., 2023; Huisman et al., 2014; Weron, 2014). While the plot displays the actual variables, the analysis will utilize differentiated variables as discussed in chapter 5.1.

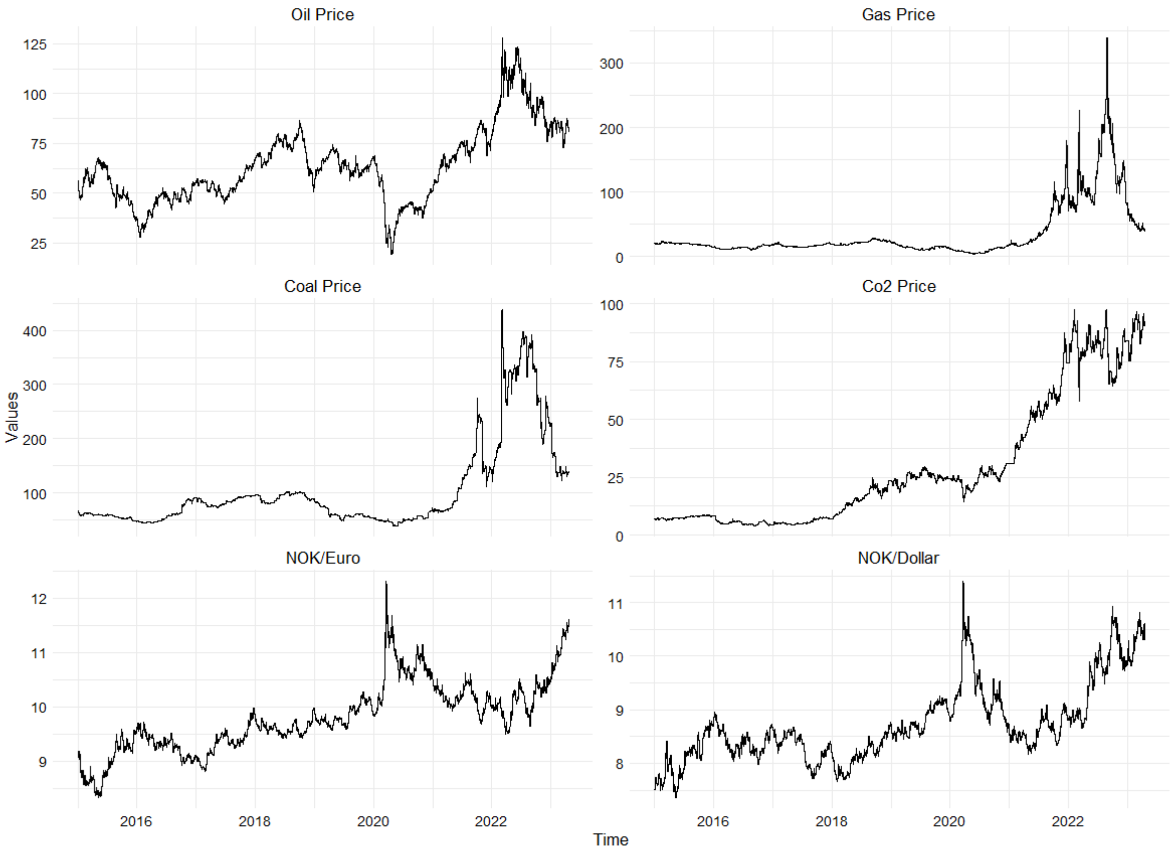

Figure 17: Time Series Plots - Market Variables

The time series data reveals a substantial price increase across all financial instruments from 2020 to 2021, a period known for a similar surge in electricity prices as seen in Section 5.2.1. This concurrent rise suggests potential causal relationship. Particularly for Coal Price and Gas Price, the parallels with the plot for Electricity Price are markedly evident.

The figure also contains exchange rates for Euro and US Dollar against the Norwegian Krone (NOK) as discussed in section 4.1.1. These plots exhibit a comparable trend in their valuation relative to the NOK.

Table 9 shows descriptive statistics for the differentiated variables, as apparent by their mean and median values. The SDs vary across the variables, with Coal Price showing the highest variability (SD = 5.23) and the NOK/EUR exchange rate showing the lowest (SD = 0.05).

Table 9: Descriptive Statistics Market Variables

Name	Mean	SD	Min	Q1	Median	Q3	Max	Skew.	Kurt.	$\rho(1)$	$\rho(7)$	EL	ADF
Gas Price	0.01	3.92	-66.6	-0.15	0.00	0.16	45.4	-1.64	78.5	0.12	-0.09	***	Δ
Oil Price	0.01	1.36	-16.8	-0.24	0.00	0.41	12.1	-0.97	18.1	-0.03	-0.10	***	Δ
Co2 Price	0.03	0.99	-16.1	-0.04	0.00	0.07	8.14	-1.56	41.7	-0.01	-0.03	***	Δ
Coal Price	0.02	5.23	-96.7	-0.15	0.00	0.20	122	1.47	200	-0.05	0.02	***	Δ
NOK/EUR	0.00	0.05	-0.29	-0.01	0.00	0.01	0.62	1.23	19.1	-0.02	0.07		Δ
NOK/USD	0.00	0.06	-0.45	-0.02	0.00	0.02	0.70	0.59	13.9	0.00	0.02		Δ

Notes: SD denotes standard deviation; Q1 and Q3 are quartiles, 25% and 75% respectively; ρ(.) is the autocorrelation of the given order; EL represents the p-value of the (Escanciano & Lobato, 2009) automatic portmanteau test of serial correlation, while Skew. and Kurt. are skewness and kurtosis, respectively. Δ denotes a variable that was differentiated because it was not considered to be stationary as indicated via our testing procedure. Statistics are computed over the whole sample of 72.768 observations, starting from January 1st, 2015, and ending on April 20th, 2023.

Negative skewness values for gas, oil, and CO2 prices suggest left-skewed distributions, potentially indicating a concentration of higher values and longer left tails. In contrast, the positive skewness for coal, NOK/EUR, and NOK/USD suggests right-skewed distributions, potentially indicating a concentration of lower values and longer right tails. The kurtosis values shows higher kurtosis values for gas, oil, and CO2 prices indicate heavy-tailed distributions with potential outliers and more extreme values. The very high kurtosis for coal price further emphasizes the heavy-tailed nature of its distribution, suggesting significant potential for extreme price movements.

5.2.6 Economic Uncertainty - G_t^{T}

The plots presented in Figure 18 show the VIX-index and GEPU-indicator over the observed period.

The time series under consideration serve a common purpose, yet they exhibit differences in the aspects they reflect. While the plots reveal similarities in their trends, they do not precisely follow each other. Notably, both plots exhibit a distinct peak in January

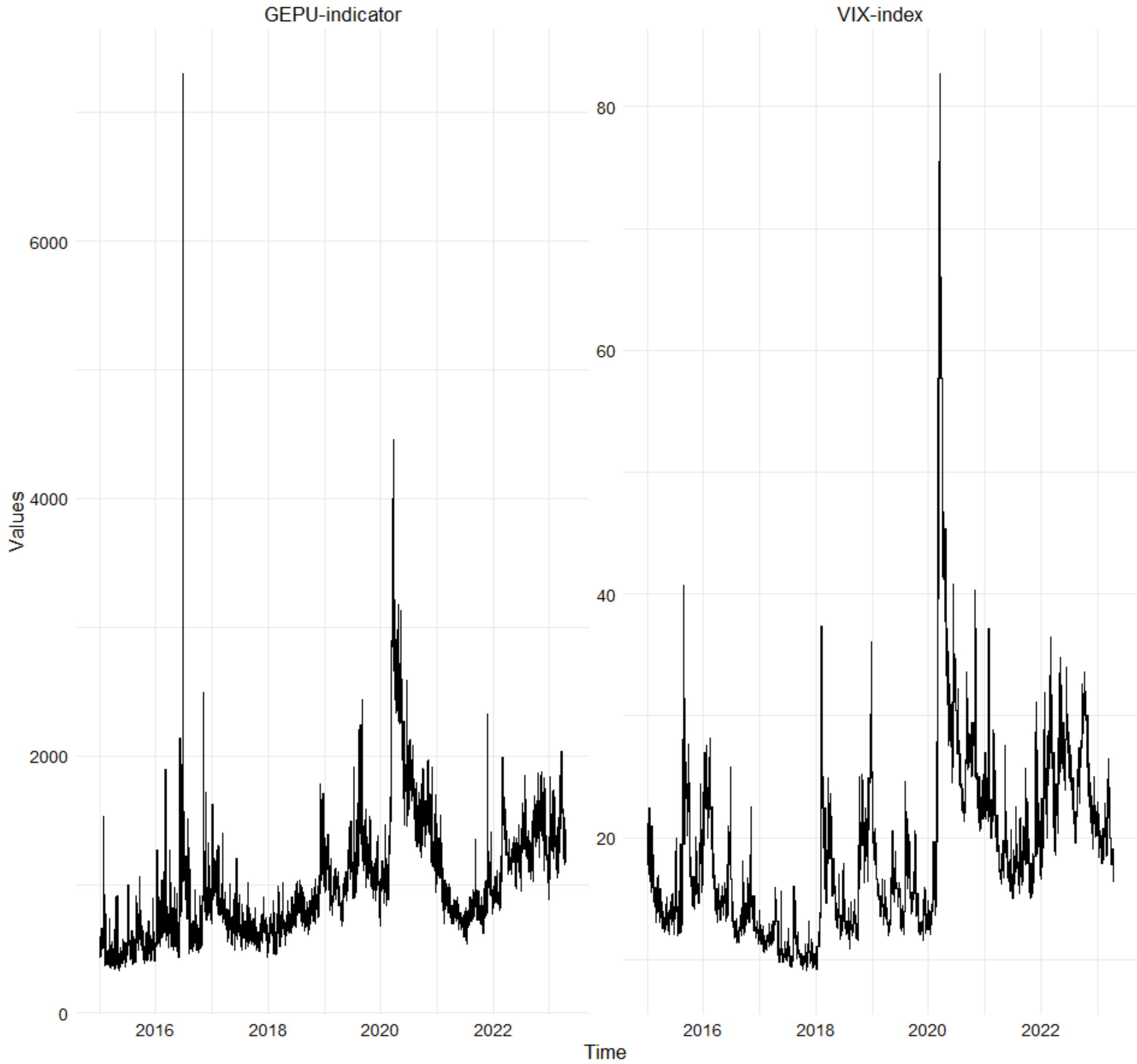

Figure 18: Time Series Plots - VIX-index and GEPU-indicator

2020, coinciding well with the onset of the official COVID-19 outbreak. Furthermore, the GEPU-indicator displays a prominent peak in June 2016, aligning with the period of the Brexit referendum.

The observed similarities and divergences in the time series plots indicate both shared and unique underlying drivers influencing the variables of interest. Despite the overall resemblance in their developments, the deviations suggest the presence of additional factors that contribute to the dynamics of each series. In relation to our thesis including both these variables will give a better understanding of the effect of economic uncertainty on the price of electricity in NO2.

Table 10: Descriptive Statistics GEPU and VIX

Name	Mean	SD	Min	Q1	Median	Q3	Max	Skew.	Kurt.	$\rho(1)$	$\rho(7)$	EL
GEPU-indicator	1000	487	336	671	876	1237	7298	2.34	13.7	0.89	0.83	***
VIX-index	18.8	7.54	9.14	13.4	17.2	22.5	82.7	2.30	10.4	0.95	0.89	***

Notes: SD denotes standard deviation; Q1 and Q3 are quartiles, 25% and 75% respectively; $\rho(.)$ is the autocorrelation of the given order; EL represents the p-value of the (Escanciano & Lobato, 2009) automatic portmanteau test of serial correlation, while Skew. and Kurt. are skewness and kurtosis, respectively. Statistics are computed over the whole sample of 72.768 observations, starting from January 1st, 2015, and ending on April 20th, 2023.

Table 10 presents the descriptive statistics of the GEPU-indicator and VIX-index.The mean value of the GEPU-indicator is 1000, with a SD of 487, indicating a considerable dispersion in the data. The minimum and maximum values are 336 and 7298, respectively, highlighting the broad range of the data. The skewness and kurtosis values of 2.34 and 13.7, respectively, suggest a positively skewed and leptokurtic distribution, indicating a greater likelihood of extreme values than in a normal distribution.

The VIX-index has a mean value of 18.8 and a SD of 7.54, reflecting a lower level of dispersion compared to the GEPU-indicator. The minimum and maximum values are 9.14 and 82.7, respectively. The skewness and kurtosis values of 2.30 and 10.4, respectively, again suggest a positively skewed and leptokurtic distribution.

Both variables exhibit elevated autocorrelation values, signifying a substantial level of serial correlation.

5.2.7 Electricity Transmission - $\boldsymbol{F}_{h,1}^{\mathbf{T}}$

Figure 19 presents a time series plot of the net electricity flow between the NO2 region and all interconnected countries and national zones. The net flow is calculated by adding together all inbound electricity per hour in one variable and all outbound electricity per hour in another variable. The inbound variable is then subtracted from the outbound variable. Consequently, when the net flow variable is positive, it indicates that the export from NO2 exceeds its import from other areas.

This figure provides a visual understanding of the situation in the NO2 region. As can be seen, the net flow variable predominantly resides on the positive side, suggesting that NO2 has a surplus of power and leans toward export of electricity to other regions. However, there are notable periods dominated by import, particularly in the years 2019 and 2022.

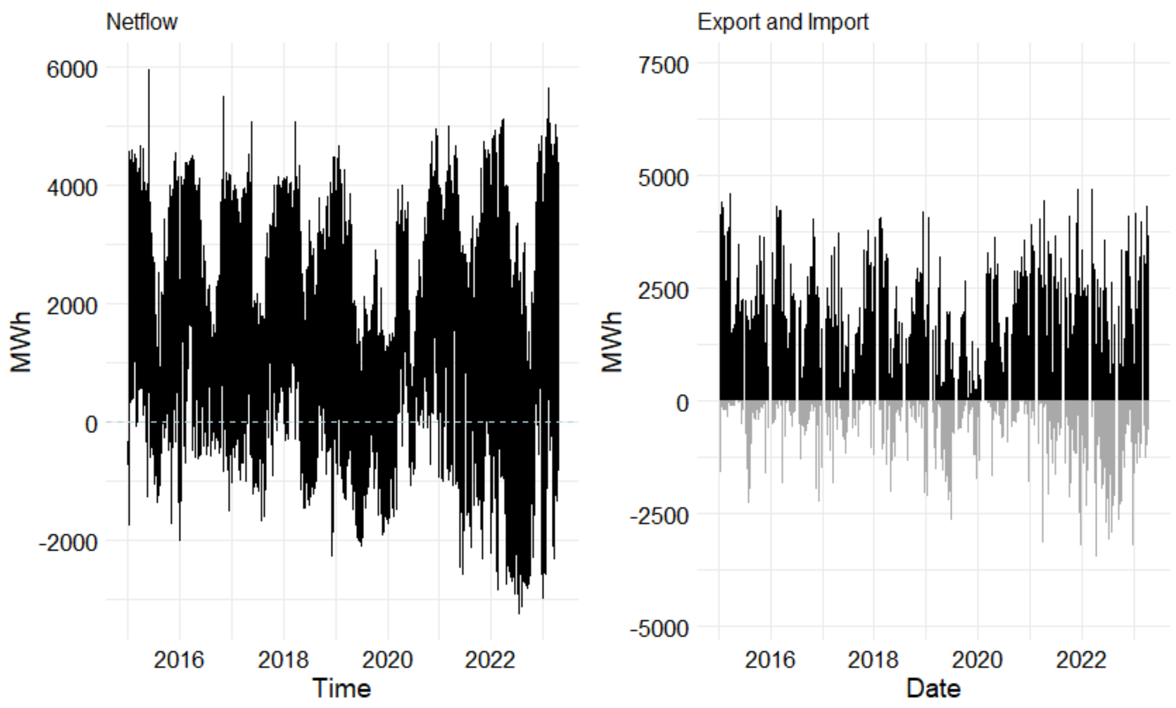

Figure 19: Electricity Transmissions NO2

Moreover, a relatively distinct seasonal pattern is evident in the plot. The export of electricity is considerably higher in the colder months, reflecting the increased demand for heating during this period and a lower production capacity in solar power. Conversely, the net flow tends to approach zero or become negative during the summer months, indicating a decrease in export or an increase in import. This could be attributed to the lower demand for heating and the potential increase in renewable energy production, such as solar power, during these months.

Given that hydroelectric power accounts for 90% of the production in the NO2 region ("Om magasinstatistikken - NVE", n.d.), it is reasonable to assume that lower reservoir levels also could significantly influence this scenario. Hydroelectric power generation is heavily dependent on the water levels in the reservoirs. In periods of low reservoir levels, the capacity for hydroelectric power generation may be reduced, potentially leading to decreased electricity exports or increased imports.

This could particularly impact the net electricity flow in months when the demand for electricity is high, and the reservoir levels are low due to less rainfall or lack of snowmelt. Conversely, during the wetter months, when reservoir levels are typically replenished, the capacity for hydroelectric power generation can increase, potentially leading to higher electricity exports (Gran et al., 2023; Huisman et al., 2014).

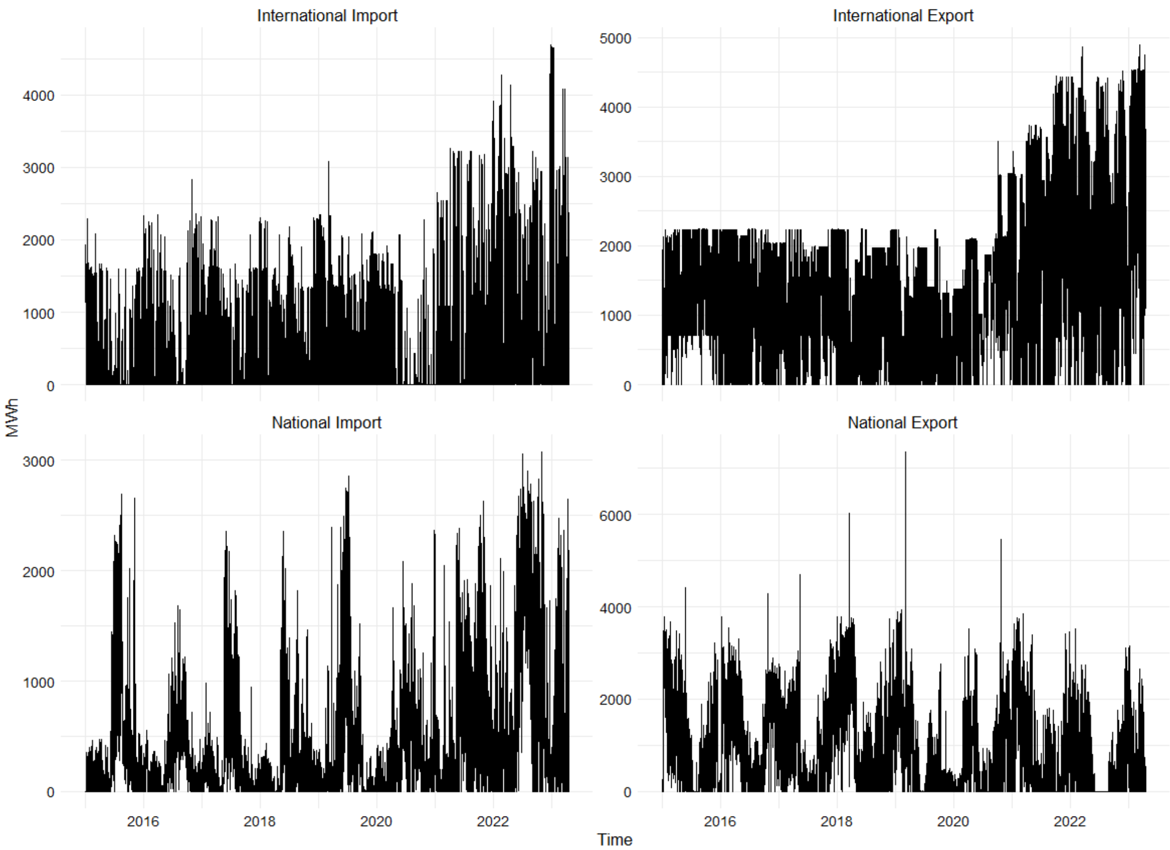

Figure 20: Time Series Plots - Aggregated Flows

Figure 20 provides a more detailed breakdown of the net electricity flow, dividing it into smaller categories. International Import and Export depict the flow through overseas cables, while National Import and Export represent the electricity flow within the Norwegian price zones.

When examining the export and import from other countries, intriguing patterns emerge. The time series data appear much more balanced, suggesting that the internal connections within Norway are primarily responsible for the frequently positive net flow. This is further corroborated when we examine the national flow, where export shows broader and longer-lasting peaks. Although the import has the same volume at its peak, it appears to be much more transient.

Additionally, there is a seasonal variation in the national flow. We see more national export during the winter months, likely due to the higher demand for electricity for heating purposes. Conversely, we observe more import during the summer months. This could be attributed to potentially lower production in NO2 due to reduced hydroelectric power generation as reservoir levels may be lower during these drier months.

Another factor that becomes apparent in this figure is the export limitation in the overseas cables up until 2021. It is noticeable in the time series for foreign export that there has been a maximum limit of around 2250 during this period. There is a clear line at the top up until 2021, indicating this cap on foreign export.

Subsequently, we observe an increase in export, which aligns with the opening of the new overseas cable to Germany and Luxembourg in the spring of 2021, and later to Great Britain in the fall of 2022. This development in the international energy infrastructure has likely played a significant role in the observed increase in foreign export.

This underlines the importance of infrastructure capacity in influencing electricity flows. The opening of these cables has linked the Norwegian energy market more closely with those in Germany, Luxembourg, and Great Britain, increasing the capacity for electricity export. This highlights the need for considering infrastructural developments and capacity constraints when analyzing and forecasting electricity market dynamics.

For electricity transmissions we have again decided to present descriptive statistics for selected hour only. Table 11 presents the descriptive statistics for total import and export variables, further divided into international and national flows. It is observed that the sum of national and international exports approximates the total export value, barring minor discrepancies attributable to rounding errors.

Table 11: Descriptive Statistics Electricity Transmission

Name	Mean	SD	Min	Q1	Median	Q3	Max	Skew.	Kurt.	$\rho(1)$	$\rho(7)$	EL
Panel A: Hour 03:00 - 04:00												
Export	1687	1000	0.00	917	1606	2308	5000	0.50	-0.22	0.74	0.53	***
Import	1065	813	0.00	401	957	1543	4693	0.93	0.98	0.68	0.50	***
International Export	1059	1023	0.00	146	706	1684	4858	1.09	0.84	0.70	0.48	***
International Import	610	801	0.00	0.00	160	1106	4693	1.51	2.57	0.63	0.36	***
National Export	628	772	0.00	0.00	264	1100	3652	1.20	0.66	0.81	0.60	***
National Import	455	630	0.00	0.00	173	649	3059	1.60	1.75	0.82	0.63	***
Panel B: Hour 08:00 - 09:00												
Export	2523	1128	0.00	1744	2514	3416	6019	-0.09	-0.65	0.68	0.65	***
Import	618	681	0.00	150	370	871	4630	1.84	3.93	0.62	0.57	***
International Export	1528	947	0.00	730	1555	2041	4727	0.52	0.35	0.60	0.53	***
International Import	258	584	0.00	0.00	0.00	103	4630	3.01	10.8	0.46	0.54	***
National Export	996	952	0.00	41.5	792	1773	4130	0.63	-0.73	0.81	0.69	***
National Import	360	475	0.00	33.0	216	445	3078	2.26	5.43	0.79	0.68	***
Panel C: Hour 15:00 - 16:00												
Export	2327	1157	0.00	1446	2239	3226	5936	0.12	-0.79	0.76	0.65	***
Import	711	749	0.00	176	443	1056	4513	1.58	2.42	0.64	0.54	***
International Export	1299	939	0.00	666	1259	1907	4702	0.69	0.43	0.64	0.49	***
International Import	407	696	0.00	0.00	0.00	650	4137	1.99	3.84	0.54	0.34	***
National Export	1028	944	0.00	91.8	846	1768	4419	0.61	-0.69	0.83	0.66	***
National Import	304	433	0.00	0.00	162	400	2651	2.36	5.99	0.79	0.66	***
Panel D: Hour 19:00 - 20:00												
Export	2638	1078	0.00	1852	2614	3497	5427	-0.04	-0.70	0.77	0.57	***
Import	563	588	0.00	159	372	753	3378	1.66	2.65	0.70	0.57	***
International Export	1716	934	0.00	1050	1716	2140	4848	0.65	0.52	0.70	0.50	***
International Import	168	432	0.00	0.00	0.00	0.00	3250	3.22	11.6	0.46	0.23	***
National Export	921	917	0.00	0.00	686	1645	3654	0.68	-0.66	0.87	0.71	***
National Import	396	484	0.00	67.0	245	491	2714	2.06	4.33	0.83	0.71	***

Notes: SD denotes standard deviation; Q1 and Q3 are quartiles, 25% and 75% respectively; $\rho(.)$ is the autocorrelation of the given order; EL represents the p-value of the (Escanciano & Lobato, 2009) automatic portmanteau test of serial correlation, while Skew. and Kurt. are skewness and kurtosis, respectively. Statistics are computed hourly with 3032 observations starting from January 1st, 2015, and ending on April 20th, 2023.

Across all hours and for all variables, export values exceed import values, reaffirming Norway's role as Europe's battery, as referenced in "How Norway can become Europe's battery", n.d.

A noteworthy pattern emerges in the export variables in Panels B, C and D, where both mean and median values see a significant upswing compared to Panel A. This surge can likely be attributed to the increased production and load demand during waking hours, as indicated in Tables 6 and 7.

Contrastingly, the import variables exhibit an inverse trend, with higher mean and median values typically recorded during the hour of 04:00 as opposed to the remaining selected hours.

The kurtosis of the data is predominantly lepotkurtic, with the exception of the total export and national export variables, which exhibit platykurtic tendencies across all hours, save for the national export during the 04:00 hour. This implies that the total export and national export variables are subject to a lower frequency of outliers.

Table 12 provides descriptive statistics for national electricity transmission in Norway, focusing on import and export variables during selected hours. The variables are further divided based on the regions NO1 and NO5. The table gives interesting insights into the internal mechanisms in the Norwegian electricity market. Upon examining the data, we discern a significant disparity between NO1 and NO5 in their relation to NO2. For NO1, the mean export value consistently surpasses the mean import value across all hours, indicating a predominant trend of exporting electricity. Conversely, NO5 demonstrates the opposite pattern, with the mean import value generally exceeding the mean export value.

Moreover, the overall volume for NO5 is considerably lower than that for NO1, suggesting a lesser degree of electricity transmission activity in the former region.

Additionally, the SD is notably high for all hours in both regions. This high variability implies a substantial fluctuation in volume, indicating that the quantity of electricity imported and exported is not constant but varies significantly across different hours.

Table 12: Descriptive Statistics National Electricity Transmission

Name	Mean	SD	Min	Q1	Median	Q3	Max	Skew.	Kurt.	$\rho(1)$	$\rho(7)$	EL
Panel A: Hour 03:00 - 04:00												
Import NO1	265	488	0.00	0.00	0.00	343	2390	2.00	3.20	0.82	0.64	***
Export NO1	568	714	0.00	0.00	206	1034	3296	1.19	0.66	0.81	0.59	***
Import NO5	191	211	0.00	0.00	117	348	925	0.84	-0.39	0.75	0.53	***
Export NO5	59.9	107	0.00	0.00	0.00	81.2	552	1.86	2.59	0.70	0.46	***
Panel B: Hour 08:00 - 09:00												
Import NO1	131	352	0.00	0.00	0.00	0.00	2423	3.20	10.3	0.76	0.66	***
Export NO1	968	936	0.00	0.00	784	1729	4130	0.61	-0.79	0.82	0.69	***
Import NO5	229	202	0.00	24.0	200	381	864	0.54	-0.76	0.73	0.56	***
Export NO5	27.2	74.0	0.00	0.00	0.00	0.00	534	3.24	10.6	0.50	0.35	***
Panel C: Hour 15:00 - 16:00												
Import NO1	111	318	0.00	0.00	0.00	0.00	1909	3.40	11.5	0.77	0.67	***
Export NO1	987	918	0.00	10.0	819	1704	4293	0.59	-0.72	0.83	0.67	***
Import NO5	193	193	0.00	0.00	149	333	851	0.72	-0.54	0.75	0.54	***
Export NO5	40.7	87.0	0.00	0.00	0.00	20.0	456	2.34	4.78	0.58	0.34	***
Panel D: Hour 19:00 - 20:00												
Import NO1	145	361	0.00	0.00	0.00	0.00	2273	2.92	8.21	0.82	0.70	***
Export NO1	899	903	0.00	0.00	670	1614	3465	0.66	-0.74	0.87	0.71	***
Import NO5	251	203	0.00	60.0	230	408	918	0.41	-0.83	0.79	0.57	***
Export NO5	21.8	65.4	0.00	0.00	0.00	0.00	450	3.60	13.4	0.58	0.31	***

Notes: SD denotes standard deviation; Q1 and Q3 are quartiles, 25% and 75% respectively; $\rho(.)$ is the autocorrelation of the given order; EL represents the p-value of the (Escanciano & Lobato, 2009) automatic portmanteau test of serial correlation, while Skew. and Kurt. are skewness and kurtosis, respectively. Statistics are computed hourly with 3032 observations starting from January 1st, 2015, and ending on April 20th, 2023.

The skewness and kurtosis of the data reveal that the distribution of import and export variables is skewed towards higher values, with a few exceptions. The Import NO1 and Export NO5 variables exhibit high positive skewness and kurtosis values, suggesting a higher frequency of outliers.

In terms of autocorrelation, the $\rho(1)$ and $\rho(7)$ values are generally high across all variables and hours, indicating a strong correlation between the current and past values of these variables. The exception is Export NO5 which shows a moderate autocorrelation during waking hours. A lower autocorrelation infers that this variable experiences swift alterations, which is further evidenced by high skewness, kurtosis, and SD.

Table 13: Descriptive Statistics International Electricity Transmission

Name	Mean	SD	Min	Q1	Median	Q3	Max	Skew.	Kurt.	$\rho(1)$	$\rho(7)$	EL
Panel A: Hour 03:00 - 04:00												
Import DK	415	551	0.00	0.00	0.00	850	1623	0.95	-0.64	0.57	0.34	***
Export DK	468	580	0.00	0.00	21.5	980	1633	0.78	-0.96	0.56	0.33	***
Import GB	162	329	0.00	0.00	0.00	6.00	1150	1.85	1.93	0.59	0.33	***
Export GB	398	483	0.00	0.00	3.00	694	1400	0.68	-1.08	0.76	0.52	***
Import NL	95.3	215	0.00	0.00	0.00	0.00	732	2.11	2.89	0.58	0.39	***
Export NL	347	313	0.00	0.00	398	704	707	-0.00	-1.80	0.71	0.56	***
Import DELU	208	427	0.00	0.00	0.00	41.5	1447	1.86	1.89	0.55	0.23	***
Export DELU	537	513	0.00	0.00	470	989	1407	0.42	-1.29	0.50	0.16	***
Panel B: Hour 08:00 - 09:00												
Import DK	168	391	0.00	0.00	0.00	0.00	1615	2.36	4.41	0.39	0.31	***
Export DK	785	577	0.00	69.5	876	1286	1635	-0.17	-1.43	0.45	0.36	***
Import GB	103	267	0.00	0.00	0.00	0.00	1150	2.68	6.15	0.57	0.28	***
Export GB	450	481	0.00	0.00	280	699	1400	0.49	-1.26	0.75	0.58	***
Import NL	29.4	124	0.00	0.00	0.00	0.00	732	4.55	20.1	0.23	0.31	***
Export NL	465	284	0.00	204	615	704	707	-0.75	-1.11	0.65	0.60	***
Import DELU	130	342	0.00	0.00	0.00	0.00	1446	2.66	5.82	0.37	0.16	***
Export DELU	628	504	0.00	132	585	1102	1407	0.23	-1.33	0.45	0.24	***
Panel C: Hour 15:00 - 16:00												
Import DK	256	455	0.00	0.00	0.00	359	1617	1.63	1.31	0.46	0.23	***
Export DK	623	584	0.00	0.00	584	1160	1633	0.28	-1.45	0.48	0.28	***
Import GB	98.6	273	0.00	0.00	0.00	0.00	1399	2.81	6.85	0.50	0.29	***
Export GB	507	497	0.00	0.00	574	1050	1400	0.31	-1.41	0.69	0.59	***
Import NL	59.5	173	0.00	0.00	0.00	0.00	732	2.93	7.32	0.45	0.41	***
Export NL	424	300	0.00	0.00	505	704	707	-0.47	-1.52	0.68	0.61	***
Import DELU	256	455	0.00	0.00	0.00	328	1432	1.53	0.76	0.40	0.24	***
Export DELU	466	477	0.00	0.00	364	776	1407	0.67	-0.84	0.46	0.22	***
Panel D: Hour 19:00 - 20:00												
Import DK	128	339	0.00	0.00	0.00	0.00	1623	2.83	7.09	0.42	0.19	***
Export DK	845	570	0.00	290	950	1332	1633	-0.28	-1.33	0.52	0.24	***
Import GB	43.4	175	0.00	0.00	0.00	0.00	1099	4.46	20.0	0.39	0.24	***
Export GB	587	500	0.00	2.00	694	1086	1400	0.04	-1.46	0.79	0.65	***
Import NL	8.46	61.7	0.00	0.00	0.00	0.00	731	8.77	83.6	0.28	0.08	***
Export NL	524	255	0.00	424	703	705	707	-1.22	-0.03	0.81	0.66	***
Import DELU	72.6	246	0.00	0.00	0.00	0.00	1436	3.74	13.72	0.38	0.17	***
Export DELU	763	489	0.00	404	761	1221	1407	-0.18	-0.18	0.47	0.15	***

Notes: SD denotes standard deviation; Q1 and Q3 are quartiles, 25% and 75% respectively; $\rho(.)$ is the autocorrelation of the given order; EL represents the p-value of the (Escanciano & Lobato, 2009) automatic portmanteau test of serial correlation, while Skew. and Kurt. are skewness and kurtosis, respectively. Statistics are computed hourly with 3032 observations starting from January 1st, 2015, and ending on April 20th, 2023. For DELU and GB statistics are computed starting from January 1st, 2021, and ending on April 20th, 2023.

Table 13 illustrates the descriptive statistics for international electricity transmission, focusing on import and export variables during selected hours. The variables are further divided based on the regions of Denmark (DK), Great Britain (GB), Netherlands (NL), and Germany/Luxembourg (DELU). This table offers a detailed overview of the international electricity market dynamics involving Norway NO2.

A critical observation from the data reveals distinct patterns in the relation of these regions to NO2. All areas import more electricity from NO2 than they export to it, once again reinforcing Norway being referenced as "Europes Battery" (“How Norway can become Europe’s battery”, n.d.). Notably, the overall volume for GB and NL is lower than that for DK and DELU, suggesting a lesser degree of electricity transmission activity and capacity in the former regions.

The SD is high for all hours in all regions, implying substantial fluctuations in volume. This suggests that the quantity of electricity imported and exported is not constant but varies significantly across different hours.

Furthermore, the skewness and kurtosis of the data reveal that the distribution of import and export variables is skewed towards higher values, with a few exceptions. For example, Import GB and Import NL exhibit high positive skewness and kurtosis values, suggesting a higher frequency of outliers.

The autocorrelation values, $\rho(1)$ and $\rho(7)$, are generally high across all variables and hours, indicating a strong correlation between the current and past values of these variables. This suggests a significant degree of temporal dependency in the import and export activities.

5.3 Baseline Model Results

In this subsection will present the baseline results for selected hours. We will first analyze the performance of hour model, and then go through the result for the variables in our model. For the variables we will illustrate the results using plots that show the coefficients over all hours while highlighting hours with significant results. Significance is measured at a 5% level.

We will start by reviewing the models performance, then the different variables. Results for trend, GEPU-indicator and VIX-index will not be shown as they yielded no significant results. Results are attached in Appendix C.

Daylight Hours and Holiday effects will be commented under Panel A and Panel B, respectively. Subsequently, Panel D and Panel F will not be commented specifically.

Tables 14, 15 and 16 show results from the regression model for selected hours. These are meant as examples, and we've used the same hours as previously in the thesis.

Table 14: OLS-regression Selected Hours Part I

Variable	04:00	09:00	16:00	20:00
Panel J: Model characteristics				
$\rho(1)$	0.36	0.36	0.40	0.41
$\rho(7)$	-0.04	0.03	0.03	-0.02
R^2	0.89	0.87	0.87	0.92
$Adjusted R^2$	0.89	0.87	0.87	0.92
Serial correlation (EL-test)	***	***	***	***
Breusch-Pagan	***	***	***	***

Notes: SD denotes standard deviation; Q1 and Q3 are quartiles, 25% and 75% respectively; ρ(.) is the autocorrelation of the given order; EL represents the p-value of the (Escanciano & Lobato, 2009) automatic portmanteau test of serial correlation, while Skew. and Kurt. are skewness and kurtosis, respectively. Statistics are computed hourly with 3032 observations starting from January 1st, 2015, and ending on April 20th, 2023. These notes are also applicable for Tables 15 and 16.

Table 15: OLS-regression Selected Hours Part II

Variable	04:00		09:00		16:00		20:00	
Constant	124		233		294		89.3	
Panel A: Prices								
Price NO2	0.66	***	0.46	***	0.57	***	0.73	***
Price Lag 7	0.20	***	0.34	***	0.31	***	0.19	**
Price Lag 14	0.10		0.12	*	0.00		-0.02	
Price Lag 21	-0.07		-0.03		0.00		0.07	
Price Lag 28	0.07		0.02		0.00		-0.05	
Panel B: Weekdays								
Monday	-38.0	*	89.0	***	47.0	*	79.2	***
Tuesday	6.69		136	***	70.8	***	66.2	***
Thursday	-23.8	*	-9.86		-17.4		0.36	
Friday	-23.6		8.87		-24.5		0.03	
Saturday	-24.5		-49.0	**	-69.9	***	-21.1	
Sunday	-42.2	**	-75.0	***	-61.2	***	16.3	
Panel C: Months								
January	-114		-181	*	-159	*	-220	***
February	-88.9		-161	**	-126	**	-186	***
March	-19.9		-71.4		-43.6		-79.2	*
April	45.4		4.27		33.5		25.4	
May	92.2		66.7		86.3		118	*
June	150	*	139		138	*	167	*
July	142	*	147		122	*	149	*
August	134	*	171	*	128	**	146	**
October	-63.9		-110		-82.5		-110	*
November	-76.6		-116		-89.4		-139	*
December	-124		-197	*	-146		-253	**
Panel D: Other control variables								
Daylight Hours	-17.3		-19.9		-19.8		-26.2	*
Holiday	-28.6		-86.6	***	-83.7	**	-34.9	*
Trend	0.03		0.03		0.03		0.02	

Table 16: OLS-regression Selected Hours Part III

Variable	04:00	09:00	16:00	20:00
Panel E: Market Variables				
Gas Price	12.4 ***	12.2 ***	8.77 **	7.10
Oil Price	-10.9 **	-11.9 *	-8.58	-5.42
Coal Price	1.53	4.61	2.75	2.41
Co2 Price	-3.68	-9.47	1.43	-1.97
NOK/EUR	-270	-140	-121	18.9
NOK/USD	86.5	13.7	-65.0	-57.4
Panel F: Global Uncertainty				
VIX-index	-0.02	-2.16	-1.08	0.24
GEPU-indicator	-0.00	0.04	0.00	-0.00
Panel G: Weather and Climate				
Heating Degrees	0.48	-4.87	-3.22	3.40
Cooling Degrees	-0.44	-2.03	-0.61	4.25
Mean Wind	5.90 *	6.80	4.04	2.99
Mean Precipitation	-12.7	-37.3 *	-25.9	-19.6
Panel H: Production and Consumption				
Production	0.01	0.03	0.02	0.00
Load	-0.01	-0.08	-0.02	0.01
Forecasted Load	0.02	0.05	0.00	0.05
Panel I: Electricity Transmission				
Import DK	0.02	0.04	0.01	0.06 *
Export DK	-0.01	-0.06 **	-0.04 *	-0.01
Import GB	-0.16	-0.13	0.10	-0.06
Export GB	0.05	-0.03	0.14 *	0.16 ***
Import NL	-0.03	-0.16 *	-0.08 *	-0.15 *
Export NL	-0.02	0.03	-0.01	-0.05
Import DELU	0.02	0.19 *	0.13 *	-0.07
Export DELU	-0-04	0.06	-0.07	-0.04
Import NO1	0.04	0.16 **	0.10	0.09 *
Export NO1	0.00	0.00	0.01	-0.00
Import NO5	-0.03	0.00	0.04	-0.10 *
Export NO5	-0.03	-0.25 **	-0.11 *	-0.18 **

Panel J - Model characteristics: The model shows a high level of fit, as indicated by the R^2 and adjusted R^2, which are all above 0.87. The EL-test for serial correlation and the Breusch-Pagan test results both yield significant findings, leading to the rejection of the null hypothesis of no serial correlation and homoscedasticity in residuals. We therefore relied on the Newey-West method to estimate coefficient standard error and consequently the p-values.

Figure 21 shows the accuracy of the regression model over all hours as presented by R^2. In general, the plot shows an acceptable accuracy for the model, with R^2 ranging from 0.862 to 0.947. The model shows a higher accuracy at evening and night, while there is general decrease in R^2 between hours 07:00 and 19:00. This reflects the variations seen in price, production and load in Chapter 5.2.7.

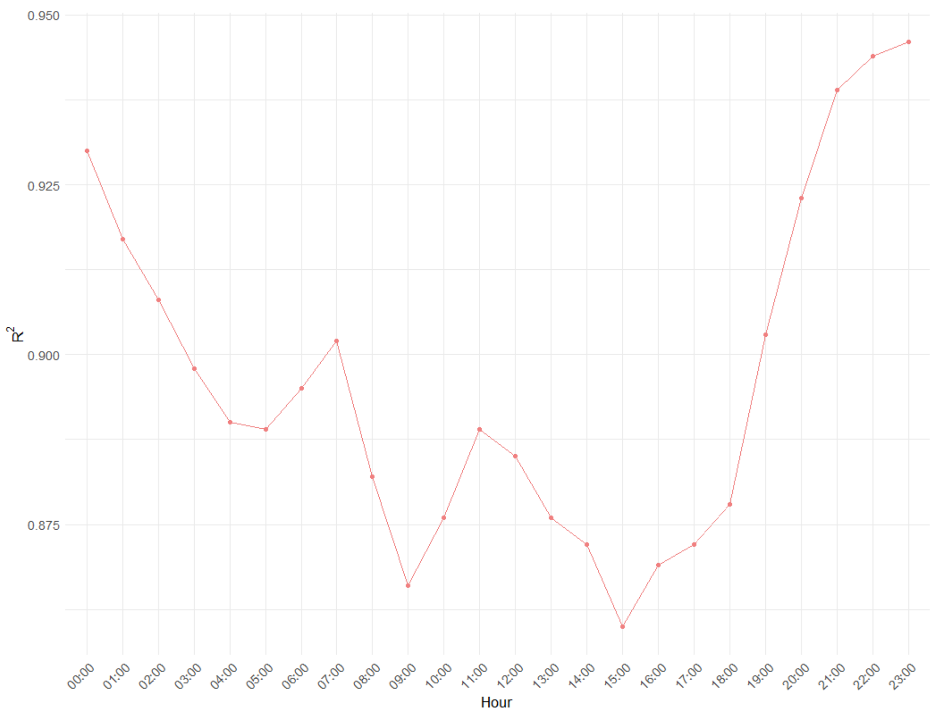

Figure 21: Accuracy of OLS-model

Figure 22 illustrates the precision of the model for selected hours. The black lines represent the actual values of the price variable, while the red lines depicts the predicted values.

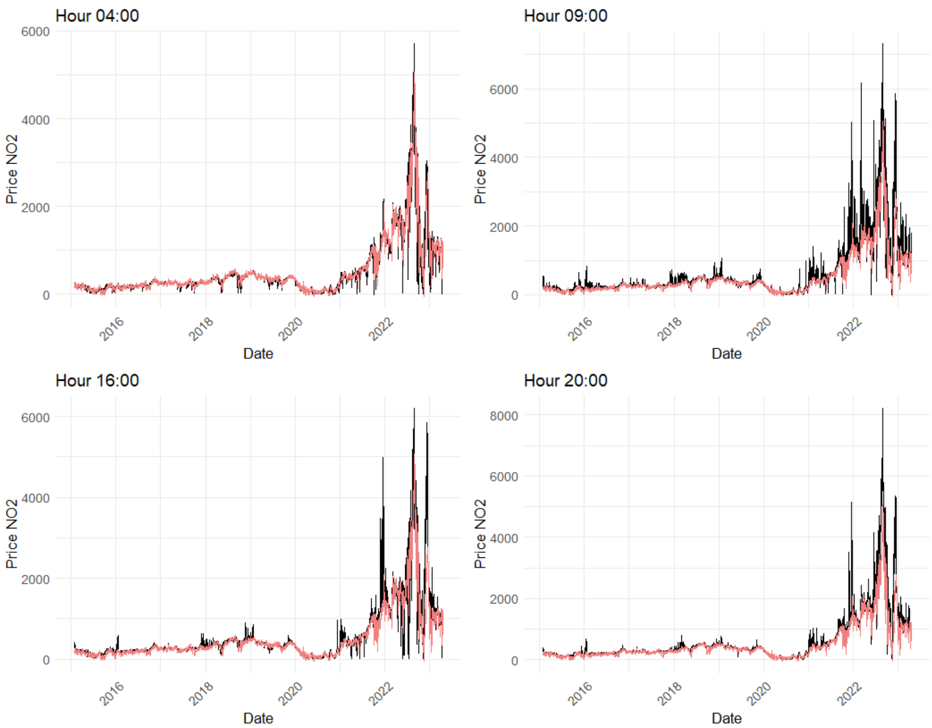

Figure 22: Predicition of OLS-model for Selected Hours

This is an in-sample prediction, and it is evident that the two plots mirror each other closely. However, it's also observable that the model encounters difficulties in accurately predicting the peaks and valleys possibly highlighting the difficulties of more RES entering the system. This is also observable from the drop in R^2 during daytime hours.

Panel A - Prices: The coefficients of 'Price NO2' and 'Price Lag 7' are significant at the 0.1% level across all the time slots, suggesting a strong positive relationship between these variables and the selected hours. 'Price Lag 14' is only significant at the 5% level for the 09:00 slot. The remaining price lag variables show no significant relationship.

Figure 23 illustrates the computed impact of various price lags, with today's price exerting the most substantial effect. Notably, the price variable exhibits a higher influence during the evening and night hours, diminishing to a lower level between 06:00 and 18:00. Price Lag 7 displays a converse trend, demonstrating a significant peak during these same hours.

As for the magnitude of the coefficients, a downward trend is observed for the different lags. The coefficients for today's price range approximately from 0.50 to 0.80. In contrast, for Price Lag 7, the coefficients range roughly from 0.10 to 0.35. For Price Lag 14, the

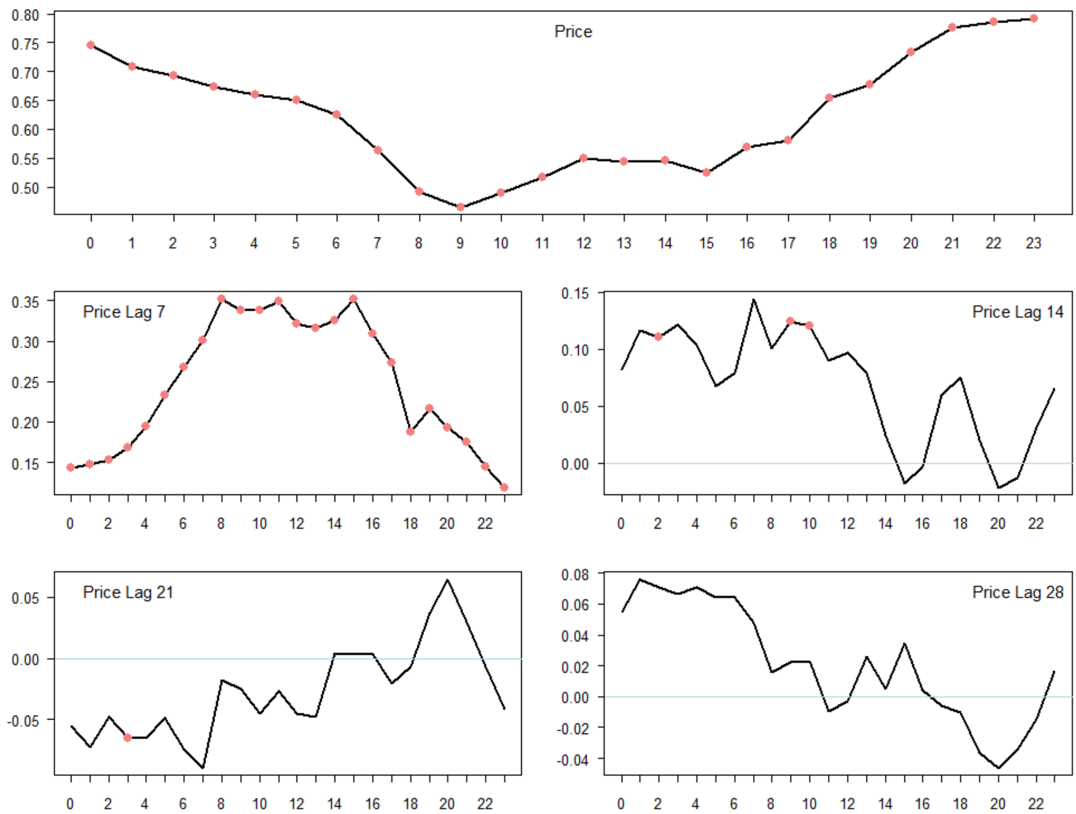

Figure 23: Effects of Price Variables

range is from -0.05 to 0.15.

The results for both the current Price and Price Lag 7 are statistically significant across all hours at a 5% level. For Lag 14, there are three significant observations, while for Lag 21, only one significant observation is noted. Lag 28 yields no significant observations. This pattern suggests a declining trend in both the number of significant observations and the magnitude of coefficients as we move further back in time.

Panel B - Weekdays: During peak hours, the prices on Mondays and Tuesdays tend to be higher compared to Wednesdays, while the prices over the weekend tend to be lower. However, during the off-peak period from at 04:00, the pattern changes and almost all days display lower price levels than Wednesday. All days, except Friday, yield significant findings, with the weekends and the beginning of the week being particularly noteworthy. The variable 'Holiday' shows a negative relationship with the 09:00, 16:00 and 20:00 slots being significant at the 0.1%, 1% and 5% level respectively.

The plots for weekdays as shown in Figure 24 indicates that electricity prices are notably lower on Saturdays and Sundays, and also during the night transitioning from Sunday to Monday. However, a significant surge in prices is observed from Monday morning through Tuesday, with the coefficients being markedly higher.

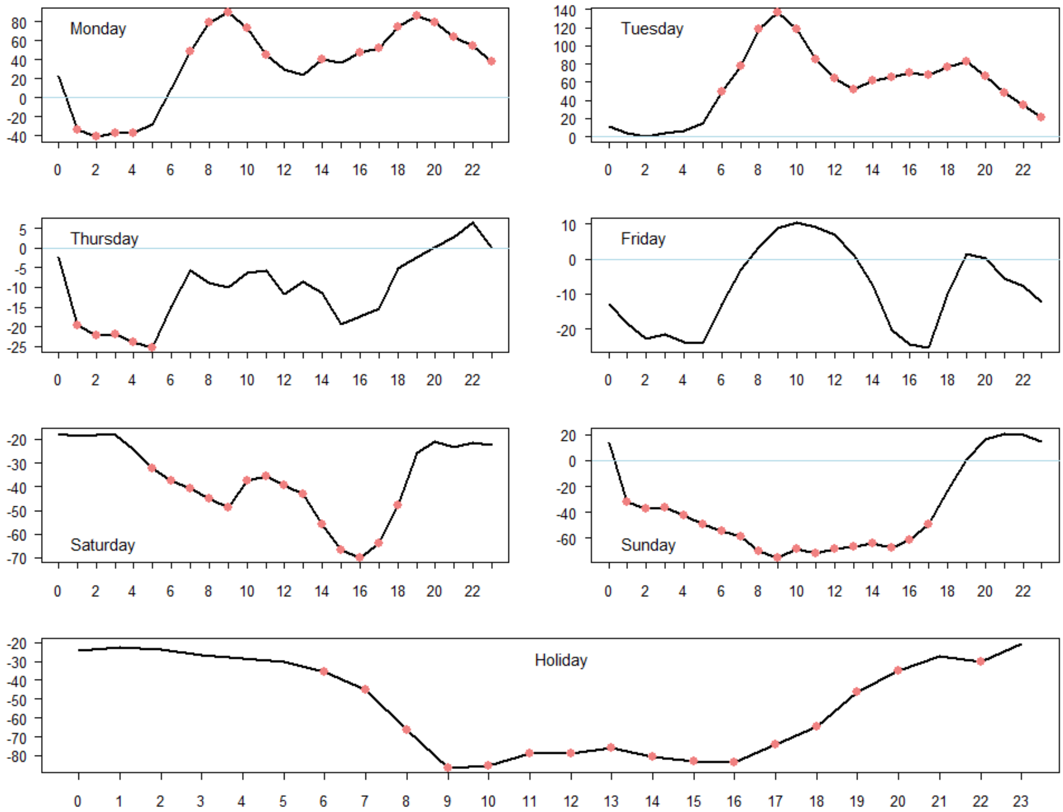

Figure 24: Weekday Effects

The latter part of the week shows a slight dip, with Thursday and Friday exhibiting somewhat lower coefficients. Interestingly, Friday presents a peak during working hours, where the prices rise above the general trend for the day.

The lower weekend prices could reflect reduced commercial and industrial activity, while the surge on Monday and Tuesday corresponds with the resumption of these activities. The peak on Friday during working hours further underscores the influence of business activity on electricity prices.

The Holiday variable show significant effects throughout the day, underscoring the reduced industrial activity and the possible change of consumption patterns related to public and soft holidays.

Panel C - Months: We observe once again that the patterns of results vary between off-peak and peak hours. In comparison to September, the months of January, February, and the Autumn season generally display lower prices. Conversely, the summer months, spanning from June to August, tend to exhibit higher prices, even during the off-peak hour slot at 04:00. These findings corroborate that, in addition to weekly seasonality, there is also a pronounced within-year seasonality in prices, as indicated by the size of the coefficients, which are measured in Norwegian Krone (NOK). The variable 'Daylight Hours' shows a negative relationship with the Price NO2, the 20:00 slot is significant at the 5% level.

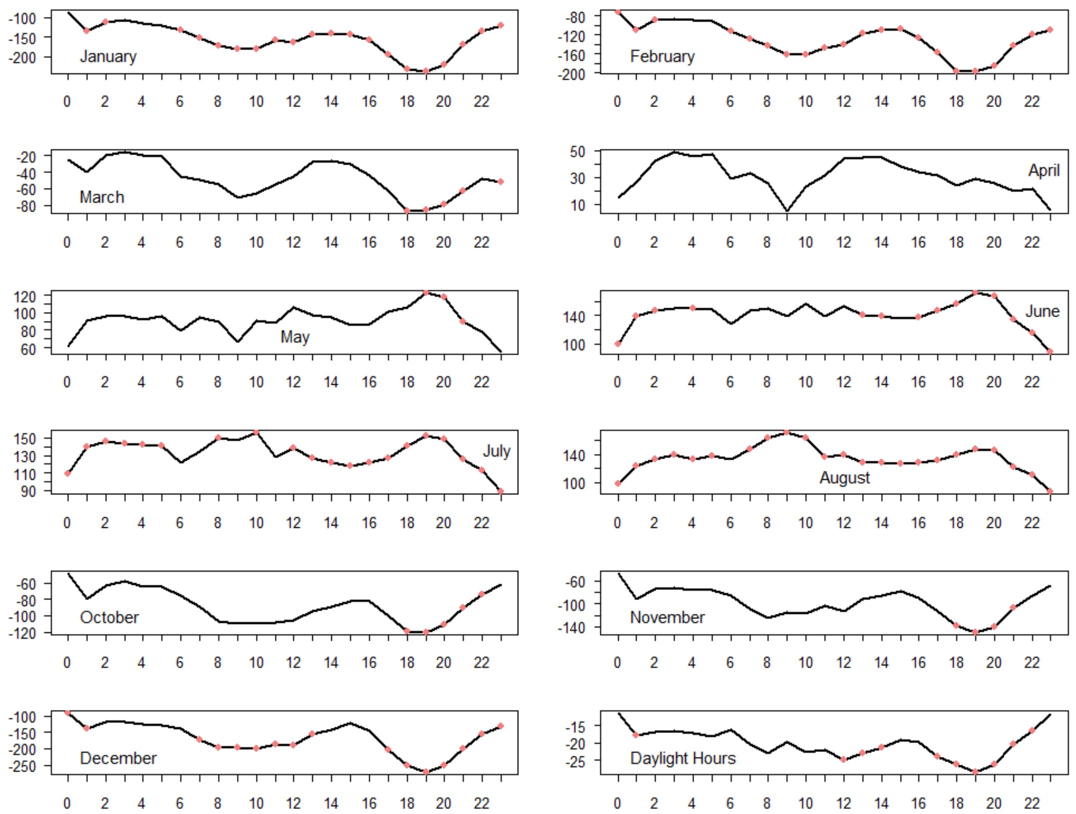

Figure 25: Annual Effects

This distinct seasonal pattern is also observed in Figure 25. From October through March, all coefficients are negative. The magnitude of these coefficients increases from October, peaking around December and January, before decreasing towards March. Conversely, from April onwards, the coefficients become positive, with June, July, and August exhibiting the highest magnitudes.

This contrast between the colder and warmer months is also reflected in the statistical significance of the results. The winter and summer months essentially show significant results for all hours, with only a few exceptions. This pattern aligns with expectations, given that these periods typically experience less variation in weather conditions, leading to more predictable patterns of electricity demand.

The Daylight Hours variable shows significant results, especially at evening hours where the effect of more daylight is most pronounced. It has a negative relation to Price NO2 as expected.

Panel E - Market Variables: 'Gas Price' and 'Oil Price' both have significant impacts on the selected hours at all significance levels, indicating that these factors are important in determining the dependent variable for certain hours. However, 'Coal Price', 'Co2 Price', 'NOK/EUR' and 'NOK/USD' do not show significant influences.

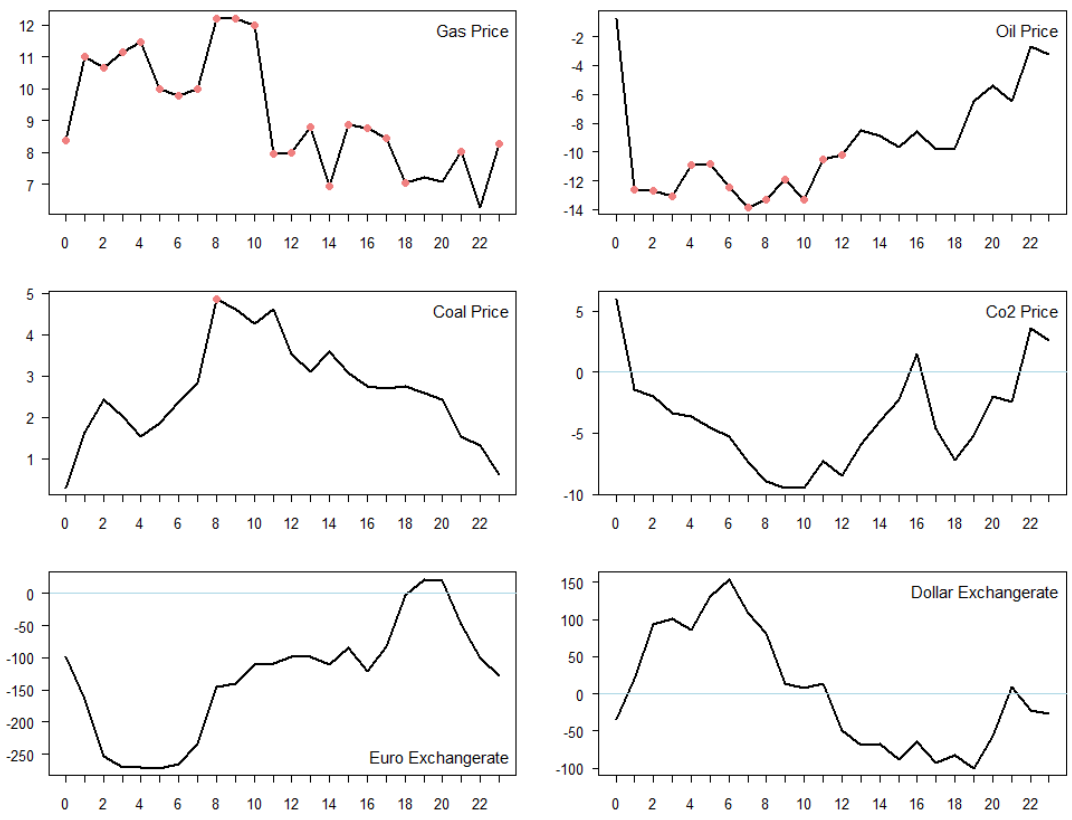

Figure 26: Effects of Financial Markets

Interestingly, the gas price is associated with a positive coefficient. This suggests that a unit increase in the gas price results in an increase in the electricity price by 11.4, 12.2, and 8.76 for the hourly slots at 04:00, 09:00, and 16:00, respectively. Considering the approximate exchange rates of 10 NOK/EUR or 9 NOK/USD, these coefficients suggest a nearly one-to-one transmission from the gas and oil markets. The positive impact of gas prices is likely due to the fact that gas is used to generate electricity in Europe. However, the coefficient for the oil price exhibits mixed signs, suggesting a more complex relationship.

The coefficients for the fundamental market variables reveal distinctive patterns, as seen in Figure 26. Gas prices exhibit positive coefficients, ranging from 6 to 12. The coefficients peak at 12 during hours 08:00-10:00, then stabilize between 7 and 9 for the remainder of the period. This is as expected as natural gas is one of Europe's primary sources for energy generation, resulting in high influence on electricity prices in NO2.

In contrast, oil prices display entirely negative coefficients. These vary between -12 and -14 during hours 1 to 12, then decrease steadily to -1 at hour 0.

Coal prices demonstrate a positive trend. Starting at zero at hour 0, the coefficients increase to between 4.5 and 5 during the morning hours of 07:00 to 09:00. Following this peak, they decrease steadily until midnight. We would have expected to see more significant observations, especially due to Germany reactivating coal resources in the latter years. However, this could be the net effect of the Energiewende, as pointed out by Hirth, 2018.

CO2 prices fluctuate, but are predominantly negative. The coefficients turn positive during the evening hours, decrease towards the morning, then rise to a positive peak at hour 16. They turn negative again at hour 18:00 and then rise once more to 3 at hour 22:00. The pattern that emerges is surprising, and is hard to attribute to any specific market dynamic. This is contrary to both Bublitz et al., 2017 and Gran et al., 2023.

Panel G - Weather and Climate: 'Mean Wind' displays a positive and significant relationship at the 5% level with the 04:00 slot. 'Mean Precipitation' shows a negative relationship with the 09:00 slot and is significant at the 5% level. The remaining variables do not show significant influences.

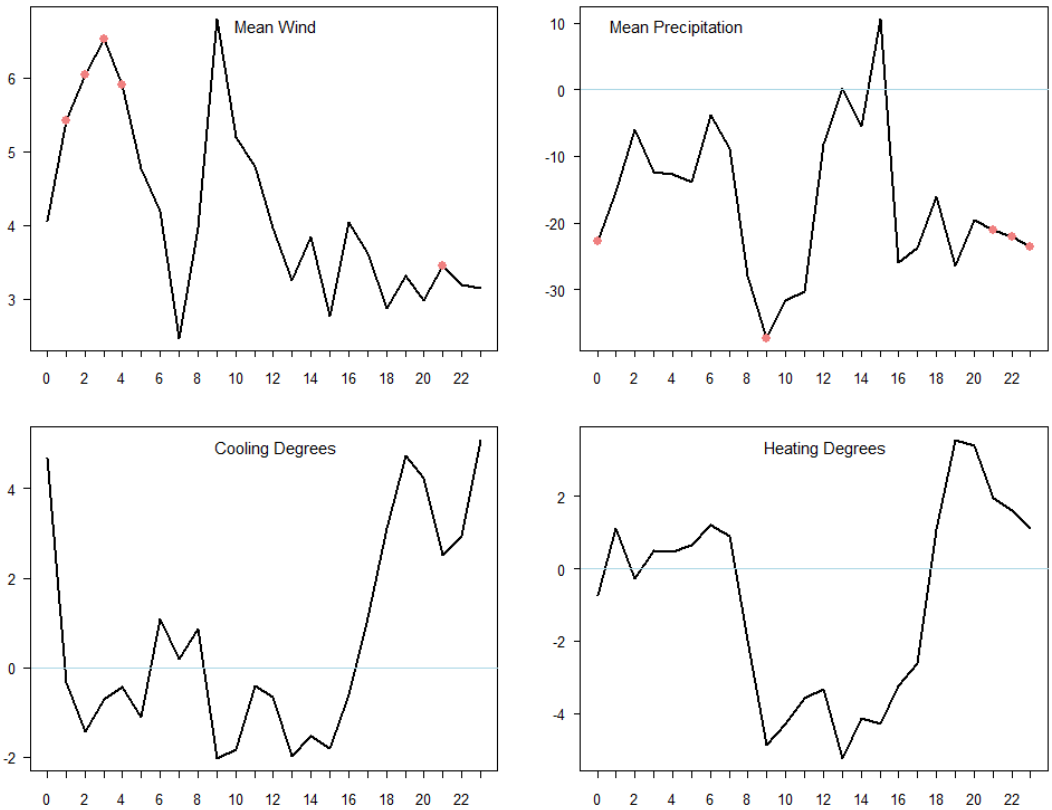

Figure 27: Effects of Weather variables

Interestingly, our analysis yields few significant results for these weather and climate variables over all hours, as shown in Figure 27. The only significant effects are observed for wind from 01:00 to 04:00 at night, and for precipitation at hour 00:00, hour 09:00 and from 21:00 to 23:00. This is in line with Voronin et al., 2014 who argues that weather effects are already reflected in demand.

Panel H - Production and Consumption: In Table 17 neither Load, Forecasted Load nor Production show significant results for selected hours.

Looking at all hours in Table 28 there are still no significant results for Load and Forecasted Load. This could be influenced by both the COVID-pandemic ("Varmt vær og pandemi førte til mindre energibruk", n.d.) and the Norwegian government's support scheme (Norwegian Ministry of Energy, 2023), resulting in a dampening effect on load. The Production variable has a few significant observations, but in general these variables show fewer significant findings than expected. One possible explanation for this is the effect of these variables already being reflected in the dependent variable.

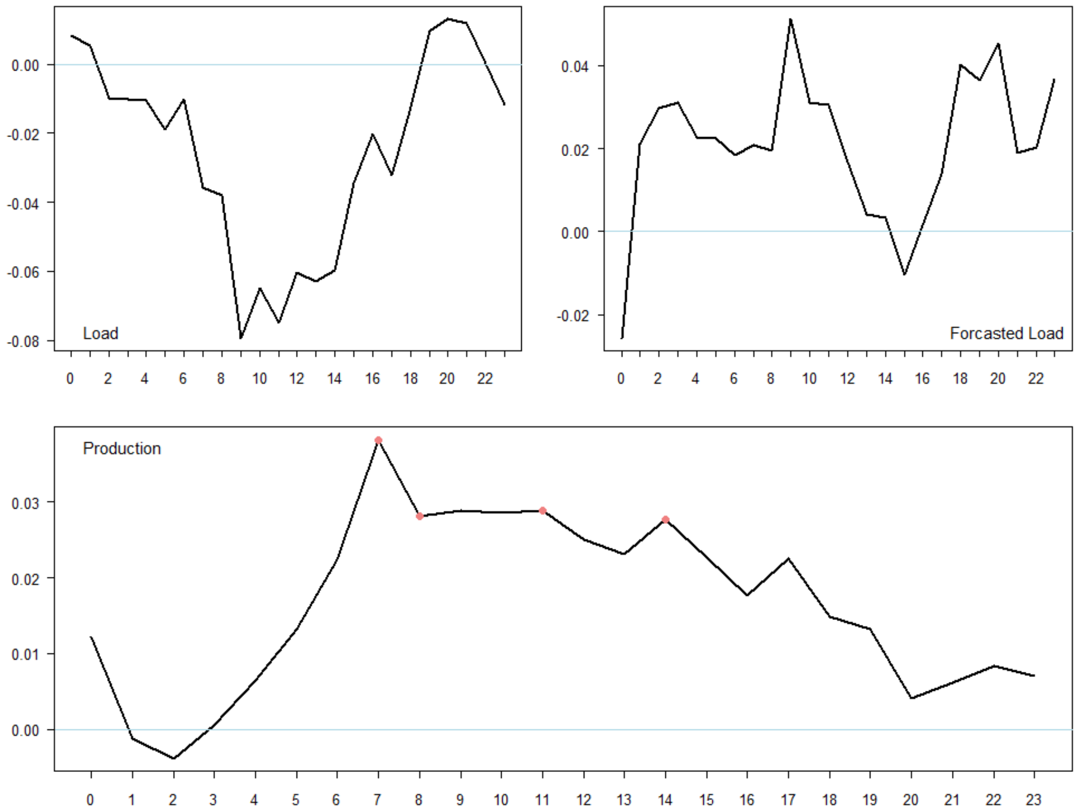

Figure 28: Effects of Load and Production

Panel I - Electricity Transmission: Some variables in this panel, such as 'Export DK', 'Export GB', 'Import NL', 'Import NO1', 'Export NO5', and 'Import NO5', show significant relationships with the selected hours at the 1% and 5% levels. This suggests that these electricity transmission factors play a role in the dependent variable.

A detailed analysis of results for electricity transmission will be presented in subsection 5.5.

5.4 Discussion

Our analysis indicates that time-related variables such as weekly seasonality and annual trends play a substantial role in electricity pricing in NO2. The model highlights that during peak hours on weekdays, prices are generally higher, reflecting increased demand from commercial and residential consumers. This pattern shows the importance of managing peak loads and may suggest opportunities for demand response initiatives that could smooth price fluctuations, as well as enhancing system reliability and efficiency as highlighted by Deane et al., 2015.

The annual variation in NO2, with higher prices observed in the summer months, may reflect a combination of factors including potentially lower water reservoir levels impacting hydroelectric power generation, higher costs of alternative generation methods and increased import as seen in Figure 20. Increased solar-production will likely dampen the price effects during the summer months, known as the merit order effect (Spodniak et al., 2021). While in other parts of Europe, the load increases due to warmer weather, the need for cooling in Norwegian households is rather rare (Sørgard et al., 2023). However, since electricity generally flows from one bidding area with lower price, to areas with higher prices (Figure 5, hydro-producers in NO2 retains water to produce in periods they believe prices in other areas will be higher to maximize value (Gran et al., 2023). This could explain the effect of comparatively higher prices in NO2 during summer, and it is lower prices during winter - since the NO2 prices has to be lower than prices in adjacent areas to export. This is also reflected in the increased export during winter months in Figure 20

Our findings confirm the significant influence of gas and oil prices on electricity prices within NO2, which aligns both with previous studies indicating the interconnectedness of global energy markets but also the inherit market structure. The systematically positive relationship between gas prices and electricity prices highlights the dependency on gas-fired power generation in periods of high demand or insufficient supply from renewable sources. However, oil surprisingly shows a negative effect on NO2 electricity prices. One possible explanation could lie in the Merit Order. As the oil price increases, this increases the marginal cost of oil and shifts oil-based electricity generation further to the right in the supply stack, see Figures 7 and 8. As oil only accounts for 1.2% of Europes electricity generation ("IEA - Energy Mix", n.d.), this moves oil to a point where the oil based generators are not activated, subsequently the market clearing price is set lower. Oil-prices are though known to be an indicator of the underlying economic activity, which could be reflected in demand. This effect in the merit order could also drive hydro-producers in NO2 to not export, if they as a consequence of lower MCP decides to retain water, reducing the effect of European prices on NO2. Hydro-producers maximizing profits is part of a possible explanation for the surge in prices, as Gran et al., 2023 notes high production and export in 2021 followed by record low reservoirs level in 2022 - drove Norway to rely more on imports in 2022. Interestingly, CO2 price in addition to coal does not show significant results contrary to Bublitz et al., 2017. This is surprising, especially due to Germany's reactivation of coal production during the gas-crisis following the Ukraine-war and Nord Stream sabotage.

The analysis suggests that global economic and market uncertainties do not independently affect electricity prices in NO2, as their effects are likely captured by other more direct pricing factors such as gas and oil prices. This finding could indicate that the electricity market in NO2 is more influenced by tangible supply and demand dynamics than by speculative or external economic factors.

Contrary to initial assumptions that weather and climate might present unpredictability in price determination, our model suggests that these factors are effectively anticipated in the pricing mechanisms, likely through the incorporation of historical weather patterns and their impact on electricity demand and generation capacity. This observation supports the utility of advanced weather forecasting and historical data analysis in mitigating price volatility caused by climatic variations. This lack of significant results aligns with existing literature, which suggests that the effects of weather and climate variables may be subsumed by the effects of other variables, such as load and production. In other words, while weather and climate conditions can influence electricity demand and production, their direct impacts on prices may be overshadowed by the more immediate effects of supply-demand dynamics (Voronin et al., 2014). However, with increased investment in renewable energy sources such as wind or solar in the NO2 area we could see more significant results on weather in the future.

5.5 Impact of Electricity Transmission

In the final subsection of this chapter, we turn our attention to one of the main research questions of our thesis: the flow of electricity in and out of the NO2 bidding zone. Understanding these transmission dynamics is crucial, as it can provide valuable insights into the interdependencies between different electricity markets and the impact of cross-border electricity trade on our specific market.

Just like the previous subsection, we will present a series of plots to visually represent our findings. These plots will depict the coefficients of variables related to electricity transmission, with markings to indicate statistical significance. By presenting our findings in a manner consistent with the previous subsection, we aim to maintain coherence in our analysis and facilitate easier comparison across different areas of our research.

We will examine the flow of electricity to and from other zones and countries, focusing on the patterns, magnitude, and significance of these flows. We will also explore the potential factors influencing these transmission dynamics, such as price differentials, demand-supply imbalances, and policy regulations. This subsection, therefore, not only contributes to our understanding of the drivers of electricity prices in our specific market but also broadens our perspective by highlighting the interconnectedness of electricity markets.

5.5.1 Results - Electricity Transmissions

The analysis of electricity transmission to and from the Norwegian price zone NO2, as depicted in Figure 29, offers insightful observations. The figure comprises four separate plots, each illustrating the OLS-regression coefficients against the hours of the day, with significant results marked at a 5% significance level.

The first plot, representing international import, exhibits primarily positive coefficients. However, there is a noticeable negative dip between 1 am and 6 am. The peak coefficient value occurs hour 17:00, standing at 0.04. This means that international imports have the most impact during daytime and evening, reflecting a traditional consumption pattern.

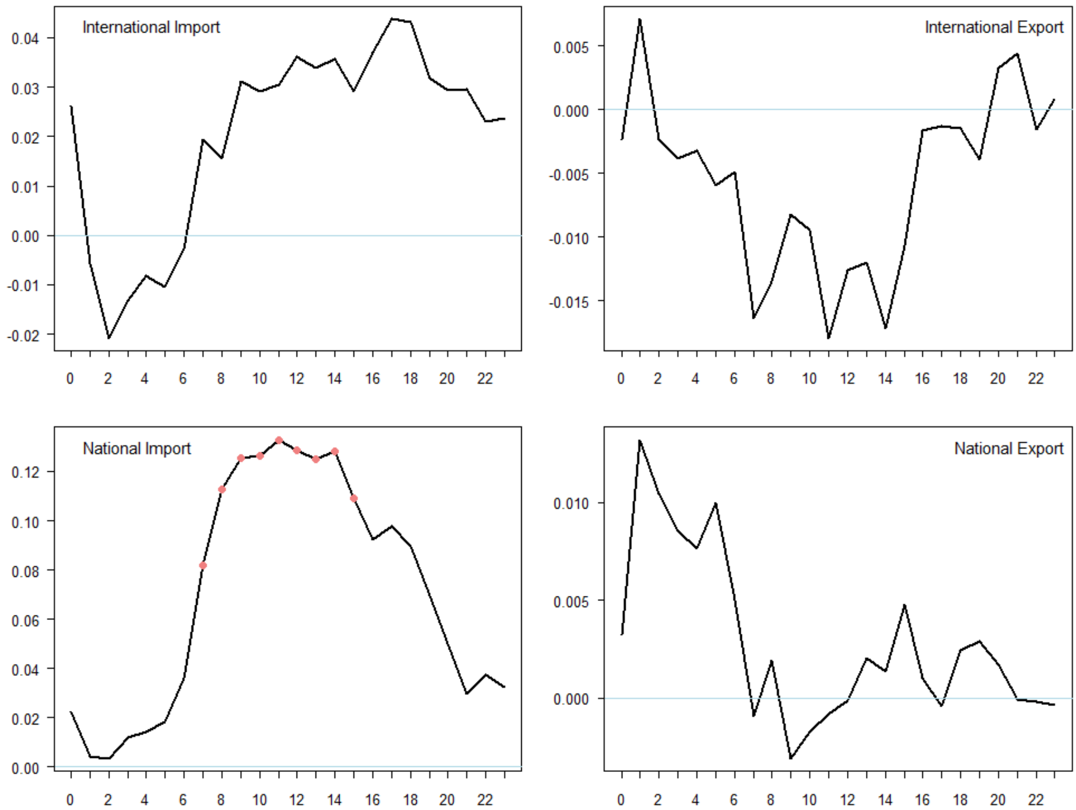

Figure 29: Aggregated Electricity Transmission

The subsequent plot illustrates the international export, with coefficients predominantly negative, barring slight positive deviations at 01:00 and 21:00. The greatest magnitude is observed at hour 11:00, approximately at -0.02. Coefficients for the international export are generally of small magnitude, ranging between -0.02 and 0.005.

The third plot focuses on national import of electricity. The coefficients are consistently positive, with distinct peaks at hours 05:00 and 09:00. The range lies between 0.02 and 0.03, with the highest points observed between 8 am and 3 pm, peaking at 0.14.

Lastly, the plot for national export shows that the export of electricity from NO2 to other Norwegian price zones is primarily positive, with a negative dip observed in the morning and evening, peaking at -0.004. The coefficients displayed in this plot are generally modest in magnitude, ranging from -0.004 to 0.015.

Interestingly, when examining electricity transmission at this aggregated level, we find a scarcity of significant results. The sole plot displaying statistically significant outcomes is that of national import, which yields significant results at the 5% level during the hours of 07:00 to 15:00. This time frame encompasses the period with the highest coefficients, rendering these results both statistically significant and potentially impactful. This potentially highlights an interesting point, that it is not the actual volume or direction of electricity that influences prices, however this does not necessarily mean that the cross zonal connections does not have a effect.

Moving forward, Figure 30 provides a more granulated view of the same electricity flows, allowing us to delve deeper into the intricacies of electricity transmission within the NO2 zone. We will focus mainly on the plots showing statistically significant results.

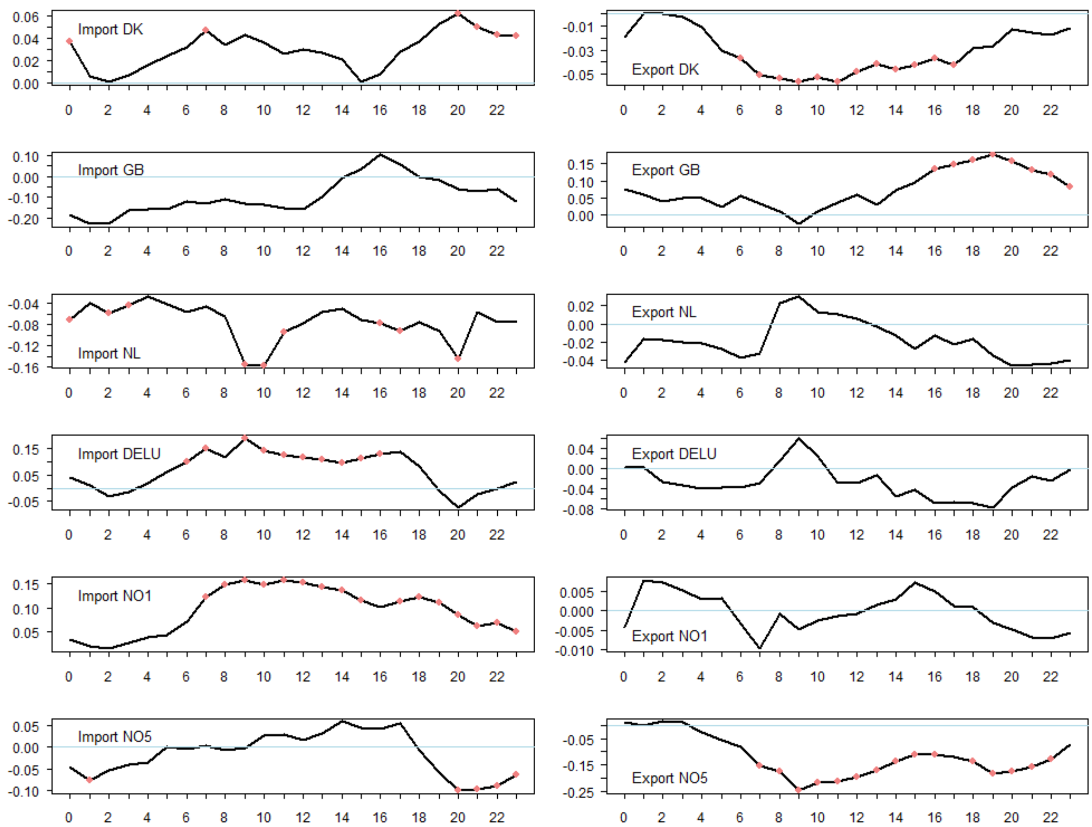

Figure 30: Specific Electricity Transmission

For the transmission associated with Denmark, the import displays exclusively positive coefficients, which fluctuate in magnitude throughout the day. Two significant peaks are observed at 07:00 and 20:00, with coefficients of 0.05 and 0.06, respectively. These peaks are also statistically significant.

In contrast, the export to Denmark presents solely negative coefficients, forming a U-shaped pattern. The coefficients start from 0.00 at 01:00 - 02:00, dip to -0.05 during 09:00 - 10:00, and then ascend back to 0.00. The results are statistically significant during the hours of 06:00 to 17:00, coinciding with typical working hours.

For the transmission to Great Britain, there is only one period that yields significant results. This period falls within the export section from 16:00 to 23:00, with coefficients ranging from 0.10 to 0.16 and peaking at 19:00. In general, the coefficients for imports are predominantly negative, while those for exports are mostly positive, with a few exceptions.

In the case of transmissions to and from the Netherlands, significant results are only observed on the import side and are spread throughout the day. The coefficients for both import and export are primarily negative, with a few exceptions on the export side. Notably, the hours with the most significant coefficient magnitudes are also marked as statistically significant.

In the case of transmissions to and from DELU (Germany and Luxembourg), significant results are exclusively observed on the import side. The magnitude of the coefficients exhibits an almost bell-shaped pattern, increasing from 0.00 at 01:00 to a peak of about 0.18 at 09:00. The magnitude then stabilizes at around 0.10 from 09:00 to 16:00 before decreasing again. The hours between 05:00 and 16:00, excluding 08:00, are all statistically significant.

While there are a few negative hours on the import side, the coefficients are predominantly positive. Contrastingly, the export to DELU is characterized by mostly negative coefficients, with a notable positive peak at 09:00. These findings highlight the complex dynamics of electricity transmission between NO2 and DELU.

In terms of import and export to and from NO1, all coefficients for import are positive, forming a bell-shaped curve that rises from hour 2 and gradually falls from hour 12. The results from hour 7 to 23 are all significant, with the exception of hour 16, implying a substantial impact from NO1. The export coefficients vary between positive and negative throughout the day, and the magnitude of these coefficients is relatively small. There are no statistically significant results in the export data.

For NO5, the coefficients start at -0.07 at hour 1, slowly rise to 0.06 at hour 20, and then decline again from hour 17. The coefficients are most negative between 20:00 and 23:00. It is worth noting that there are significant findings at the lowest point at 1:00 and between 20:00 and 23:00.

The export begins at 0.00 at midnight, then gradually drops to -0.25 at 9:00, before moving toward zero again. The results from hour 7 to hour 22, when the coefficients exhibit the highest negative magnitude, are all statistically significant. These findings highlight the intricate dynamics of electricity transmission between NO2 and NO1, and NO2 and NO5.

Overall, the effects of the cross-zonal connections are small in magnitude, but there are significant effects across all hours. When quantifying the effect of each hourly coefficient by leveraging the calculated mean for price and its corresponding variable, the estimated influence of electricity transmissions, on average, approximated around 1%.

In general we expected to see consistent positive or negative effects on import and export, due to the described market effects illustrated in Figure 5. With this not being the case, one could argue that it highlights the intricacies of the electricity market. With the model predicting prices 2 days in advance (Figure 12), this could also complicate the interpretation of the quantitative effects.

5.5.2 Volatility Split

In the following section, we will segment the dataset at the 8^{th} of August 2021, following the volatility test conducted in R as referenced in Chapter 4.2. The ICSS algorithm identified two volatility shifts; however, we have chosen to focus on the 8th of August as it aligns with the opening of transmission cables and the subsequent increase in price, as discussed in the introduction. Our objective is to investigate whether the changes in the volatility of Price NO2, as observed in Figure 13, are reflected in the transmission dynamics.

To this end, we will calculate the same regression models for two distinct periods: from 01.01.2015 to 07.08.2021, and from 08.08.2021 to 20.04.2023. By comparing the resultant plots, we aim to discern any significant changes in the transmission dynamics between the two periods. This comparison will provide further insights into the impact of price volatility on electricity transmission within the NO2 zone.

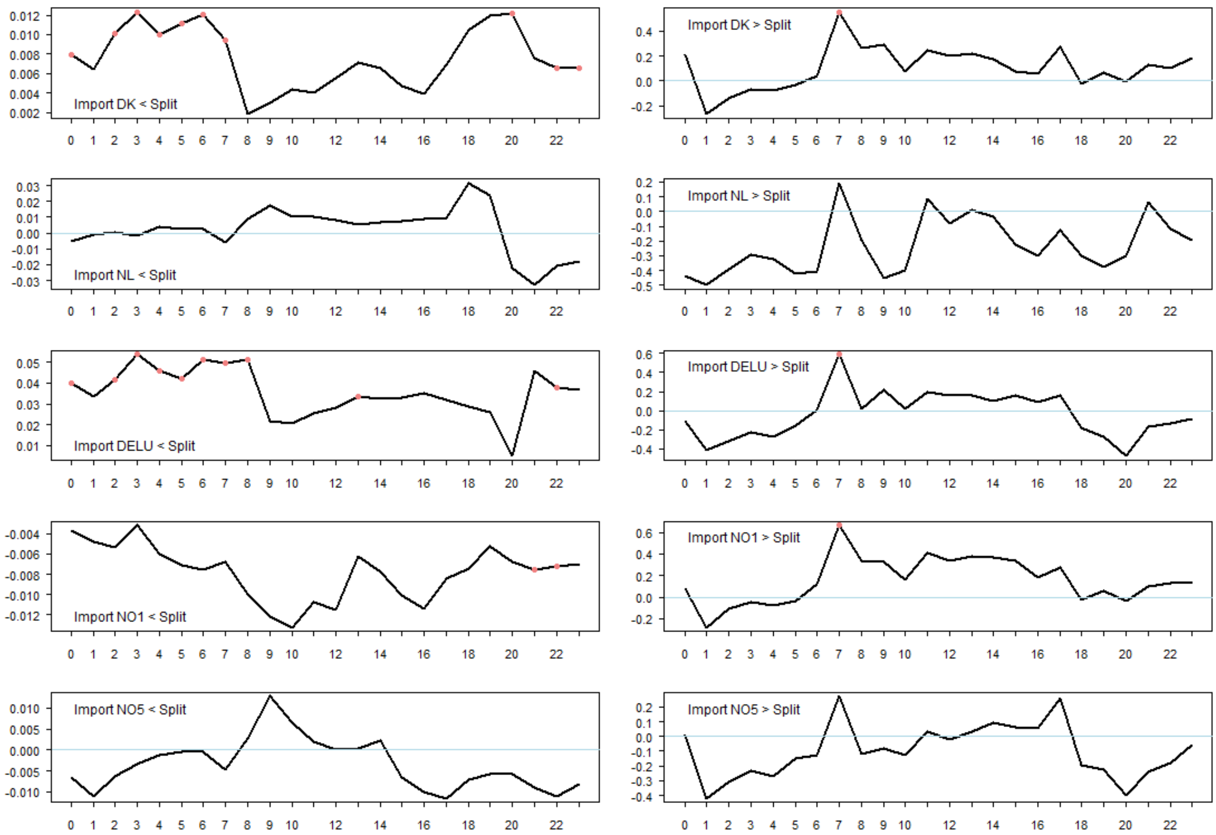

Figure 31: Electricity Import - Volatility Split

In Figure 31, we present an overview of electricity import from Denmark, the Netherlands, Germany/Luxembourg, Norway Zone 1, and Norway Zone 5. We have intentionally excluded the transmission cable data to Great Britain due to its limited availability, spanning only from the 10^{th} of September, 2022, to the 20^{th} of April, 2023. The figure is divided into two sections, with the left side representing coefficients prior to the 8^{th} of August, 2021, and the right side showing coefficients post this date. Results with a significance level of 5% are emphasized.

The magnitude of the coefficients have increased for all interconnections from the first period to the second. This escalation is not just nominal but quite significant. Overall, the coefficients continue to oscillate between positive and negative values throughout the day. An interesting point is the shift in coefficients for Denmark and Germany/Luxembourg. These were consistently positive for all hours prior to the split but have transitioned to containing negative values during the night and evening hours.

Another important observation is that there are almost no significant observations after the split. This can also be said of results before the split, but before the split Denmark and Germany/Luxembourg have significant during the nightly hours.

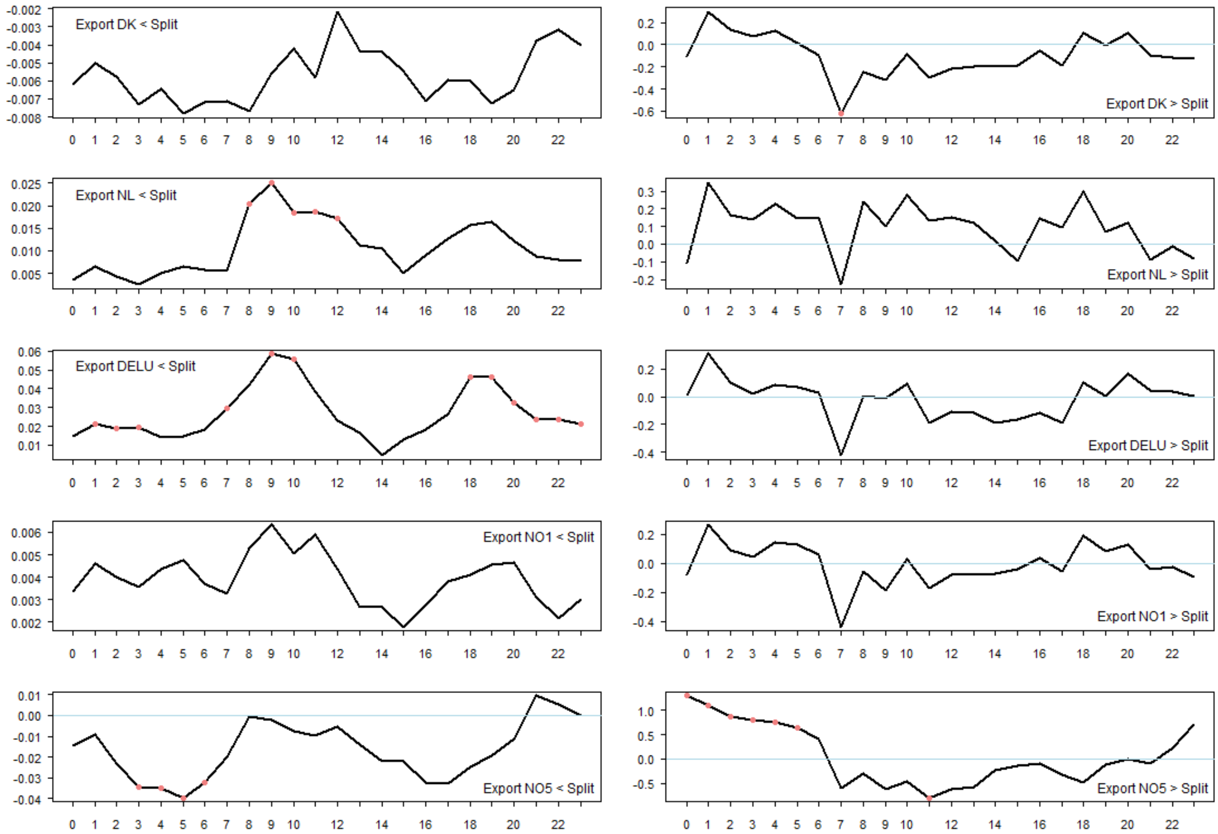

Figure 32: Electricity Export - Volatility Split

Figure 32 shows the export of electricity from NO2 to Denmark, the Netherlands, Germany/Luxembourg, Norway Zone 1 and Norway Zone 5. Similar to Figure 31 we have split our data on 08.08.2021, showing observations prior to this date on the left side and observations post this date on the right side. Results with a significance level of 5% are emphasized.

Also on the export side we observe that the magnitude of the coefficients have changed significantly from the first period to the second period. Examining the export to NO5, we observe a variation ranging from -0.04 to 0.01 in the initial period. Contrarily, in the subsequent period, the variation extends from -0.6 to 1.3. This represents significant alterations between the two periods as can also be seen on all other variables.

We observe an increased level of volatility in the data following August 8, which is as expected. Before the split, the variables exhibited a stable trend, either uniformly positive or uniformly negative. Variables that were positive maintained their positive values throughout all hours, while those that were negative remained negative. However, NO5 is an exception, with a handful of observations deviating in the evening hours.

After the split, all variables display a mix of positive and negative observations, suggesting a more dynamic and complex pattern. In general, there is a broader span in the observed values post-split, indicating increased variability in the electricity export patterns. As on the import side, the export side also has fewer significant observations in the second period.

Summing up, comparing the plots for both electricity import (Figure 31) and export (Figure 32), several commonalities emerge. In both cases, there is a noticeable increase in the magnitude of the coefficients from the first period to the second. This not only indicates a significant change in the transmission dynamics but also suggests a heightened level of volatility in both the import and export of electricity post the split date of the 8^{th} of August, 2021. This is also highlighted by another shared characteristic; the shift from consistently positive or negative values for the variables in the first period to a more complex pattern of both positive and negative observations in the second period.

Furthermore, both plots exhibit a reduction in significant observations in the second period compared to the first. This could suggest that the changes observed in the transmission dynamics, despite being substantial, may not be statistically significant. This reduction in significant observations could be attributed to the increased volatility and broader range of observed values, making it more challenging to identify consistent trends or patterns with a high degree of certainty. As seen in Figure 13 the number of potentially price driving events occurring increases dramatically for the latter period. This in combination with fewer observations, could influence the model's ability to identify patterns.

Within the context of our thesis, we indeed observe a heightened magnitude of the coefficients following the split. Nonetheless, the limited presence of significant observations restricts us from conclusively asserting that the direction or volume of electricity transmitted are responsible for the surge in prices.

Despite this, it is evident that there has been a notable shift in volatility. However, without substantial evidence, we must exercise caution in attributing this increased volatility directly to the transmission cables. This suggests that while the dynamics of transmission have undeniably altered, they may not be the principal factor contributing to the price escalation. Further comprehensive research is required to identify the primary drivers of these observed changes.

Although we quantitatively can't attribute the increased prices and volatility to the volume or direction of electricity transmitted between NO2 and connected regions, it is critical to acknowledge that the extant market structure would be untenable in the absence of these interconnections. The existence of these links facilitates the sale of hydroelectric power by Norwegian producers in foreign markets, thereby integrating Norway, and specifically the NO2 region, into a Pan-European energy framework. In a hypothetical scenario where NO2 lacked interregional connections during the period from 2021 to 2023, it is likely that the region would have experienced considerably lower electricity prices. This raises an interesting question, as these connections let's Norway serve as "Europe's battery" and join a common European project in reducing emissions. However, as electricity prices become more similar to the rest of Europe exporting industries in Norway loose their competitive advantage relative to their European counterparts. In addition, as noted by Gran et al., 2023 Norway's surplus of electricity will likely be reduced to zero within 2028 due to the increase in demand outgrowing increase in production. This underscores the emerging importance for interconnections due to security of supply.

5.6 Limitation of the Thesis

This study, while providing valuable insights, has certain limitations that need to be acknowledged. One of the primary limitations is the scope of the data used. While we have incorporated production and weather data from our market of study, Norway NO2, there are potentially other relevant data that have not been included in this study. Due to the continuous incorporation of renewable energy sources we believe that weather and production data from other interconnected markets more dependent on renewable energy sources could enhance the precision of the model.

This research recognizes the limitations of the OLS-regression model used. While OLS is a conventional choice for estimating parameters in a linear regression model, it might not be the most accurate or efficient for this dataset or research question. Alternative models, such as time series, non-linear regression, or machine learning algorithms, could potentially offer more precise predictions or better encapsulate electricity price dynamics. Although our model is multivariate by nature, it does not account for possible non-linear relationships among variables, which could impact prediction accuracy.

Additionally, the application of out-of-sample predictions could significantly contribute to the robustness of our study. Out-of-sample predictions test the model's performance on data not used in model development, and can provide a more robust and generalizable measure of predictive accuracy. As OLS-regression models expected values, it could be the case that transmission only matters for extreme prices. In a quantile regression model we could observe whether transmission impact extreme price levels only. This is something to consider in future research.

6 Conclusion

Our thesis examines the complex dynamics of electricity prices within Norway's NO2 region, with a particular spotlight on the impacts of cross-zonal connections. It contributes to the research on interconnected markets and to the existing literature on price drivers in general.

In this study, we seek to add to the existing academic literature by focusing specifically on the NO2 bidding area in Norway. Our review of the literature indicates that there are no prior studies that have explored the same width and combination of variables that our research incorporates. Consequently, our thesis is positioned to make a significant and novel contribution to the understanding of electricity price dynamics within the NO2 area.

Our findings highlight the substantial role of temporal variables, such as time of day, day of the week, and month, in predicting electricity prices. These factors reflect the fundamental dynamics of supply and demand that vary with human activity patterns and seasonal changes. For instance, the increased electricity prices during weekday peak hours underscore the heightened demand from both residential and commercial sectors, while the seasonal fluctuations emphasize changes in generation capacity and consumption habits influenced by weather conditions.

One of the more pronounced outcomes of this study is the significant impact of natural gas prices on electricity prices within the NO2 zone. This result underscores the interconnectedness of global commodity markets and energy prices, illustrating how fluctuations in gas prices, driven by international market trends and geopolitical events, directly affect electricity markets. This dependency highlights the vulnerability of electricity prices to shifts in the availability and cost of natural gas, a critical input for power generation during periods of peak demand or when renewable energy sources are insufficient.

Interestingly, other expected market influences such as coal and CO2 prices did not exhibit a significant impact in our model. This could suggest a possible decoupling of these factors due to evolving energy policies, technological advancements in energy production, or the increasing penetration of renewable energy sources which might be reducing the influence of traditional fossil fuels and carbon pricing mechanisms.

Our findings reveal that while electricity transmission indeed have significant impacts, in all examined periods, their overall effect on the mean price is relatively small, accounting for approximately 1% of the price variation. However, the complex interactions between physical flows and price formations highlights the nuanced role of cross-border electricity flows, influenced by regulatory frameworks, market conditions, and international energy policies. Understanding these transmission dynamics is essential for policymakers and market operators as they navigate the challenges of ensuring energy security, market stability, and economic efficiency in an increasingly interconnected energy landscape.

Furthermore, our research methodology and findings could be applicable to other regions and markets, providing a robust framework for analyzing electricity price dynamics. Our thesis, therefore, not only contributes to the understanding of Norway's NO2 region but also offers a transferable model for electricity price analysis in other contexts.

Looking ahead, we see ample opportunities for further research in this area. Future studies could build upon our work by incorporating different or additional variables especially on the interconnected regions. With the increasing introduction of renewables and new technology being developed, this requires a continuous development of research design. This would further enrich our understanding of electricity prices and the factors that drive them also in the future.

7 References

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8 Appendix

A Overview Variables

Table 17: Overview Control Variables

Variable	Denotation	Hourly	Daily	Source
Panel A: Financial Markets				
Gas Price	GAS_t		X	ICE
Oil Price	OIL_t		X	ICE
Coal Price	$COAL_t$		X	ICE
Co2 Price	$CO2_t$		X	EEX
Exchange Rate NOK/EUR	EUR_t		X	NB
Exchange Rate NOK/USD	USD_t		X	NB
Panel B: Volatility and Uncertainty				
VIX-index	VIX_t		X	ICE
GEPU-indicator	GPU_t		X	(“GPR”, n.d., “EPU”, n.d.)
Panel C: Weather and Climate				
Heating Degrees	$HD_{t,h}$	X		MET
Cooling Degrees	$CD_{t,h}$	X		MET
Mean Wind	$WND_{t,h}$	X		MET
Mean Precipitation	$PRC_{t,h}$	X		MET
Reservoir Level	WLV_t		X	NVE
Panel D: Production and Consumption				
Production	$PROD_{t,h}$	X		ENTSO-E
Load	$LOAD_{t,h}$	X		ENTSO-E
Forecasted Load	$FORC_{t,h}$	X		ENTSO-E

Table 18: Overview Control Variables

Variable	Denotation	Hourly	Daily	Source
Panel E: Electricity Transmission				
Netflow		X		ENTSO-E
Import		X		ENTSO-E
Export		X		ENTSO-E
International Import	$INTI_{t,h}$	X		ENTSO-E
International Export	$INTE_{t,h}$	X		ENTSO-E
National Import	$NATI_{t,h}$	X		ENTSO-E
National Export	$NATE_{t,h}$	X		ENTSO-E
Import DK	$IDK_{t,h}$	X		ENTSO-E
Export DK	$EDK_{t,h}$	X		ENTSO-E
Import NL	$INL_{t,h}$	X		ENTSO-E
Export NL	$ENL_{t,h}$	X		ENTSO-E
Import GB	$IGB_{t,h}$	X		ENTSO-E
Export GB	$EGB_{t,h}$	X		ENTSO-E
Import DELU	$IDE_{t,h}$	X		ENTSO-E
Export DELU	$EDE_{t,h}$	X		ENTSO-E
Import NO1	$INO1_{t,h}$	X		ENTSO-E
Export NO1	$ENO1_{t,h}$	X		ENTSO-E
Import NO5	$INO5_{t,h}$	X		ENTSO-E
Export NO5	$ENO5_{t,h}$	X		ENTSO-E

B Price

Table 19: Overview Events - Economic and Financial

Label	Date	Description
Panel A: Energy (E)		
E1	01.01.2015	The third phase of the European Union Emission Trading System started, impacting power generation costs, especially for fossil fuel plants within the EU.
E2	01.01.2017	Approximately 171.000 migrants and refugees enter Europe by sea during 2017 increasing energy demand and putting a strain on existing infrastructure.
E3	10.08.2019	A major power outage affected almost one million people in England and Wales due to simultaneous issues at a gas-fired plant and an offshore wind farm.
E4	14.09.2019	Drone attacks on Saudi Arabia's oil facilities temporarily halved the country's oil production, causing global oil price spikes and impacting energy markets worldwide.
E5	31.03.2021	The undersea power cable connecting Norway (NO2) and Germany/Luxembourg (DELU) officially becomes operational.
E6	31.12.2021	Germany close down 3 major nuclear plants, with a collective capacity of 4.058 MW.
E7	10.09.2022	The undersea power cable connecting Norway (NO2) and Great Britain (GB) officially becomes operational.
Panel B: Financial (F)		
F1	22.06.2018	OPEC and non-OPEC countries agreed to increase oil production, affecting global energy markets and pricing strategies.
F2	09.03.2020	The failure to agree on production cuts led to a price war between two of the world's largest oil producers, Russia and Saudi-Arabia, causing a fall in the oil prices.
F3	16.10.2020	Moody's downgrade the UK's debt rating to Aa3 causing political and economic uncertainty.
F4	26.03.2021	The Suez Canal blockage disrupts global trade, potentially impacting energy markets.
F5	01.08.2021	Historically low gas prices reported in the EU.
F6	06.09.2022	In response to soaring energy prices and supply concerns, the European Union unveiled a plan to address the energy crisis, impacting energy markets and policies.
F7	19.01.2023	US hits its debt ceiling, causing market uncertainty possibly effecting the energy markets.

Table 20: Overview Events - Geopolitical, Environmental and Political

Label	Date	Description
Panel C: Geopolitical (G)		
G1	16.01.2016	The lifting of sanctions on Iran following the nuclear deal increased global oil supplies, affecting global energy markets and prices.
G2	01.10.2018	Escalating US-China trade tensions in 2018 effects the energy markets, affecting everything from oil and gas prices to the renewable energy industry. The increased uncertainty created by the trade war was also a major factor impacting the energy markets.
G3	31.12.2019	Wuhan Municipal Health Commission, China, reported a cluster of cases of pneumonia in Wuhan, Hubei Province. A coronavirus was eventually identified (WHO).
G4	24.02.2022	Russia invasion of Ukraine leads to global sanctions on Russia disrupting global energy supplies and creating an increase in global energy prices.
G5	30.05.2022	The EU agreed to a partial ban on Russian oil, affecting global energy markets and accelerating the search for alternative energy sources.
G6	26.09.2022	Nord Stream pipeline is subject to sabotage causing a disruption in energy supply and increasing political tensions.
G7	10.12.2022	Russian drone strikes leave 1.5 million Ukrainians without power.
Panel D: Environmental (M)		
M1	03.08.2015	The U.S. Environmental Protection Agency announced the Clean Power Plan aiming to reduce carbon pollution from power plants.
M2	12.12.2015	The Paris Agreement is adopted, leading to increased investment in renewable energy across Europe.
M3	12.12.2017	The One Planet Summit in Paris brought together international leaders to discuss climate action, emphasizing financial initiatives and commitments toward a greener energy future.
M4	03.07.2020	Germany passes legislation to phase out coal use within 2038.
M5	21.04.2021	The European Climate Law is adopted, making the EU's goal of net-zero greenhouse gas emissions by 2050 legally binding.
Panel E: Political (P)		
P1	23.06.2016	The UK voted to leave the European Union, leading to uncertainty in the energy markets regarding trade, energy policies and nuclear projects.
P2	08.11.2016	Trump's election led to a shift towards fossil fuels and away from environmental regulations in the U.S. energy markets.
P3	07.05.2017	Emmanuel Macron's victory in the French presidential election leads to a push for more renewable energy and climate-friendly policies in France.
P4	01.06.2017	President Trump announced the intention to withdraw the United States from the Paris Agreement, affecting global climate initiatives and energy policies.
P5	24.09.2017	Angela Merkel's party wins the German elections but with a reduced majority, leading to a push towards more renewable energy policies.
P6	08.05.2018	The US withdraws from the Iran nuclear deal potentially impacting global energy markets.
P7	10.01.2019	Venezuelan presidential crisis impacts the global energy markets through its effect on the country's oil production and exports.
P8	30.01.2020	The Director-General declares the coronavirus a Public Health Emergency of International Concern.
P9	31.12.2020	Brexit transition period ends, and the UK formally completes its EU separation.

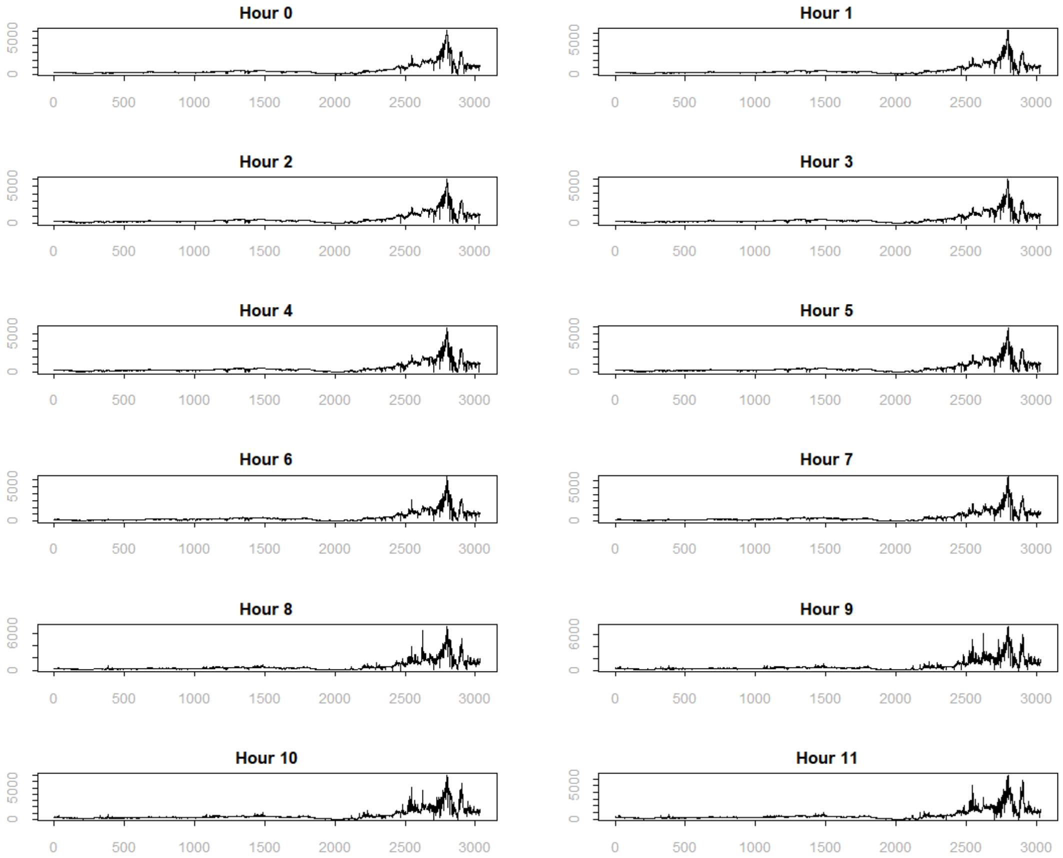

Figure 33: Time Series Price NO2 - Hourly - 00:00-11:00

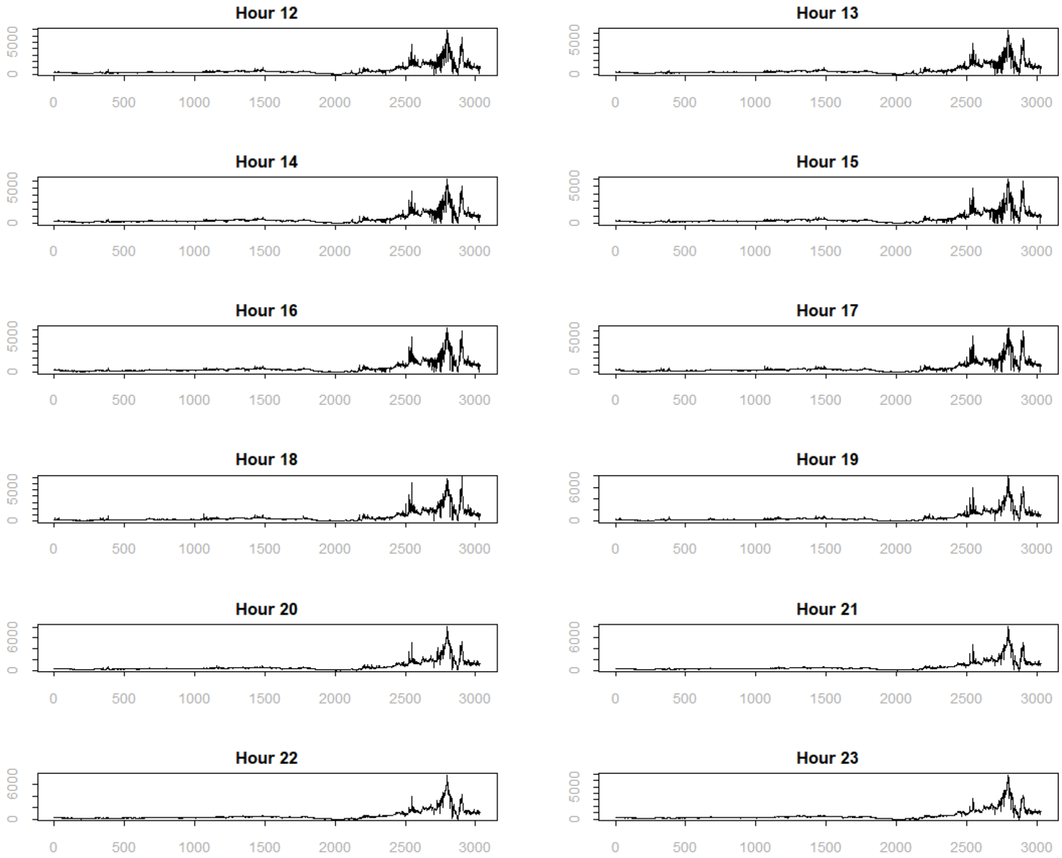

Figure 34: Time Series Price NO2 - Hourly - 12:00-23:00

C Findings

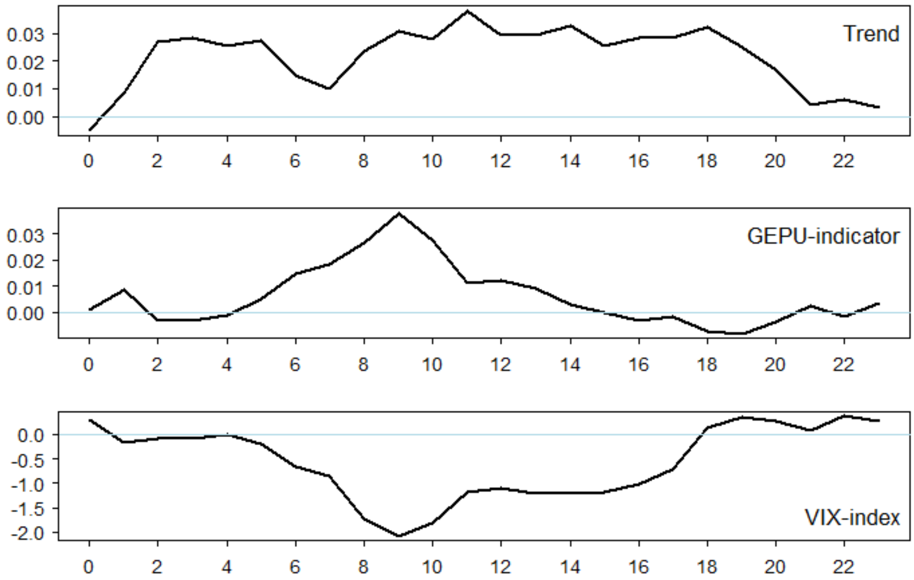

Figure 35: Findings GEPU-indicator, VIX-index and Trend