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Weathering the Market: Analyzing the Impact of Climate Change on the Norwegian Electricity Market

A Price Volatility Time Series Analysis

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Abstract

This thesis investigates the dynamics of the Norwegian electricity market, focusing on how hydro and wind generation affect average price levels and volatility. In addition, the analysis investigates how the increased occurrences of changed weather patterns due to climate change might affect these relationships. The research aims to explore the complex interplay between weather-dependent electricity sources and market prices, offering insights into how these elements interact within the different price areas in Norway.

Methodologically, this study employs a statistical ARMA-EGARCH modeling framework to analyze the electricity market. The empirical findings indicate a statistically significant impact of increased hydrological balance and wind generation on reducing average price levels. However, the effects on price volatility present a contrast: an increased hydrological balance is associated with greater stability, while wind generation, explained by its intermittent nature, contributes to increased volatility. These results highlight the distinct influences of different renewable energy sources on market dynamics.

The analysis reveals "inverse leverage effects" across all Norwegian price areas, underscoring the market's greater ability in adapting to negative market shocks. A comparative analysis with a historical control period has highlighted a potentially increased influence of hydrological balance and wind generation on market prices. Looking ahead, given the projections on climatic and structural developments, this trend is anticipated to continue, potentially escalating risks and consequently, could diminish incentives for investments in production.

The object of this study is to contribute to a better understanding of the complexities inherent in an electricity market dominated by renewable sources, and evolving climatic and structural changes.

Keywords – Electricity Market, Price Areas, Norway, Renewable Electricity, ARMA-EGARCH, Volatility, Hydropower, Wind Power, Climate Change

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List of Abbreviations

Acronym	Description
ACF	Autocorrelation Function
ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heteroskedasticity
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BIC	Bayesian Information Criterion
CET	Central European Time
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GWh	Gigawatt-Hour
LL	Logarithmic Likelihood
MA	Moving Average
MLE	Maximum Likelihood Estimation
MSE	Mean Squared Error
MWh	Megawatt-Hour
NVE	The Norwegian Water Resources and Energy Directorate
NO1	Østlandet
NO2	Sørlandet
NO3	Midt-Norge
NO4	Nord-Norge
NO5	Vestlandet
PACF	Partial Futocorrelation Function
RMSE	Root Mean Squared Error
SARIMA	Seasonal AutoRegressive Integrated Moving Average
TSO	Transmission System Operator
TTF	Title Transfer Facility
TWh	Terawatt-Hour

1 Introduction

1.1 Relevance of the Research Topic

For over 150 years, Norway has played a leading role in developing the electricity sector, establishing a competitive advantage by effectively utilizing its renewable electricity resources (F. Lund et al., 2023). This has influenced Norway's economic and social development, resulting in a robust and reliant electricity market (Bye, 2003). However, in recent years, there has been a reduction of new investments in the market, and the surplus and stability of Norwegian electricity have faced increasing challenges. As a consequence, the established competitive advantage is about to be lost (F. Lund et al., 2023).

Electricity, once taken for granted, is now subject to escalating prices and increased market volatility, raising concern among households and industrial sectors. Research shows households are adjusting their consumption habits, saving electricity by shifting their usage to hours when prices are lower (Gran et al., 2023; Hovland, 2023). This concern surpasses the worry caused by rising inflation and grocery expenses, placing electricity prices as the main issues for the Norwegian households (Hovland, 2023). These market conditions have additionally affected businesses, particularly electricity dominated industries, resulting in reduced production or temporary closures during extreme-price intervals (Gran et al., 2023, p. 97). Comprehending the underlying causes of these price shifts and market instabilities is important, as their consequences extend to individual consumers and the overall economic framework.

The recent "energy crisis" has highlighted the potential extreme fluctuations and electricity prices can occur in the market (Hovland & Vartdal, 2023). The year 2019 is often referred to as the last "normal" year before these dramatic changes. In 2020, the sharp decrease in electricity prices was largely due to a surplus in supply, a result of favorable weather conditions in Norway and Europe. However, in the subsequent years, the situation changed drastically. High electricity prices followed, a direct consequence of dry weather and low water reservoir levels.

The rising unpredictability of weather patterns has heightened uncertainty in the utilization of renewable resources (DTN, 2019). With an increasing occurrence of power shortages in the Norwegian electricity market, there is a likelihood of increased market instability and a diminished capacity to manage unforeseen events. Furthermore, the 2021 introduction of interconnectors, NordLink and North Sea Link, linked Norway more closely with the European electricity market, coincided with an increase in electricity prices (Gran et al., 2023). This market dependence was particularly evident in 2022, in light of the geopolitical Ukraine-Russia conflict. The conflict led to a drastic 40% reduction in total European natural gas supply, a key component of the European energy portfolio, culminating in record-high electricity prices in both Europe and Norway in August 2023 (Zeniewski et al., 2023). Following a period of volatility, 2023 is appearing to be a comparatively “normal” year with more stable electricity prices. However, these prices remain higher and more volatile than those before the energy crisis, prompting analysts to view this as the new market standard (Galimberti et al., 2023).

Norway holds a unique position in the global landscape, deriving almost 100% of its electricity generation mix from renewable technologies (Samland, 2016). As the world progresses towards a green transition, Norway’s increasing reliance on renewable sources makes it more vulnerable to climatic variations. One of the global consequences of climate change is steadily rising temperatures, expected to significantly affect climatic patterns (Rommetveit et al., 2021). This trend is particularly critical for Norway, located near the poles, where climate change is anticipated to have a more rapid impact (Rommetveit et al., 2021). The Norwegian Meteorological Institute has observed a temperature increase of 1.9 degrees Celsius since 1960, noting that 18 of the past 20 years have recorded temperatures above the normal average (Steiro, 2023).

In summary, these observations signal a trend of heightened uncertainty within the Norwegian market, underscoring the relevance for an in-depth analysis of the dynamics characterizing this evolving market landscape.

1.2 Research Question Development

The importance of comprehending the inherent risks in the electricity market has grown, particularly in light of renewable resources’ dependence on climatic conditions. Consequently, investigating the impact of climatic factors on electricity pricing and market volatility becomes crucial (Gernaat et al., 2021). The aim of this study is therefore to analyze how climate variables influence Norwegian market price levels and volatility, providing insights into the complex relationship between climate and the renewable electricity market.

In light of Norway's hydro-dominated electricity market, it becomes crucial to explore the role of hydropower. Døskeland et al. (2022) underscore this importance, noting that Norwegian electricity prices are significantly influenced by reservoir levels and precipitation. Furthermore, the Norwegian market is increasingly emphasizing wind power, introducing the interest of wind's contribution in the Norwegian market. The reliance on intermittent resources, such as wind, presents unique characteristics. Woo et al. (2011) highlight that the intermittency of wind energy, along with electricity storage difficulties, amplifies the frequency and extent of price fluctuations. This makes the examination of wind power's influence on the Norwegian market particularly interesting in light of the already increasing market uncertainty. Considering hydropower's central role, this thesis aims to dissect the effects of both hydro and wind electricity generation on market dynamics, specifically focusing on their impact on price levels and market stability.

In recent years, Norway has experienced notable regional disparities in electricity pricing. Within the country there are diverse geographical and climatic characteristics between the north and south, east and west. Possibly resulting in interesting differences within the national market characteristics. During the electricity crisis, internal discrepancies reached historic levels, with the most extreme cases showing electricity prices in the south being 278 times higher than the prices in the north (Ulvin, 2022). This highlights significant inequalities across the country. Consequently, in this thesis, we will segment the market into distinct price areas to assess the varying impacts across these diverse geographical regions. This segmentation is interesting for identifying potential regional price variations and for examining how risks and fluctuations in hydro and wind generation may differ. Such characteristics are often observed in electricity markets that are divided into price areas (Woo et al., 2011).

Recent research, including findings by Ketzler et al. (2021), indicates that climate change has impacted weather patterns in Norway, especially over the past two decades. This provides an interesting opportunity to examine how these climatic shifts may have influenced electricity prices and market volatility. These climatic changes could suggest that the future market will become more vulnerable. Statnett has reported that the green transition is accompanied by a lack of flexibility, likely leading to greater price variation and volatility (Hovland, 2023). Therefore, the study will include a control period, allowing for a comparison between current and historical relationships. This will contribute to an interesting discussion about potential shifts in market dynamics.

This study is driven by the following research question:

What are the impacts of hydro and wind power generation on the price levels and volatility within the Norwegian electricity market, and how might the occurrences of climate change affect these relationships?

1.3 Structure

The thesis is structured into eight sections. In the initial section, the research question is introduced, and provides contextual information to underscore the significance of the study. Progressing to Chapter 2, the focus shifts to a review of international literature relevant for the research question. Further, research on the Norwegian market and our contribution to existing literature will be presented. An overview of the Norwegian electricity market, particularly focusing on its price dynamics and structure, is presented in Chapter 3. Next, in Chapter 4 the dataset is presented including a detaild exploration of the included variables. Further, Chapter 5 reviews the statisitcal methodology applied in the thesis.

Moving forward Chapter 6 presents the data analysis. This chapter encompasses the processing phase for constructing a robust time series model and determining the appropriate model specifications. Subsequently, Chapter 7 will present and discuss the empirical results. Finally, the thesis reaches the concluding section, Chapter 8 and the key findings are summarized.

2 Literature Review

This chapter examines the expanding literature on the effects of renewable technology on electricity prices, focusing on both average price levels and volatility. In the global shift towards sustainability and a greener transition, there has been found a notable increase in research exploring these aspects in recent years. The chapter highlights key findings from the literature, showcasing how renewable electricity influences market dynamics, pricing structures and modeling approaches.

2.1 An Overview of Relevant Literature

Hydropower is characterized as a stabilizing force in electricity pricing, despite its inherent seasonal fluctuations linked to water availability. Research in the Nord Pool market, particularly by Huisman et al. (2013), underscores the significant role of hydro capacity in shaping electricity prices. Their findings suggest that higher reservoir levels, indicative of increased hydropower capacity, lead to a notable decrease in electricity prices, highlighting the benefits of integrating low marginal cost renewable electricity into the market. This relationship is further explored by Kilic and Trujillo-Baute (2014), who emphasize hydropower's capacity to reduce volatility in intraday markets. Extending this understanding to the United States, Owolabi et al. (2022) observed a similar trend in the New England states, where hydropower's contribution to reducing both electricity prices and volatility is evident, offering a stable alternative to fossil fuel-dependent energy sources.

The dynamics of wind power, however, presents a contrasting scenario. The impact of wind generation on electricity prices and volatility has been subject of thorough investigation in various international markets. Studies by Kyritsis et al. (2017) in Germany and Woo et al. (2011) in Texas highlight the dual nature of wind electricity's impact: while contributing to a reduction in average electricity prices, wind power simultaneously increases price volatility. This phenomenon is attributed to the nature of wind electricity, challenging the flexibility and predictability of the electricity market. This pattern of decreased average prices but increased volatility with wind integration is highlighted in studies across Spain, Germany, the UK, Netherlands, Greece, and Canada (Green & Vasilakos, 2010; Ketterer, 2014; Maniatis & Milonas, 2022; Mulder & Scholtens, 2013; Pereira et al., 2017; Stringer et al., 2023).

The intersection of hydro and wind power in the market have also been studied. Pereira et al. (2017)'s study on the Spanish market illustrates how the intermittent nature of wind power elevates price volatility, which can be effectively mitigated by the stabilizing influence of dispatchable hydropower. Similarly, Wen et al. (2022) in New Zealand demonstrate that while wind power reduces electricity market prices, it also increases price variability, especially in dry seasons, suggesting that a balanced mix of wind and hydropower is crucial for maintaining market stability. Overall, the literature is consistently indicating that renewable electricity decreases market spot prices (Ketterer, 2014; Moreno et al., 2012; Paraschiv et al., 2014).

Interestingly, regional differences in identified relationships is evident, as demonstrated by Rintamäki et al. (2017), who noted increased intraday price volatility due to wind power in Germany, whereas in Denmark, which is dominated by wind generation, the effects observed were notably different: wind generation decreased price volatility. Further highlighting the complexity of these impacts, Owolabi et al. (2022) present that the influence of a technology on market dynamics can vary based on factors such as the technology's prevalence, the composition of the electricity portfolio, market and incentive structures, and seasonal and temporal fluctuations in electricity demand. This underscores the importance of considering specific regional characteristics when assessing the impact of renewable energy sources on electricity markets.

The electricity market, recognized by sporadic, unforeseen price fluctuations and sudden spikes (Geman & Roncoroni, 2006a). Escribano et al. (2011) complement these characteristic observations by highlighting the seasonality, pronounced volatility, and clustering tendencies in electricity prices. Ketterer (2014) also emphasized its distinct characteristics, exhibits a pattern of mean-reverting electricity spot prices.

In addressing these complex characteristics of electricity prices, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, particularly the General GARCH and the Exponential GARCH (EGARCH) models, are frequently employed in the litterature (Liu & Shi, 2013). GARCH models, frequently used in financial and commodity markets, effectively capture volatility fluctuations and clustering, making them particularly suitable for explaining price dynamics in the notably volatile electricity markets (Higgs & Worthington, 2008). These models, alongside autoregressive moving average (ARMA) processes, are adept at illustrating how volatility shocks in electricity markets can cluster, persist, and eventually revert to a normative level. This method has been utilized by Ketterer (2014) and Kyritsis et al. (2017) in their investigations of the conditional mean and volatility in spot electricity markets.

In equity markets, negative price movements typically lead to greater volatility, known as the "leverage effect" (Nelson, 1991). This phenomenon describes how equity volatility increases after a decline in equity prices as a consequence of increased leverage ratio in the company, defined as debt relative to its equity value. To accurately represent this asymmetry, the employment of EGARCH models is commonly adopted in financial analysis (Choi & Richardson, 2016).

Interestingly, Knittel and Roberts (2005) identified that electricity prices may demonstrate asymmetric volatility, characterized as an "inverse leverage effect." This study highlights the efficacy of the EGARCH model in modeling electricity prices, notably for its superior performance in out-of-sample forecasting. Bowden and Payne (2008) highlights that positive price shocks, such as unexpected increase of demand, result in greater volatility, and can be explained by the activation of generators with higher marginal costs with increased demand. Liu and Shi (2013) further underscores the EGARCH model's ability to demonstrate the presence of an "inverse leverage effect." However, the phenomenon is not uniform across all electricity markets (Erdogdu, 2016; Girish & Vijayalakshmi, 2018), but in the electricity markets where the effects are identified, Erdogdu (2016) highlights that the general GARCH model may not fully capture the nonlinear and asymmetric properties inherent.

2.2 Contribution to Existing Literature

Within the scope of existing literature, a notable study by Koopman et al. (2007) researched the influence of water reservoir levels and consumption on Norway's pricing and market dynamics. Utilizing a REG-ARFIMA-GARCH model, their findings demonstrated a statistically significant decrease in electricity prices with an increasing reservoir level. This findings aligns with findings by Bye (2003), who observed a similar relationship during the

Nordic market's shortage of precipitation inflow in 2002 and 2003. Further research was expanded by Huisman et al. (2014) by illustrating how price dynamics and competitive pressures within the Nordic market significantly differed between periods of high and low reservoir levels, using a demand and supply model. Collectively, these studies indicate a negative correlation between electricity prices and reservoir levels. Additionally, an ARIMA-GARCH model analysis of the system price by Rudberg (2022) revealed that while temperature and demand had minimal impact on price and volatility, supply and rainfall played a more substantial role in explaining the system price's level and volatility.

Mauritzen (2011) studied the relationship between hydro and wind power in the Norwegian and Danish markets using simple econometric distributed lag models. The findings indicated that while wind power influenced trade patterns between the countries, it had a minimal effect on Norwegian spot prices and daily variance. Furthermore, previous master thesises, has employed Ordinary Least Square (OLS) estimation and Two-Stage Least Squares (2SLS) analysis to investigate the effect of increased wind power generation on electricity price volatility in Norway (Gjerland & Gjerde, 2020). The findings revealed no significant relationship between daily wind power production and intra-daily price volatility.

Building upon existing research, the thesis aims to integrate the effects of both hydro and wind generation on the pricing and volatility within Norwegian pricing areas, while also include how the occurrences of climate change might affect these relationships. As Mideksa and Kallbekken (2010) have identified that climate change influences electricity markets through both demand and supply. The contribution to existing research lies in a combined analysis on the Norwegian market, using a more recent dataset.

3 Background

3.1 Nordic Electricity Market Characteristics

The Norwegian electricity market operates within the common Nordic wholesale market, which is closely integrated with the broader European electricity market. The evolution of this market has been characterized by significant deregulation and integration initiatives that have fundamentally shaped its current configuration.

Norway was one of the first countries to initiate the deregulation of its electricity market in 1991. This shift towards a liberalized market was crucial, influencing influencing the other Nordic countries to transition from nationally controlled electricity markets to a unified and competitive framework (Hope & Bye, 2007).

Post-deregulation, Nord Pool was established. Starting out for Norway, it transformed into the first international power exchange by 1996, expanding to include Sweden, Denmark, and Finland. The expansion continued and further integrated Estonia, Lithuania, and Latvia (Norwegian Ministry of Petroleum and Energy, n.d.). Nord Pool's evolution represents a pivotal shift in the electricity sector, moving from nationally controlled electricity markets to a market-driven system. For Norway, this transition has been essential in fostering the development and efficient operation of its electricity market.

Nord Pool has evolved into a central hub for electricity trading, effectively connecting producers and consumers. The platform ensures a transparent, efficient, and reliable trading environment (NordPool, n.d.). By facilitating the free and efficient trade of electricity among member countries, Nord Pool has been crucial in improving the security of electricity supply. Furthermore, this integration plays a vital role in maximizing the utilization of available power capacities across the Nordic and Baltic regions.

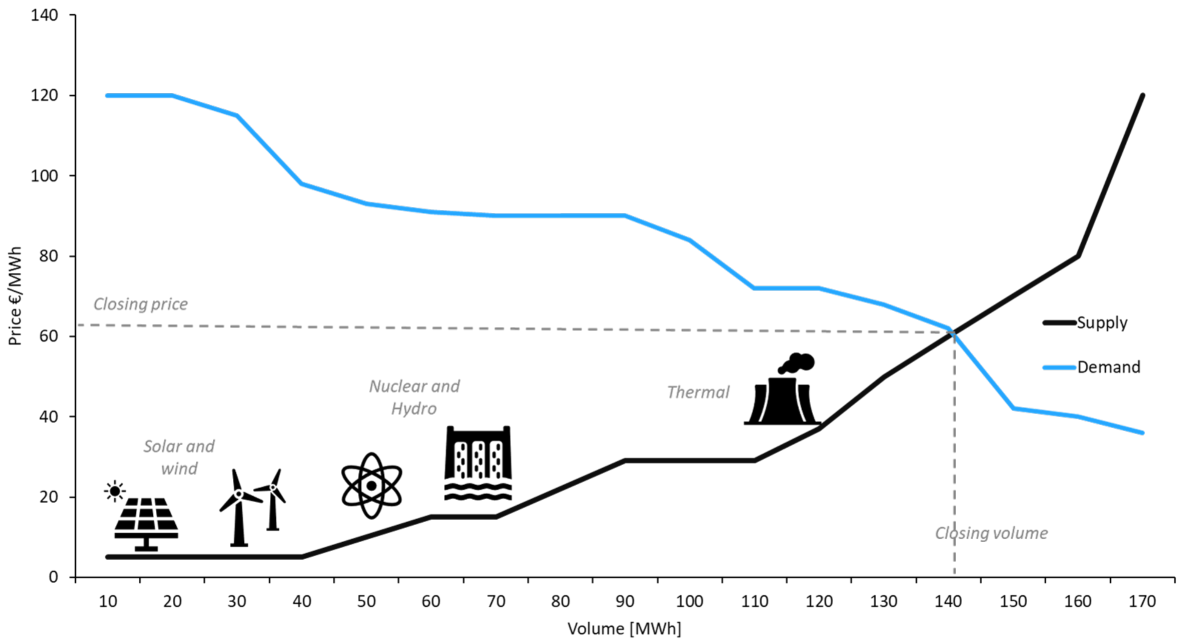
3.1.1 Electricity Price Dynamics

Electricity prices in the market are fundamentally determined by the equilibrium between supply and demand. Various factors influence this delicate balance, leading to fluctuations in electricity prices. The demand side of the electricity market reflects the cumulative need for electricity from residential, industrial, and commercial sectors. It is characterized not only by the overall volume required but also by temporal and seasonal variability (Førsund, 2015, pp. 9–13). Factors such as daily usage patterns, weather conditions, and socio-economic parameters contribute to demand fluctuations. Peak hours and extreme weather conditions can lead to surges in demand, impacting electricity prices. Additionally, technological advancements and sustainability policies, including the adoption of electric vehicles and heating systems, influence market demand. Ensuring a consistent supply to meet this dynamic demand is a crucial aspect of market management.

The supply aspect of the electricity market is shaped by a variety of factors. Predominantly, it is the generation capacity, coupled with the cost of production and accessibility of input resources, that dictates the supply dynamics. Geopolitical events, natural disasters, and market trends can cause fluctuations in electricity prices as they lead to changing needs and increased uncertainty. The incorporation of renewable electricity sources adds complexity to the supply side, as their availability is directly influenced by weather conditions. Moreover, intermittent technologies such as wind, solar, and small-scale hydro can only contribute to the supply side when specific weather conditions are met (Førsund, 2015, p. 161). Infrastructure maintenance and upgrades are essential to ensure consistent electricity delivery, while international connectors expose local markets to global influences and crises. Technical outages and scheduled maintenance work may limit supply, leading to price surges (EuropeanCommission, 2022). Regulatory policies, technological advancements, and investments in the electricity sector significantly influence the supply landscape, determining the prioritization and integration of electricity sources. Environmental considerations, such as carbon pricing and emissions regulations, further influence the shaping of supply dynamics (EuropeanCommission, 2022).

Navigating the interplay of demand and supply, the "Merit Order Effect" plays a pivotal role in determining system prices in the Nordic market (Apunn, 2015). The mechanism ranks the total Nordic supply of electricity sources based on their marginal costs, creating a merit order from the lowest to the highest as illustrated in Figure 3.1.

Renewable electricity sources occupy the bottom of this order due to their near zero marginal costs, as a consequence of the lack of fuel and minimal workforce. Conventional power plants, with higher marginal costs, are arranged in ascending order. As total demand fluctuates, different electricity sources are activated sequentially, starting from the lowest-cost source (Biggar & Hesamzadeh, 2014, p. 100). The system price is ultimately determined by the marginal cost of the highest-cost technology required to meet total demand. This pricing mechanism ensures that all participating generators receive the same market price, creating a transparent, unified pricing structure. The demand for electricity exhibits inelastic characteristics in the short-run, stemming from the constrained ability to change consumption habits. Consequently, the demand curve in the electricity market is characterized by its steepness (Hoel & Bye, 2009, p. 35).



Source: Rystad Energy research and analysis

Figure 3.1: Illustration of the Merit Order

This theoretical nature of the system price is based on the assumption of no congestion within the Nordic transmission grid. The system price serves as a unified reference for the entire Nordic market and plays a central role as a benchmark for price-setting within the financial power market of the region (Norwegian Ministry of Petroleum and Energy, n.d.). When grid limitations are incorporated, different area prices occur resulting from transmission bottlenecks, balancing incoming purchase and sale bids across distinct price areas within the Nordic region.

3.1.2 The Day-Ahead Market

In the wholesale market, price formations and actors operate across three primary markets: the day-ahead market, intraday market, and balancing market (Norwegian Ministry of Petroleum and Energy, n.d.). In the wholesale market, price formation and participants operate across three primary markets: the day-ahead market, intraday market, and balancing market. Trading in the day-ahead and intraday markets takes place on the Nord Pool exchange, while the balancing market is managed by the country's Transmission System Operator (TSO), Statnett, in Norway. The day-ahead market serves as the primary platform for electric power trading, enabling real-time adjustments and refinements to trading strategies. Any remaining imbalances are addressed in the balancing market to maintain grid stability.

The day-ahead market facilitates a closed auction where buyers and sellers trade energy for the upcoming 24-hour period (Nordpool, n.d.). Its primary objective is to establish a credible market, determining individual area prices for the forthcoming 24-hour. The operational process of this market involves several key steps. At 10:00 Central European Time (CET), available capacities on interconnectors and within the grid are published. Between 10:00 and 12:00 CET, buyers and sellers submit their final bids. These submitted bids are then systematically matched, resulting in a singular price being determined for each hour and price area. Hourly clearing prices are typically announced by 12:45 CET on the day before the trading period, and individual results are reported to each participant. This culminates in Nord Pool nominating trades to the respective country's imbalance settlement process (Nordpool, n.d.). This operational framework, encompassing the 12-hour advance notice for the following day and the 24-hour forecasting window, effectively extends the planning horizon to a 36-hour interval. This extended period is crucial for market participants to adapt their strategies and manage resources effectively (Eikeland et al., 2022).

3.2 The Norwegian Electricity Market

Norway's electricity market stands out within the traditional Nordic and European markets, owing to its substantial dependence on renewable technologies and the country's significant reliance on electric power. Electricity plays an essential role in the functioning of

Norwegian households, industries, and public infrastructure, demonstrating the thorough integration of electric power into daily life and industrial activities. To illustrate, statistical data from 2021 showed that Norway's per capita electricity consumption surpassed the European average by over threefold (Ulvin, 2022; WorldBank, 2023). This significant consumption profile not only accentuates the critical role of electricity within Norway's socioeconomic landscape, but also underscores the market's pronounced vulnerability to fluctuations and uncertainties. Furthermore, projections indicate a substantial rise in electricity consumption in Norway over the next decade, primarily driven by the process of electrification. This increase is attributed to multiple factors, including the transition towards electric transportation, the implementation of more eco-friendly practices in industrial sectors, and the growth of electricity-intensive industries (Kirchner et al., 2022, pp. 20–21).

3.2.1 Electricity Generation Mix

Norwegian electricity generation places a significant emphasis on hydropower. Over the last five years, more than 90% of Norway's total electricity output has been generated from hydropower sources (Holstad, 2023). An overview of the generation technologies with respective percentage contributions to the total volume, is presented in Table 3.1.

Table 3.1: Electricity Generation by Source

% of Total	**2018**	**2019**	**2020**	**2021**	**2022**	**Sep. 2023**	**Fcst. 2040**
Hydro	95%	93%	92%	91%	88%	90%	70%
Thermal	2%	2%	2%	1%	2%	2%	1%
Wind (onshore)	3%	4%	6%	7%	10%	8%	11%
Wind (offshore)	-	-	-	-	-	-	14%
Solar	-	-	-	-	-	-	14%
Total (TWh)	147	135	154	157	146	112	207

Source: Kirkerud et al. (2023) and SSB (2023)

The characteristics of hydropower, combined with the extensive availability of storage solutions, enhances the flexibility of the market. Water reservoirs facilitate the storage of water during periods of surplus, making it available for use in times of shortage. This feature allows the electricity market to more effectively align generation with demand, ensuring a stable and reliable electricity supply even amid regular seasonal variations.

However, this reliance on hydropower also creates a significant vulnerability, especially in the context of shifting rainfall patterns or prolonged droughts, which could present substantial challenges to the market (Kirchner et al., 2022, pp. 20–21).

According to projections by Statkraft and the Norwegian Water Resources and Energy Directorate (NVE), a moderate increase in hydropower generation is expected during normal years (Gunnerød et al., 2023; Kirkerud et al., 2023). In contrast, wind power generation in Norway has experienced a significant increase in recent years, a development that is expected to persist over the coming decades. Further, NVE's forecasts predict the incorporation of offshore wind into Norway's electricity mix by 2030, contributing to the overall growth in wind power. Solar power is expected to become a larger part of the electricity portfolio, growing steadily but likely remaining a small contributor to the total. The exact magnitude and timeline of this expansion remain somewhat uncertain. However, there is a consensus among the Norwegian electricity authorities that the proportion of hydropower in Norway's electricity mix will slowly decrease over the coming decades. Projections suggest a more varied electricity portfolio, with hydropower's share reducing to around 70% by 2040, as detailed in Table 3.1.

3.2.2 Price Areas

The electricity landscape in Norway varies significantly across different geographical regions, creating imbalances that exceed the compensatory capacity of the existing electrical grid (Statnett, 2023). To address this challenge, Norway has implemented a system of distinct price areas. Since 2010, the power grid has been divided into five areas: Østlandet (NO1), Sørlandet (NO2), Midt-Norge (NO3), Nord-Norge (NO4), and Vestlandet (NO5), as illustrated in Figure 3.2. This segmentation is crucial in enabling efficient allocation of Norway's power resources, providing precise market signals about areas of surplus and scarcity, while also ensuring the security and stability of the power supply. Importantly, this structuring enables refined control over the distribution of electricity, permitting areas with excess electricity to export to those experiencing shortages (Statnett, 2023).

Source: Statnett (2023)

Figure 3.2: Overview of Norwegian Price Areas

To demonstrate the variation in Norway's electricity generation mix, Table 3.2 provides a detailed overview in terawatt-hours (TWh) by price area, utilizing the generation data from 2022. When capacity constraints limit the transfer of electricity through the grid, distinct power prices emerge across different regions. This leads to the incentive of selling electricity from areas with a surplus to lower prices, with higher price levels, ensuring power availability where it is most required. These price differences play a crucial role in the market. In the short term, they guide immediate adjustments in generation and consumption. In the longer term, they signal priorities for infrastructural and operational developments (Statnett, 2023).

Table 3.2: Electricity Generation by Area 2022

Generation TWh	NO1	NO2	NO3	NO4	NO5
Hydro	15	38	22	26	27
Wind	1	5	6	3	-
Thermal	0	0	0	1	0
Total Generation	16	43	29	30	28

Source: Elhub

4 Data

The dataset employed in the thesis is outlined in this section. Primary variables of interest are electricity prices, acting as the dependent variable, hydrological balance and wind generation, identified as external regressors. The incorporation of load as a control variable allows for a more nuanced exploration of the dynamics between electricity prices and main renewable electricity sources in Norway.

The dataset contains observations from January 1, 2018 to September 30, 2023, aggregated to daily frequency, resulting in 2099 observations. The time series are divided into peak and off-peak observations to reflect distinct market characteristics during the day. In line with previous literature, it is stated that treating peak and off-peak hours separately provides a insightful understanding of the complex electricity market (Ballester & Furió, 2015; Lucia & Schwartz, 2000; Pereira et al., 2017). Peak hours cover hours 09:00-20:00, while off-peak hours cover hours 01:00-08:00 and 21:00-24:00, each spanning 12 hours.

In accordance with the day-ahead market dynamics, as detailed in Chapter 3, the inclusion of forecasted variables in the dataset, instead of actual, is preferred due to consistency (Kyritsis et al., 2017; Morales et al., 2011). However, when forecasted data are unavailable, actual observations are used as a proxy of the day-ahead value, a methodology also employed by Mauritzen (2011) in studying the Danish and Norwegian electricity market. All variables included in the dataset have been meticulously sourced from reliable and accessible sources, with an overview detailed in Table 4.1.

Table 4.1: Data Source Overview

Variable	**Unit**	**Hourly**	**Daily**	**Weekly**	**Source**
Day-Ahead Prices	NOK/MWh	X			Nord Pool
Hydrological Balance	GWh			X	NVE
Day-Ahead Wind	MWh	X			ENTSO-E
Actual Load	MWh	X			Hafslund

4.1 Day-Ahead Electricity Prices

Day-ahead electricity prices for each individual price area have been collected from Nord Pool's FTP server. The price data are observed hourly and measured in Norwegian Krone per megawatt-hours (NOK/MWh). The daily frequency for each area is calculated by average the hourly prices within the peak and off-peak intervals.

Peak and off-peak electricity prices for NO1, as depicted in Figure 4.1, illustrate a time series with prices initially maintaining a low and stable level around 759 NOK/MWh, potentially suggesting a mean-reverting characteristic until September 2021. Subsequently, an increase in volatility is observed, pointing to significant external influences or shifts affecting market dynamics. The steep price spike reaching 6617 NOK/MWh in August 2022 marks a notable surge in electricity prices. After this surge, a reversion towards previous price levels is noticeable, yet prices continue to exhibit higher volatility than seen in the pre-2021 period. Within the time series, instances of negative pricing are also observed. The initial occurrence of prices descending below zero in the NO1 region was recorded on July 6, 2020. However, the first instances of negative daily prices in NO1 occurred on July 2, 2023, for peak hours and August 8, 2023, for off-peak hours.

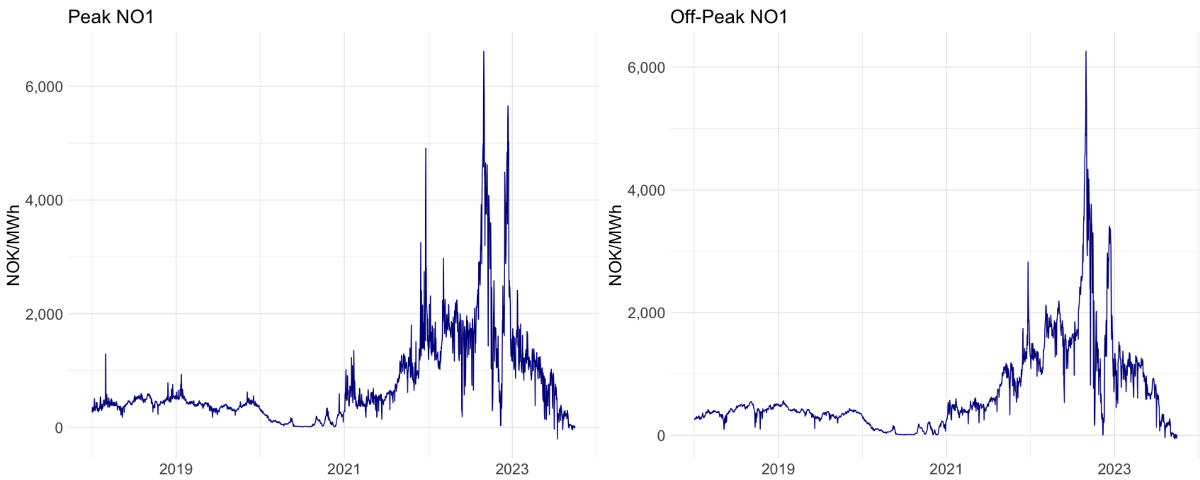


Figure 4.1: Electricity Prices NO1

The analysis of the price series plot in Figure 4.1 indicates that both peak and off-peak intervals are characterized by occasional positive and negative price spikes, along with significant volatility and volatility clustering, aligning with the findings of Geman and Roncoroni (2006b). The volatility clustering is specifically visible through the sharp spikes in 2021 and 2022 followed by less dramatic changes. The volatility is particularly apparent during winter months, reflecting seasonal variations with prices typically escalating due to increased demand. Complementing this, the histograms in Figure 4.2 reinforce these observations. The distribution exhibits leptokurtic behavior, characterized by high kurtosis (fat tails), within a right-skewed distribution. This leptokurtic nature is suggestive of the frequent occurrence of extreme price events. This indicates that substantial positive prices occur more frequently than significant negative prices, suggesting the presence of asymmetry and an "inverse leverage effect" in the market.

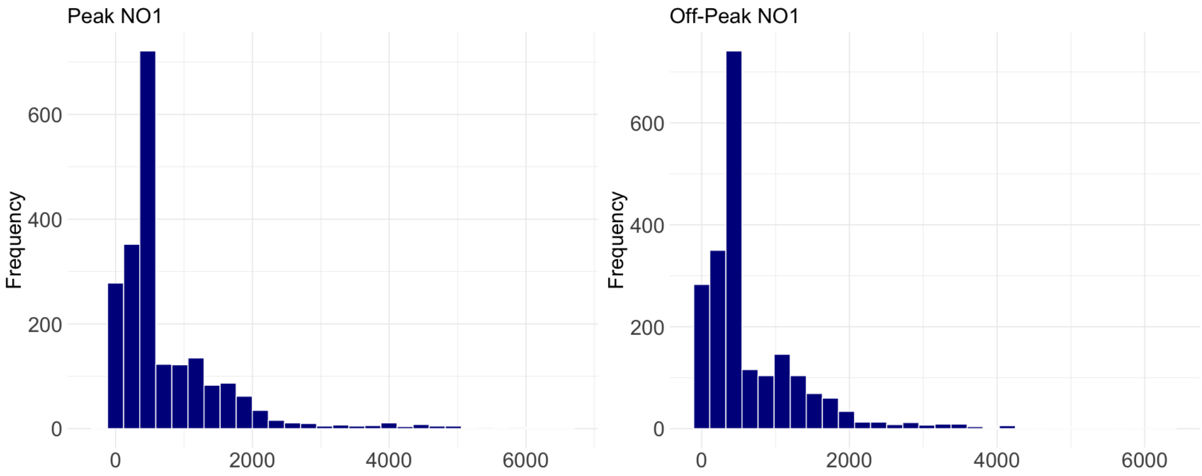


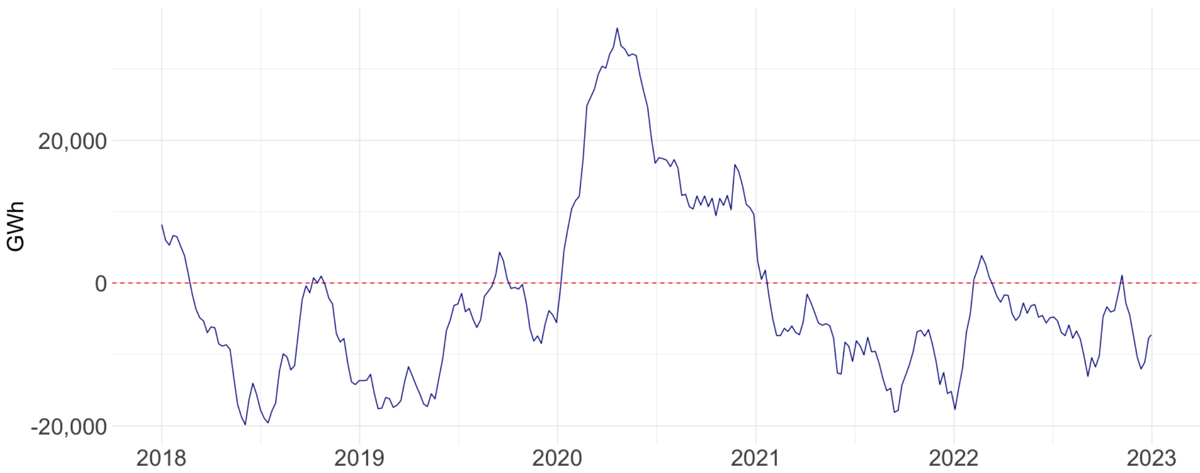
Figure 4.2: Histogram Electricity Prices NO1

4.2 Hydrological Balance

The weekly hydrological balance data are sourced from NVE, recorded every Monday and expressed in gigawatt-hours (GWh). The hydrological balance, as defined by NVE, is the cumulative sum of hydrological deviations measured against a 20-year historical median. It encompasses the deviation from the historical average in reservoir levels and the aggregated deviation from the historical average in snow reserves, soil, and groundwater levels for the relevant week (“Hydrologiske data”, 2023). To convert the weekly data into a daily frequency, linear interpolation is used. This approach assumes a constant hydrological balance throughout each day, without accounting for potential variations during peak and off-peak hours.

The inherent capability of hydropower to store energy and adjust generation strategically in response to market demands introduces an endogenous relationship between hydro generation and electricity prices. This characteristic distinguishes hydropower from other technologies lacking storage capabilities. The opportunity to store water resources for future use introduces an alternative cost for the producers (Bye, 2014, pp. 325–333). In periods where water is not utilized, it can be stored for future generation. Producers expecting higher future prices, assuming no reservoir limitations, can be better off storing water, leading to a temporary withholding in resources. Thus, producers often strategically align their output with price development to maximize profit, and the direct inclusion of hydro generation creates an endogenous relationship in market analyses.

Producers base their production decisions on both the current reservoir levels and their projections about future market development and water inflow. The hydrological balance provides a broader perspective of the market dynamics. This approach takes into account deviations from long-term normal levels across: reservoir levels, snow, soil- and groundwater. Such a broader hydrological definition is of interest in terms of informed decision-making. In relation to the research question, which aims to assess the impact of hydro generation on the market and the implications of potential climatic shifts, a focus on deviations from historical norms is preferred. This approach extends beyond mere considerations of precipitation and reservoir inflow, offering a broader understanding of the factors influencing hydro generation.



- - - Balance deviation from zero ("normal")

Figure 4.3: Hydrological Balance NO

Furthermore, hydrological balance is assessed at a national level to capture its stabilizing influence across the entire Norwegian electricity market. This approach is informed by the unique storage capabilities of large hydropower systems and the interconnected nature of the market, where areas with lower shortages can draw support from regions with higher reservoir levels. The approach enables an exploration of how fluctuations in water resources affect electricity price volatility and overall market stability. Figure 4.3 illustrates the historical development in the national hydrological balance from 2018 to 2023.

4.3 Day-Ahead Wind

Hourly day-ahead wind generation for each price area is sourced from the transparency platform European Network of Transmission System Operators for Electricity (ENTSO-E). These forecasts detail wind power generation in megawatt-hours (MWh) for each hour. To effectively process this data, the day-ahead wind forecasts are aggregated into daily peak and off-peak cumulative totals. This method involves summing all the day-ahead wind forecasts within the time interval for each period, providing a comprehensive summary that accurately reflects the wind electricity generation for each area.

The growing reliance on wind power in the Norwegian generation mix increasingly influences electricity prices. This is due to the inherent dependency of wind electricity generation on fluctuating wind conditions. High wind speeds enable wind turbines to generate electricity at greater capacities, which can lead to an oversupply in the market and lower prices. In contrast, during periods with low wind speeds, the diminished output from wind turbines can reduce supply from wind generation. The unpredictable and variable nature of wind further complicates electricity market forecasting. Unlike hydropower, which benefits from the storage capabilities, wind power generation is subject to rapid and less predictable changes, adding a layer of complexity to market dynamics.

While hydropower shows an endogenous relationship with market prices through its storage capabilities, wind power is characterized by an exogenous relationship due to its intermittent nature. The need for immediate consumption of wind-generated electricity, along with transmission constraints and the intricacies of the market, highlights the importance of examining each price area separately. This approach helps in understanding the specific impact of wind on market volatility, emphasizing the distinct nature of wind power in the electricity market landscape.

Figure 4.4 illustrates the daily variations in wind power generation characterized by significant volatility. The graph reveals a subtle seasonal pattern, where wind generation levels in the winter, and slightly lower output during the summer. This development demonstrates the changing availability of wind resources across days and seasons.

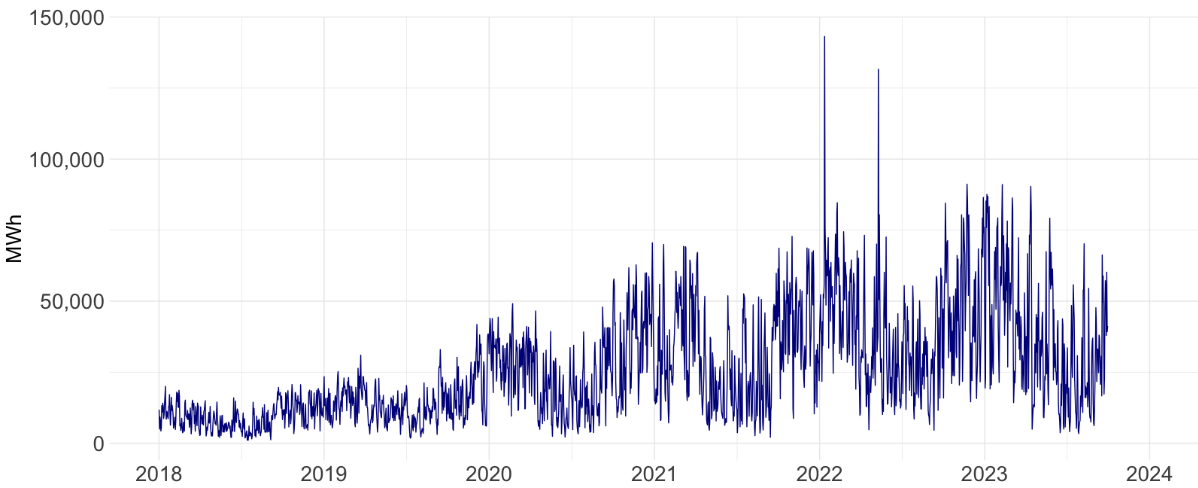


Figure 4.4: Day-Ahead Wind Generation NO

4.4 Actual Load

Hourly actual load data provided by Hafslund in MWh, is aggregated into peak and off-peak series for analysis. Actual rather than forecasted data is included to maintain analytical consistency with the control period[1].

In the electricity market, demand is a key determinant of price formation, characterized by both fluctuating and steadily increasing trends. This variability in demand is evident in the daily, weekly, and seasonal patterns of electricity usage. Moreover, an overall rise in demand is observed, driven by the gradual electrification across various sectors. Particularly in Norway, a significant portion of electricity consumption within both the service sector and households is related to heating and cooling, demonstrating a high sensitivity to weather conditions (Sørgård et al., 2023).

In this market context, electricity demand is quantified by the total load. Therefore, load serves as a crucial control variable, in the analysis. The profound effect of load on electricity prices is undeniable, necessitating a detailed examination of the interplay between day-ahead electricity prices and the supply-demand equilibrium.

[1]This study employs Hafslund's load data available from 2010, instead of the ENTSO-E's day-ahead data starting from 2014. This selection extends the observation window and ensures a uniform data foundation for both models.

As illustrated in Figure 4.5, there is a marked seasonal pattern in electricity demand, with notable peaks in winter and valleys in summer. Recognizing and integrating these demand fluctuations into the market analysis is essential, as it offers a reliable perspective on the dynamics influencing electricity market behavior.

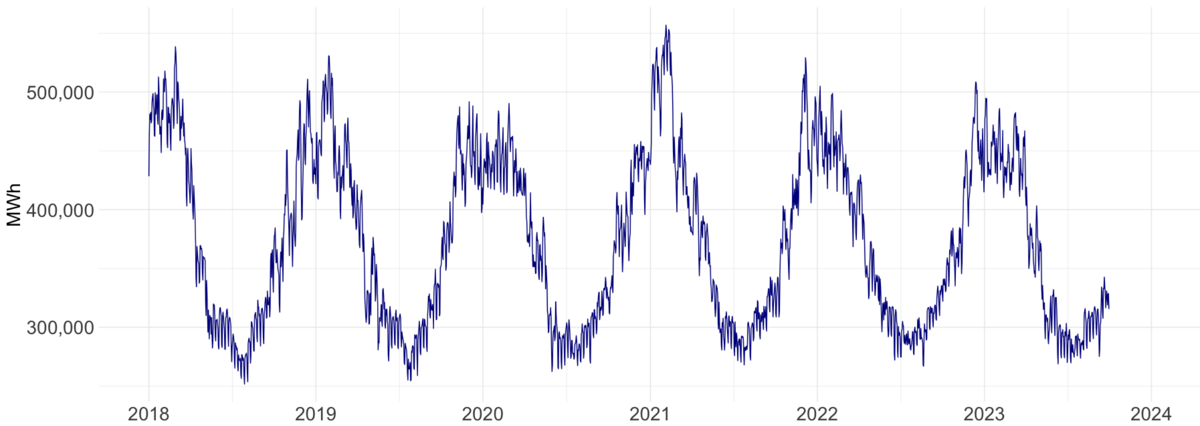


Figure 4.5: Actual Load NO

Table 4.2 and 4.3 below provide a summary of the dataset's descriptive statistics, separated into peak and off-peak hours across price areas. The statistics include the minimum, maximum and mean observations of the variables. The positive standard deviation (SD) indicates that the observations are spread around the mean, and the positive skewness shows asymmetric distributions. The positive values indicate a heavier upper tails. Similarly, positive excess kurtosis suggests more extreme value fluctuations compared to a normal distribution (Wooldridge, 2018, pp. 802–809). High values of the Jarque-Bera (J-B) normality test reinforce the non-normal distributions (Jarque & Bera, 1980). Prices are reported in NOK/MWh, hydrological balance in GWh (1,000 MWh), while wind and load data are expressed in MWh.

Table 4.2: Descriptive Statistics Peak Hours

	Min	Max	Mean	SD	Skewness	Excess Kurtosis	J-B Normality
A. Price Statistics							
NO1	-203.93	6616.89	758.61	840.16	2.66	12.34	10111.67
NO2	-176.23	6616.89	807.70	907.85	2.70	12.18	9924.25
NO3	-45.20	3940.19	382.92	364.77	4.45	34.29	92568.49
NO4	-45.20	3187.90	318.19	272.93	4.50	39.70	124908.22
NO5	-49.74	6616.89	754.25	836.87	2.68	12.50	10403.72
B. Hydro Statistics							
NO	-19848.00	35720.00	-2005.51	11537.05	1.20	4.37	664.36
C. Wind Statistics							
NO1	0.00	4403.00	680.85	742.58	1.49	5.45	1301.73
NO2	45.00	51747.00	4492.32	3856.82	1.78	13.73	11180.55
NO3	31.00	31602.00	5171.74	5201.28	1.21	3.65	546.02
NO4	49.00	14516.00	2426.17	1963.08	1.43	5.34	1199.70
NO5	NA	NA	NA	NA	NA	NA	NA
D. Load Statistics							
NO1	26527.00	91288.00	50727.78	15607.66	0.49	2.14	149.57
NO2	28136.00	77503.00	51184.31	8932.46	0.47	2.27	124.15
NO3	27501.00	54418.00	38206.65	5762.94	0.26	2.01	109.05
NO4	18016.00	36901.00	27181.67	4486.36	0.13	1.81	130.71
NO5	23169.66	34986.00	23169.66	4146.889	0.20	2.64	25.610

Table 4.3: Descriptive Statistics Off-Peak Hours

	Min	Max	Mean	SD	Skewness	Excess Kurtosis	J-B Normality
A. Price Statistics							
NO1	-57.84	6258.45	681.88	729.63	2.58	12.45	10135.14
NO2	-35.69	6258.45	748.32	824.01	2.67	12.30	10070.23
NO3	-44.48	3247.01	324.61	291.29	4.33	34.61	93924.65
NO4	-44.48	1828.68	274.57	186.14	1.66	12.03	8087.64
NO5	-57.84	6258.45	682.73	729.32	2.57	12.43	10087.74
B. Hydro Statistics							
NO	-19848.00	35720.00	-2005.51	11537.05	1.20	4.37	664.36
C. Wind Statistics							
NO1	0.00	4124.00	811.95	764.09	1.19	4.59	716.16
NO2	33.00	31219.00	4467.36	3434.22	1.16	4.91	787.85
NO3	29.00	32713.00	5297.30	4948.95	1.11	3.54	451.95
NO4	23.00	14033.00	2427.63	1854.41	1.39	5.27	1124.51
NO5	NA	NA	NA	NA	NA	NA	NA
D. Load Statistics							
NO1	22706.00	83563.00	44412.48	14301.26	0.40	2.08	130.42
NO2	30949.00	73046.00	47546.82	8124.61	0.39	2.22	107.65
NO3	24749.00	51018.00	35766.78	5330.97	0.21	2.03	97.70
NO4	16661.00	34843.00	25686.47	4180.26	0.08	1.86	115.03
NO5	1514.00	32065.00	21541.27	3733.89	0.08	2.65	19.98

5 Methodology

This chapter presents the ARMA-GARCH and -EGARCH models, each comprising two main equations: the conditional mean equation and the conditional variance equation. Contrary to static, unconditional models, this framework permits the current mean and variance to be shaped by historical data and explanatory variables, facilitating a more dynamic analysis of time-dependent volatility (Koopman et al., 2007, p. 20). This aspect is particularly significant in the context of financial time series, such as electricity prices. The examination of the model's structure and functionality in this chapter provides a comprehensive understanding of its capabilities to model and interpret the level and volatility dynamics of electricity market prices. Thus, this chapter contributes to a deeper understanding of the model's capacity and relevance for complex time series.

5.1 The ARMA(p,q) Model

The ARMA model, developed by Box and Jenkins (1976), is an integration of autoregressive (AR) and moving average (MA) processes. The AR component is characterized by regression on its own previous values, while the MA component incorporates the relationship between observations and the stochastic error terms from previous periods, commonly referred to as white noise.

Within the ARMA(p,q) framework, p is the number of lagged observations influencing the current value, defining the depth of the model's memory in the autoregressive part. The moving average order, specified by q, integrates the number of past stochastic error terms, capturing the immediate effects of random fluctuations or "shocks."

Mathematically, the model is specified in Equation 5.1, providing a linear representation of the time series where past data points and past errors inform the current value.

$$y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{5.1}$$

In this framework, y_t is the conditional mean at time t, μ represents the intercept or constant term in the model. The coefficients ϕ_i reflect the influence of the series' own past values up to p lags on the current value. Meanwhile, the coefficients θ_j measure the part of the error up to q lags relevant to explain the current value.

5.2 The General GARCH(p,q) Model

The general GARCH model is based on Engle (1982)'s ARCH model, which captures the phenomenon of volatility clustering in time series data and assumes that current volatility of a time series is related to the squared residual errors from pervious periods. Introduced by Bollerslev (1986) the GARCH model further incorporates lagged conditional variances reflecting the long-term variance. The extension to the GARCH model provides a more flexible and efficient framework to handle the volatility clustering.

In a GARCH(p,q) configuration, p represents the number of lagged squared errors, expressing the ARCH effect, and the q indicates the lagged conditional variances, the GARCH effect. The GARCH(p,q) model's conditional variance equation is given below.

$$\varepsilon_t = Z_t\sqrt{h_t}, \quad Z_t \sim iid\ N(0,1) \tag{5.2}$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \tag{5.3}$$

In Equation 5.2, the error term ε_t for the current period is presumed to be white noise, implying no autocorrelation; it is essentially random and unpredictable. Within this term, Z_t is assumed to be independently and identically distributed following a standard normal distribution. h_t is the conditional variance at time t and ω provides a baseline level of variance in Equation 5.3. The α_j coefficients reflect the magnitude of the ARCH effect measuring the impact of past shocks on current volatility, and β_i is associated with the GARCH effect measuring the degree to which past volatility influences current volatility.

The GARCH model is particularly effective at capturing the volatility clustering that is a hallmark of electricity market data, where errors in variance show serial dependence. Employing the framework can result in a more exact representation of the complex volatility structures typical in electricity markets, improving upon the limitations of homoskedastic models.

5.3 The Exponential GARCH(p,q) Model

The Exponential GARCH (EGARCH) model, an extension of the general GARCH model, was introduced by Nelson (1991). The model represents the log of the conditional variance as a function of past observations. By this transformation, the EGARCH model ensures positivity and introduce the ability to handle asymmetric responses to shocks. This enables the model to explicitly address the "leverage effect," the financial concept introduced in Chapter 2 and is referred to the asymmetric impact of shocks on market volatility.

The mathematical representation of the EGARCH model that extends from the general GARCH model is as follows:

$$\ln(h_t) = \omega + \sum_{i=1}^{p} \alpha_i g(Z_{t-i}) + \sum_{j=1}^{q} \beta_j \ln(h_{t-j}) + \sum_{k=1}^{r} \gamma_k g(Z_{t-k}) \times Z_{t-k} \tag{5.4}$$

$\ln(h_t)$ represents the natural logarithm of the conditional variance at time t. The term ω is the intercept, capturing the long-term average log-variance. The coefficients α_i measure the magnitude of the ARCH effect, where $g(Z_{t-i})$ is a function of the standardized residuals, which now capture the size and direction of the effect, and the β_j coefficients correspond to the GARCH terms. The "leverage effect" is modeled by the γ_k coefficients, which multiply a function of the standardized residuals, capturing the different impacts of positive and negative shocks on volatility. The natural logarithm on the left side of Equation 5.4 ensures that the variance remains nonnegative, a direct consequence of the exponential function's strictly positive character. This aspect of the equation relaxes the parameter constraints, effectively broadening the model's ability to capture complex volatility dynamics.

The EGARCH model allows for an analysis of volatility dynamics, accommodating both the clustering of volatility and the asymmetric effects of market shocks. Within the electricity market context, the EGARCH model is able to model the "inverse leverage effect." Capturing this phenomenon becomes a valuable tool for precise volatility modeling in electricity markets where the presence of the effects are identified (Knittel & Roberts, 2005).

6 Data Analysis

The data analysis chapter includes the pre-processing phase essential for constructing a robust time series model. It outlines the steps taken to ensure that the dataset satisfies the prerequisites for time series analysis. This involves transforming variables to eliminate seasonality, conducting stationarity tests, and laying the foundation for selecting appropriate model specifications. Subsequently, the appropriate mean and variance equations are specified. To enhance the readability of the data analysis, and considering the homogeneity across the pricing areas, the presentation of the data analysis in this chapter will primarily focus on NO1 peak hours [2].

6.1 Transforming Variables

The initial step in the transformation phase involves adjusting for outliers within the dataset. Understanding that spikes could signify actual market disruptions, including extreme weather events or sudden market shifts, they are not removed unsystematically. To enhance model stability and focus on underlying development, outliers are identified as extreme price values exceeding ten times the standard deviation of the original price series. These outliers are adjusted to ten times the mean of the series. This threshold, while higher than the commonly referenced three standard deviation (Gianfreda, 2010; Ketterer, 2014), is chosen to balance between maintaining model integrity and capturing as many observations as possible. A total of six outliers were adjusted, with three in the peak prices and one in the off-peak prices, in addition to two in the peak prices of NO4, as evidenced by Table 6.1.

Table 6.1: Statistical Summary of Price Outliers

Peak	Mean	SD	#	Off-Peak	Mean	SD	#
NO1	758.61	840.16	0	NO1	681.88	729.63	0
NO2	807.69	907.85	0	NO2	748.32	824.01	0
NO3	384.74	384.89	3	NO3	324.70	292.23	1
NO4	318.79	280.67	2	NO4	274.57	186.14	0
NO5	754.25	836.87	0	NO5	682.73	729.32	0

[2] A complete appendix, including corresponding plots and tables for the remaining areas, is available upon request from the authors.

In the realm of electricity markets, demand and pricing patterns display clear seasonal trends, shaped by the cyclical nature of climatic conditions, economic activities, and social behavior. To accurately reflect the underlying market movements within the dataset, seasonal adjustments are made. A deterministic approach to weekly seasonality involves the implementation of daily dummies (Escribano et al., 2011). These variables distinguish the characteristic consumption patterns that separate weekdays from weekends. The Ordinary Least Square (OLS) regression with these dummies neutralizes weekly cyclicality, thereby refining the dataset for subsequent analysis. Significant differences (at the 5% level) between weekdays and weekends were found for both load and price, validating the inclusion of these dummies.

Similarly, meteorological seasonal dummies for summer, fall, winter, and spring capture broader, predictable fluctuations inherent in the electricity market. Echoing Lucia and Schwartz (2000)'s findings in the Scandinavian market, these seasonal variations, including increased demand and price spikes in winter, are crucial to electricity market behavior. Incorporating seasonal dummies into variables, including wind and hydrological balance, facilitates thorough seasonal adjustment. This approach acknowledges that variables are influenced by meteorological conditions beyond the day of the week. Analysis of the dummy variables revealed significant variations across all seasons for most variables. However, for wind, the significant distinction was primarily between winter and summer. Attempts to define data with monthly dummies yielded less significant results, thus underscoring the efficacy of the chosen seasonal dummies.

The year 2022 stands out in the temporal dataset, marked by exceptional market disturbances stemming from geopolitical events and electricity supply disruptions. Given these extraordinary circumstances, a specific 'year dummy' for 2022 is included. This adjustment isolates the atypical impact of these market price events, which are external to the natural market dynamics. For context, the NO1 peak price in 2022 averaged at 2034 NOK/MWh, a stark contrast to the average of 490 NOK/MWh for the other years in the dataset. The influence of the 2022 dummy is especially noticeable in the southern price areas, reflecting NO3 and NO4's shielding from broader market shocks by transmission bottlenecks. This differential impact underscores the need for region-specific analysis in understanding the full scope of market behavior during this tumultuous period.

Finally, unit root and stationarity tests are conducted to ensure compliance with the fundamental assumption of stationarity in time series analysis. The results of these tests for each series are thoroughly documented in Appendix A1. The Augmented Dickey-Fuller (ADF) test and the Dickey-Fuller GLS (DF-GLS) test are employed to assess the series under the null hypothesis of a unit root, suggesting non-stationarity (Dickey & Fuller, 1981; Elliot et al., 1996). The ADF test incorporates lags, selected based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). In contrast, the DF-GLS test, while also examining for unit roots, applies a generalized least squares (GLS) detrending procedure before testing. Conversely, the Phillips-Perron (PP) test evaluates the same null hypothesis, but is tailored to address serial correlation and heteroskedasticity in the error terms, offering a nuanced view of the data's temporal structure (Perron & Phillips, 1988). On the other hand, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test adopts a different perspective, testing the null hypothesis that the series is stationary around a constant (Kwiatkowski et al., 1992). The use of these varied tests, each with its distinct methodological focus and diagnostic capability, strengthens the reliability and ensures a thorough evaluation of the stationarity of the time series data.

Table 6.2: Unit Root and Stationarity Tests Peak NO1

Adj. Variable	ADF	DF-GLS	PP	KPSS
Price	-5.730*	-6.884*	-140.680*	2.006
Hydrological Balance	-5.051*	-4.414*	-62.060*	1.637
Wind	-8.950*	-19.689*	-1414.800*	11.985
Load	-7.383*	-5.568*	-162.430*	2.097

* Stationary at the 5% level

The results presented in Table 6.2, addressing NO1 peak hours, suggest stationarity in the series. This inference is corroborated by the majority of the tests, except for the KPSS test, which points towards non-stationarity. Nonetheless, aligning with the perspectives of Vijayalakshmi et al. (2017), the price series can be considered stationary, despite the divergent suggestion of non-stationarity by the KPSS test.

In the analysis, the inclusion of negative electricity prices is essential for a true understanding of market dynamics. Most notably, the absence of a clear trend in Figure 4.1 serves as a primary reason against the use of log transformations. This is particularly relevant as log transformations are not applicable to negative values. Furthermore, prevailing economic literature emphasizes the mean-reverting characteristic of electricity prices. This concept is supported by studies from Schwartz (1997) and Weron et al. (2004), all of which suggest that electricity prices exhibit stationary behavior. Consequently, the approach adopted involves maintaining the price series at its original levels, inclusive of negative values, without implementing any modifications.

Additionally, an examination of the overall dataset, beyond unit root and stationarity tests, considers the qualitative aspects of the series' behavior over time. This broader analysis, contemplating the historical fluctuations in the market, aligns with the statistical findings to suggest that the variables operate at a level of integration that does not necessitate further transformation. Preserving the series in their original levels allows for the retention of the data's intrinsic characteristics, which are essential for capturing the genuine dynamics of the electricity market. This approach prevents the potential loss of information that may arise from unnecessary transformations.

The coefficients are examined through an auxiliary regression and analyzed using a correlation matrix, presented in Appendix A.2, to test for potential multicollinearity. When two or more coefficients are highly correlated there is multicollinearity present (Nishimwe & Reiter, 2021). Both methods indicate an absence of significant multicollinearity. In summary, the dataset satisfies the necessary assumptions for further time series analysis.

6.2 Preliminary Model Specification

The specification of the ARMA model in this analysis follows the three-step Box-Jenkins methodology as outlined by Brooks (2019, p. 358). This method provides a systematic framework for model identification, estimation, and diagnostic checking.

The autocorrelation function (ACF) and partial autocorrelation function (PACF) are important for understanding the ARMA model's behavior, especially in identifying stochastic seasonality – a seasonality that varies over time. The PACF assists in identifying the number of AR terms p by revealing the level of correlation between a variable and its lags that cannot be attributed to previous lags. Conversely, the ACF is used to determine the number of MA terms q by displaying the correlation between the series and its lagged values. Both the ACF and PACF are instrumental in observing the presence and impact of stochastic elements. Through visual examination of ACF and PACF plots, it is possible to make an initial determination of the values for p and q.

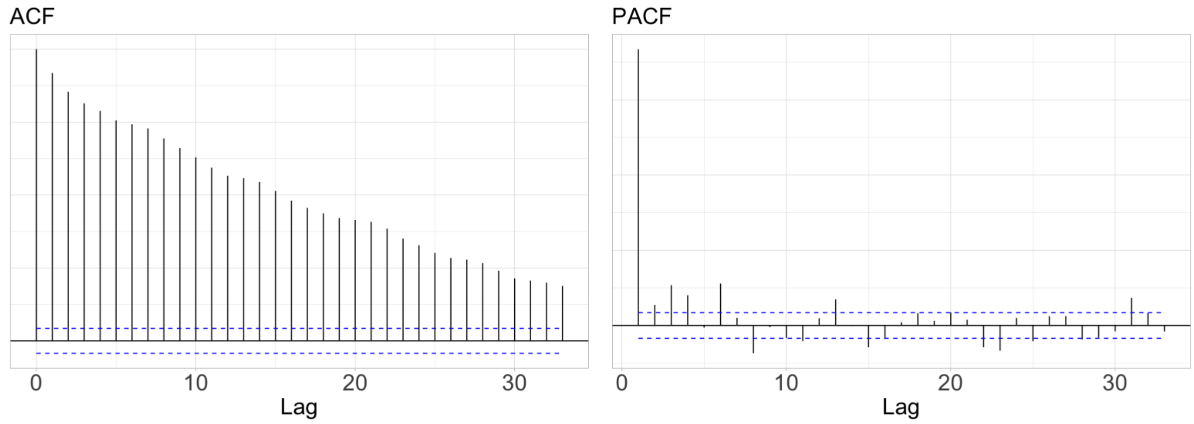


Figure 6.1: Autocorrelation Peak NO1

In Figure 6.1, the ACF and PACF plots illustrate the autocorrelation patterns in the seasonally adjusted day-ahead NO1 peak electricity prices. These plots uncover potential autocorrelation within the dataset. Considering the inherent volatility of electricity prices, influenced by the complex dynamics of demand and supply and often displaying unpredictable fluctuations (Wang et al., 2022), analyzing the time-varying patterns within the time series is crucial. To further validate, a Ljung-Box test was applied to the day-ahead prices, affirming the presence of autocorrelation in the residuals. This confirmation suggests that an ARMA model could offer a more accurate fit for the analyzed data.

Identifying the optimal model for the time series analysis involves a model fitting procedure that utilizes the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) as measures of model performance. The detailed results of this procedure, focusing on various lag specifications for ARMA models, are presented in Table A.5. The table presents a comparison of the criterias across an array of ARMA models, illustrating their effectiveness in capturing the dynamics of peak electricity prices in NO1. Notably, AIC and BIC values show relative similarity across different models, which suggests a degree of robustness in the model´s ability to be effective in capturing underlying data patterns. However, it is important to note that a slight improvement in information criteria does not necessarily imply the most suitable model specification. Instead, the choice should be based on a balance between complexity and goodness of fit.

In this scenario, the priority is to choose a model that effectively captures market dynamics. Consequently, the selection of AR lags, particularly lags 2 and 7, is based on market analysis and empirical reasoning, underscoring their relevance in reflecting market bahavior.

Given the operational intricacies affecting the day-ahead price structure, the possibility arises that the two-lag significance may align with the 36-hour operational cycle, as discussed earlier. It is important to understand both the practical market aspect and the statistical findings to fit the best model. Turning the attention to the comparative analysis of information criteria, as demonstrated in Appendix A.4, it becomes evident that the criteria values are relatively close. However, a more detailed examination of both ACF and PACF plots for the residuals of the AR(2) model reveals persistent autocorrelation issues. To address this concern, the Ljung-Box test was applied. A p-value of 0.000 confirms the presence of autocorrelation in the residuals. These results indicate the necessity for further investigation and refinement to improve the selected model's fit.

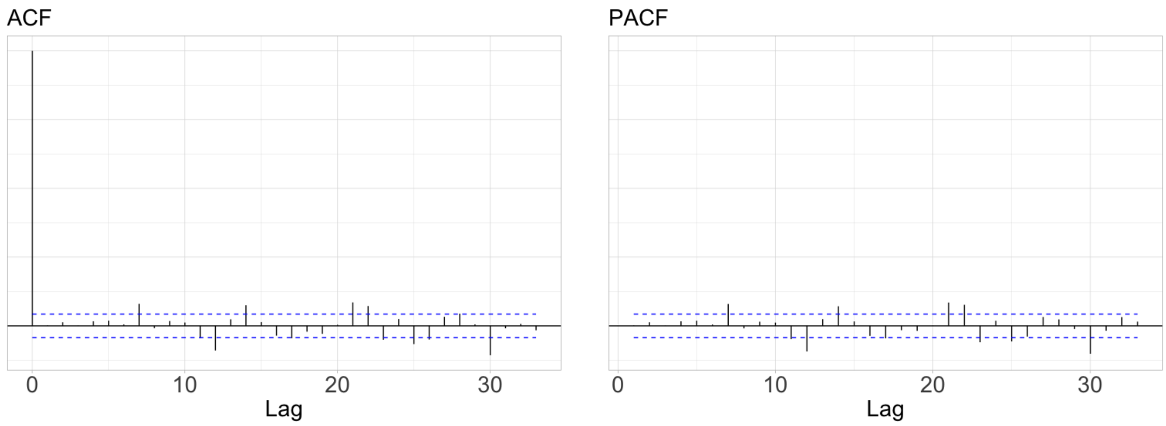


Figure 6.2: Autocorrelation AR(7) Peak NO1

In light of the well-established weekly variations in electricity prices, reflecting the cyclical nature across different days of the week, a lag of 7 days is introduced. This accounts for the complex seasonality of electricity prices, which might be overlooked by a smaller lag order. While the Ljung-Box test confirms the absence of autocorrelation in the residuals, a closer examination of Figure 6.2 reveals persistent significant spikes. This suggests the presence of autocorrelation in the residuals and underscores the need for adjustments to enhance the model's accuracy. While a Seasonal AutoRegressive Integrated Moving Average (SARIMA) model could be considered a reasonable alternative for capturing the seasonality in the dataset better (Wang et al., 2022), it falls beyond the scope of this thesis. Instead a moving average with corresponding order of seven is introduced to more accurately capture the complex dynamics in error terms.

In the ARMA(7,7) model presented below, both the ACF and PACF plots indicate that the autocorrelations predominantly fall within the confidence bounds for most lags, signifying a good fit with minimal autocorrelation in residuals. This suggests that the ARMA(7,7) model effectively captures both the autoregressive and moving average components of the time series, surpassing the performance of the AR(7) model in isolation. The improved fit offers a more precise insight into the underlying data. Despite the increased complexity of the ARMA(7,7) model, the absence of significant autocorrelation in the residuals justifies its many parameters. Furthermore, in Appendix A.4, the ARMA(7,7) model exhibits low AIC and BIC values across all price series. Based on the analysis, the ARMA(7,7) model can be justified within the scope and objectives of this thesis.

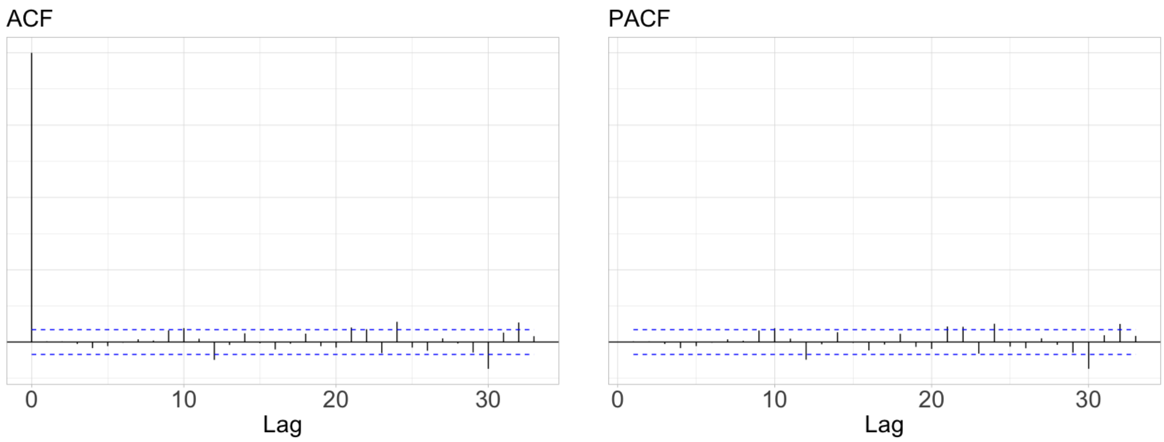


Figure 6.3: Autocorrelation ARMA(7,7) Peak NO1

The Ljung-Box test applied to the ARMA(7,7) is presented in Appendix A.7. The model yields a p-value of 0.4422, indicating insufficient evidence to reject the null hypothesis, suggesting an absence of autocorrelation in the residuals. This implies that the residuals of the model can be considered as white noise, signifying the model's effectiveness in capturing the underlying data pattern. This assumption must be satisfied to proceed with testing for ARCH effects.

Subsequently, the Lagrange Multiplier (LM) test, employed to assess heteroskedasticity in the residuals, confirms the presence of conditional heteroskedasticity in the time series. In Table 6.3 the presence of conditional heteroskedasticity is confirmed. Through tests with various lags, the null hypothesis of no ARCH effects is rejected, as evidenced by the p-values which are statistically significant at all conventional levels.

Table 6.3: Heteroskedasticity ARCH Test (LM-Test) Peak NO1

Model	Lags	Chi-squared	P-Value
ARMA(7,7)	4	197.25	0.0000
	8	228.20	0.0000
	16	301.34	0.0000
	32	401.30	0.0000

Null hypothesis: No ARCH effects

Considering the time-varying nature of price variance, ACF plots for squared residuals are presented in Figure 6.4, revealing volatility clustering through significant spikes at various lags. Significant correlations among squared residuals at different lags suggest that large variations tend to follow large variations, justifying the utilization of a GARCH model to capture this time series characteristic. Additionally, an Engle-NG test was conducted, confirming the presence of asymmetric behavior in volatility within the market. This result highlights the suitability of the EGARCH model over the general GARCH model, as it is better equipped to effectively model asymmetric shocks.

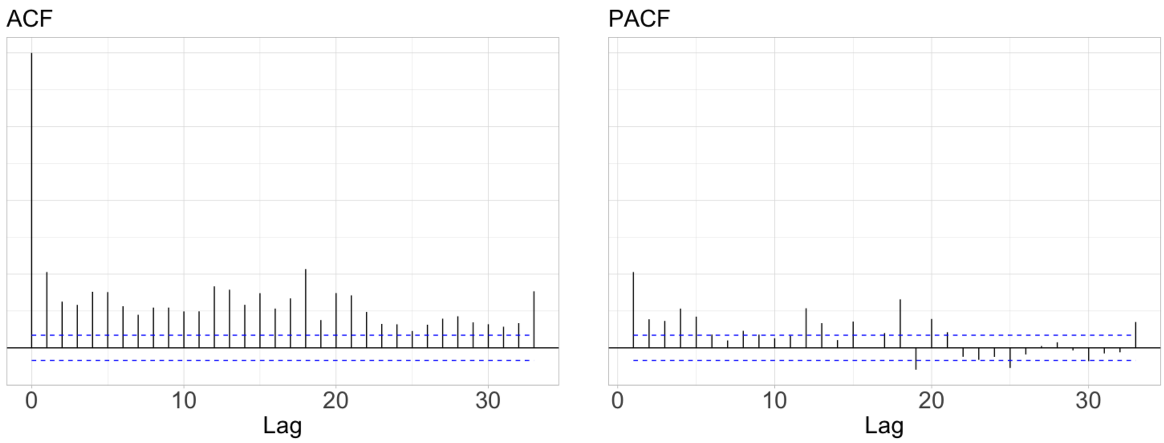


Figure 6.4: Autocorrelation Squared Residuals ARMA(7,7) Peak NO1

The selection of the appropriate EGARCH model specification is also guided by information criteria. Established literature tends to favor models with small lag orders of p and q to prevent overfitting, as the model is more likely to generalize effectively to new data. Table 6.4 presents these small lag order EGARCH models with respective AIC. Notably, the EGARCH(1,1) model emerges as the most adept at modeling the residuals within the dataset. This finding aligns with academic research, exemplified by Erdogdu (2016), which often demonstrates the superior performance of the EGARCH(1,1) framework in capturing market volatility compared to its more complex counterparts.

Table 6.4: AIC EGARCH Models Peak NO1

	(1,0)	(1,1)	(1,2)	(2,0)	(2,1)	(2,2)
Residuals	50.279	11.277	11.286	239.04	11.292	20.306

Considering conditional heteroskedasticity and the leptokurtic nature of electricity prices, as evidenced in Figure 4.2, indicating a departure from normal distribution, it's prudent to explore alternative distributional options. Heavy-tailed distributions, as the Student-t distribution may offer a better fit, in line with established literature recognizing the limitations of the normal distribution for modeling data with significant kurtosis and skewness (Koopman et al., 2007). Therefore, a Student-t distribution is chosen to improve the ability to capture observed data patterns.

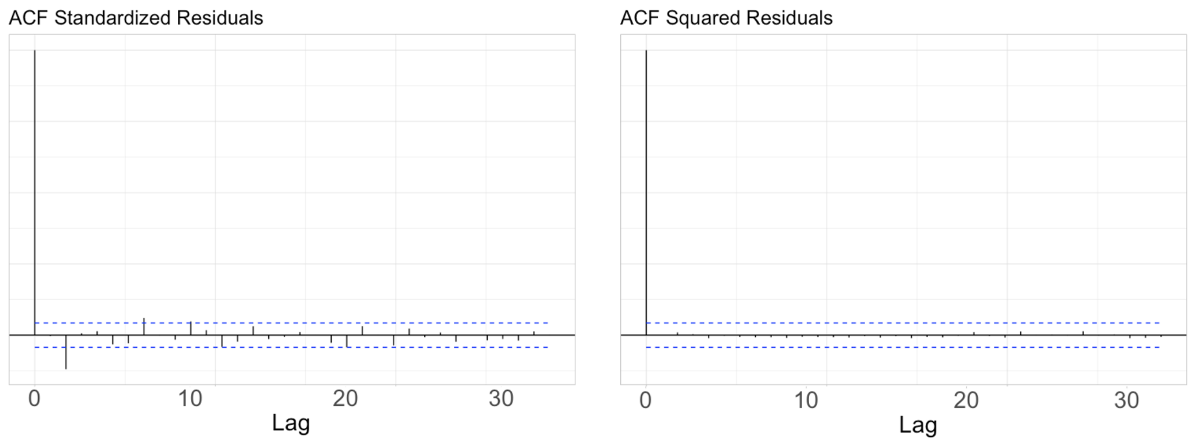


Figure 6.5: Autocorrelation Residuals ARMA(7,7)-EGARCH(1,1) Peak NO1

Minimal residual autocorrelation is required for an effective model fitting of the price series (Bollerslev, 1986, p. 308). This is confirmed by the ACF plots in Figure 6.5, which exhibit minimal autocorrelation, without any noticeable patterns associated with nonstationarity or seasonality. The standardized residuals mostly suggest an absence of significant autocorrelation indicating that the mean equation effectively captures the underlying data patterns. Similarly, the squared residuals, reflecting the variance equation fit, exhibit no significant autocorrelations. This is consistent with white noise characteristics and indicating successful capture of volatility clustering in the time series. These observations collectively imply the correct specification of the models.

7 Empirical Results and Discussion

This chapter details empirical results from applying the ARMA(7,7)-EGARCH(1,1) model to Norwegian daily electricity area prices, split into peak and off-peak hours. Using Maximum Likelihood Estimation (MLE) for precision, the study captures market dynamics (Pan & Fang, 2002) and discusses the implications, particularly concerning climate change. The aim is to deepen insights into the Norwegian electricity market through the explored relationships and effects.

7.1 Model Output

The conditional mean and variance equations for the specified ARMA(7,7)-EGARCH(1,1) model on electricity prices, incorporating external regressors, are expressed as:

$$p_t = \mu + \sum_{i=1}^{7} \phi_i p_{t-i} + \sum_{j=1}^{7} \theta_j \varepsilon_{t-j} + \delta_b b_t + \delta_w w_t + \delta_l l_t + \varepsilon_t \tag{7.1}$$

$$\begin{aligned} \ln(h_t) = \omega + \alpha_1 g(Z_{t-1}) + \beta_1 \ln(h_{t-1}) \\ + \gamma_1 g(Z_{t-1}) \times Z_{t-1} + \xi_b b_{t-1} + \xi_w w_{t-1} + \xi_l l_{t-1} + \varepsilon_{t-1} \end{aligned} \tag{7.2}$$

Here, b_t represents the hydrological balance, w_t denotes wind power generation, and l_t electricity load.

The empirical results derived from Equation 7.1 and 7.2, encompassing both peak and off-peak price analyses, are outlined in Table 7.1 and 7.2. For a thorough presentation of the model, including complete parameter estimates and diagnostic test results, please refer to Appendix B. Overall, the model proficiently captures the weekly stochastic seasonality in the data, as shown by significant autoregressive coefficients in the mean equation. The Ljung-Box test results, detailed in Section C, Table 7.1 and 7.2, indicate minimal autocorrelation. These results are consistent with the observations from the residual plots in Figure 6.5 and underscores the model's adequacy in representing both mean and variance patterns.

Table 7.1: EGARCH Model Fit Peak Hours (2018-2023)

	NO1	NO2	NO3	NO4	NO5
A. Conditional Mean Equation					
ϕ_1	-0.0008	0.0013	-0.0128	-0.0123	-0.0024
	(0.0000)	(0.0139)	(0.0153)	(0.0030)	(0.0000)
...					
ϕ_7	1.0016	1.0022	0.9647	0.9585	1.0052
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_1	0.8011	0.8196	0.8074	0.7333	0.8431
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
...					
θ_7	-0.1963	-0.1779	-0.2297	-0.2396	-0.1636
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
b_t	-48.6953	-84.7086	-95.9825	-51.6897	-19.9572
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
w_t	-5.5534	-4.9439	-14.0151	-7.1976	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
l_t	14.9124	9.5307	11.5453	14.0528	2.0377
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
B. Conditional Variance Equation					
α_1	0.0473	0.0818	0.0902	0.0397	0.0236
	(0.0250)	(0.0007)	(0.0000)	(0.0711)	(0.3188)
β_1	0.9913	0.9938	0.9696	0.9743	0.9976
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_1	0.3195	0.2798	0.5132	0.3160	0.3575
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
b_t	-0.0109	-0.0099	-0.0121	-0.0091	-0.0089
	(0.0078)	(0.0099)	(0.0665)	(0.0566)	(0.0228)
w_t	0.0201	0.0340	0.0177	0.0234	
	(0.0020)	(0.0000)	(0.0973)	(0.0028)	
l_t	-0.0254	-0.0151	-0.0026	-0.0007	-0.0109
	(0.0000)	(0.0036)	(0.7698)	(0.9166)	(0.0600)
C. Model Fit Statistics					
AIC	11.297	11.356	10.902	10.390	11.187
LL	-11830.5	-11891.7	-11416.14	-10878	-11716.89
Q(30) p-value	0.0001	0.1962	0.0518	0.4351	0.0886
$Q(30)^2$ p-value	1.0000	1.0000	0.9794	1.0000	1.0000

When analyzing the external regressors during peak hours, as presented in Table 7.1, the hydrological balance exhibits a negative and statistically significant impact on the average price across all price areas. This finding indicates that a deviation above the 20-year average median hydrological balance signals a surplus of resources compared to a normal year, while a negative deviation indicates scarcity. These results are consistent with the theoretical expectations and earlier studies on resource availability, as demonstrated by Huisman et al. (2014) and Koopman et al. (2007). Additionally, in a hydro-dominated market, the hydrological balance plays a pivotal role in stabilizing price volatility (Rintamäki et al., 2017). As observed in the conditional variance equation, a positive and statistically significant coefficient for the hydrological balance suggests that an increase in hydrological balance is associated with reduced volatility. This relationship suggests a correlation between a higher hydrological balance and a more stable, less constrained market environment. Such a pattern is likely due to its ability to provide a steady and manageable electricity supply, thereby playing a crucial role in mitigating price volatility.

Wind power generation, conversely, plays a dual role: while it contributes to lower average price levels, it simultaneously leads to increased price volatility. This observation contrasts with earlier studies in the Norwegian market, which did not observe significant impacts of wind on market dynamics (Gjerland & Gjerde, 2020; Mauritzen, 2011). Internationally, this phenomenon has been attributed primarily to the inherent unpredictability of wind power. The variability in wind power generation can cause significant short-term fluctuations in supply, thereby affecting price levels. The integration of wind power, with its zero-marginal cost, influences the electricity market's merit order, leading to a significant reduction in average prices in all areas. Therefore, the increased wind generation can contribute to a higher electricity supply, which in turn lowers peak prices. The inherent challenge with wind power lies in its reliance on wind availability and the inability to store electricity. This necessitates real-time generation and consumption of wind electricity. Unlike hydropower plants, which can regulate generation levels, wind power lacks such flexibility. As a result, the unique nature of wind electricity introduces significant variability into the electricity market. This variability, often occurring suddenly, can lead to unforeseen supply shifts, subsequently resulting in unpredictable fluctuations in electricity prices.

Table 7.2: EGARCH Model Fit Off-Peak Hours (2018-2023)

	NO1	NO2	NO3	NO4	NO5
A. Conditional Mean Equation					
ϕ_1	1.6280	0.9344	1.4845	1.9323	1.6251
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
...					

Continued on next page

Table 7.2 – continued from previous page

	NO1	NO2	NO3	NO4	NO5
ϕ_7	-0.5611	-0.0858	-0.2928	0.4921	-0.5751
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_1	-0.7263	-0.0364	-0.4799	-1.0048	-0.6743
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
...					
θ_7	0.0551	-0.0616	-0.1392	0.1096	0.0168
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
b_t	-64.1197	-85.4438	-67.9909	-49.2885	-68.9300
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
w_t	-5.4258	-6.7368	-13.5122	-6.4163	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
l_t	12.3907	7.0253	10.3045	10.3933	7.6461
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
B. Conditional Variance Equation					
α_1	0.0023	-0.0290	0.0087	-0.0670	-0.0041
	(0.9162)	(0.3186)	(0.7567)	(0.0018)	(0.8493)
β_1	0.9786	0.9777	0.9678	0.9507	0.9857
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_1	0.4473	0.4100	0.5906	0.5894	0.4383
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
b_t	-0.0145	-0.0136	-0.0142	-0.0201	-0.0093
	(0.0285)	(0.0113)	(0.0435)	(0.0200)	(0.1304)
w_t	0.0299	0.0680	0.0300	0.0232	
	(0.0007)	(0.0000)	(0.0047)	(0.0505)	
l_t	-0.0051	-0.0135	-0.0138	0.0051	0.0020
	(0.5506)	(0.0494)	(0.1609)	(0.6284)	(0.8057)
C. Model Fit Statistics					
AIC	10.273	10.545	9.9748	9.3986	10.256
LL	-10755.18	-11040.59	-10442.52	-9837.793	-10739.85
Q(30) p-value	0.0001	0.0001	0.0549	0.5208	0.0001
$Q(30)^2$ p-value	0.9988	1.0000	0.0001	0.9967	0.9993

In the analysis of off-peak hours, as detailed in Table 7.2, the effects of hydrological balance and wind power closely mirror those observed during peak hours. Both in terms of significance and the magnitude of their coefficients. This consistency underscores a comparable influence of both hydrological balance and wind generation during off-peak hours, akin to their impact during peak periods. However, despite this overall alignment, there are noteworthy distinctions to consider. Notably, the influence of hydrological balance in peak hours appears to be milder compared to off-peak hours, across all areas, suggesting a reduced role during high-demand periods. In contrast, the impact of wind power on price variation is more pronounced in off-peak hours, as evidenced by its stronger negative coefficients. This difference highlights distinct operational dynamics in the electricity market at different times, suggesting that off-peak hours may be characterized by lower demand elasticity, thereby amplifying the effect of wind generation on price changes.

The observed similarities between peak and off-peak periods in the Norwegian electricity market are intriguing and may be attributed to the unique structure of the Norwegian electricity market. Norway's reliance on hydropower with storage options provides operational flexibility and stability. These factors could contribute to a more uniform market behavior throughout the day, challenging the traditional understanding of peak and off-peak differences. This deviation, resulting from the dampening effect of hydropower, contrasts with the patterns observed in renewable markets and is also discussed in similar terms in Ballester and Furió (2015) and Pereira et al. (2017) in the context of the Spanish market. Markets that exhibit clear distinctions between peak and off-peak hours may be influenced by constraints and challenges related to generation mixes and technologies not present in the Norwegian market context. For instance, solar power generation displays an inverse seasonal pattern compared to electricity demand, resulting in reduced peak electricity prices and distinct characteristics between peak and off-peak hours (Kyritsis et al., 2017). This underscores the significance of understanding how different market structures can shape market dynamics.

Load consistently demonstrates statistical significance with positive coefficients across all hours in the mean equation, aligning with economic theory, which suggests that higher demand contributes to increased prices. The significant negative coefficients in the variance equation during peak hours for southern areas (NO1, NO2, and NO5) might indicate a stabilizing effect of high load on price volatility. During peak hours, demand patterns may be more predictable, leading to less price fluctuation. In contrast, the significant negative effect observed only in NO2 during off-peak hours suggests regional differences in how load impacts price volatility during times of lower demand. Off-peak hours might exhibit more elastic demand, leading to less predictable pricing patterns. The unique behavior in NO2 could reflect local market or grid characteristics that differ from other regions.

The model's external variables generally exhibit similar directional impacts on electricity prices, but a closer examination of the coefficients' magnitudes yields intriguing insights. In the analysis of wind's impact on electricity prices, NO2 consistently displays the highest coefficient in its variance equations throughout the day, both during peak and off-peak hours. This heightened vulnerability to wind-related risks in NO2 may be attributed to its geographical characteristics, particularly its exposure to frequent directional shifts in wind. This leads to variability in wind patterns, introducing instability in wind movements and consequently affecting wind generation (G. Lund, 2016). Additionally, NO2 is the pricing area most interconnected with foreign markets, featuring cable connections to Germany, the Netherlands, Denmark, and the United Kingdom, all hosting significant wind power generation capacities. It is plausible that fluctuations in national wind patterns are correlated with foreign wind patterns, and that the foreign power situation impacts the price in NO2 through import and export. Consequently, the heightened sensitivity of NO2 to wind fluctuations may be ascribed to its interconnections with foreign markets influenced by wind-related factors.

NO3 exhibits the highest mean coefficient on wind generation throughout the day. This observation can be attributed to NO3 having the highest wind generation both in absolute MWh and as a percentage of total consumption, defined as wind penetration, for the analyzed period. In 2022, wind electricity accounted for just over a quarter of total consumption in this region. This aligns with the argument that higher generation and wind penetration tend to lead to increased price impact. Additionally, during peak hours, NO3 is most influenced by hydro in both the mean and variance equations. In recent years, NO3 has experienced electricity shortages, making it plausible that a region with an electricity deficit relies more on, and is more responsive to changes in hydropower with storage capabilities. This is particularly relevant when the region's electricity generation is dependent on wind resources, which are inherently uncertain. Storage capabilities provide predictability, and changes in this aspect can have a more substantial impact on regions that cannot meet their own electricity demand. Consequently, this can explain the higher influence of hydro on both NO3 average price and volatility during peak hours.

NO5 presents an intriguing observation as it exhibits the least negative mean coefficient during peak hours and the least negative variance coefficient on hydro throughout the day, encompassing both peak and off-peak hours. This finding is noteworthy, considering that NO5 relies exclusively on hydropower for electricity generation. One plausible explanation for this observation is NO5's geographical advantage, characterized by the highest rainfall in Norway, with a consistent expectation of frequent precipitation, complemented by mild temperatures. Consequently, deviations in the hydrological balance in NO5 may not necessarily indicate scarcity or market pressure.

It is worth noting that NO5 has maintained the lowest average filling level compared to all pricing areas since 2010. This suggests that the observed effect is likely not attributable to a higher filling level in NO5. However, when considering that hydropower generation in NO5 amounts to about 190% of total consumption in the pricing area based on 2022 data, refer to Table 7.5, it can be argued that NO5 is largely self-sufficient in hydropower generation, with a 90% surplus. As a result, the region is less internally affected by fluctuations in the hydrological balance - meaning deviations from a "normal year." Conversely, in NO3, where hydropower generation only accounts for approximately 70% of total consumption, the most significant hydro effect in both mean and variance during peak prices is evident. Despite claims that filling levels and hydrological balances at the area level are not as pivotal as at the national level, it is important to recognize that the potential for bottlenecks in the transmission network should not be entirely overlooked.

Building on the insights into regional differences and their influence on market dynamics, the ARCH and GARCH terms offer a quantified understanding of the market's reaction to shocks and the temporal variations in volatility. During peak hours, the ARCH terms (α_1) are significant and positively correlated, underscoring the immediate increase in future volatility following market shocks in high-demand periods. This effect is in contrast with off-peak hours, where the significance of α_1 coefficients is mixed, indicating a more variable impact of volatility shocks during periods of lower demand. On the other hand, the GARCH coefficients (β_1) demonstrate notable consistency across both peak and off-peak periods. Their significant values, frequently approaching unity, suggest persistent and strong volatility over time. This indicates that volatility shocks, once they occur, are likely to have a lasting impact, regardless of the demand level at the time. The sum of α_1 and β_1 close to unity further corroborates the interpretation of persistent market shocks, highlighting their substantial influence on future market volatility (Ketterer, 2014).

Moreover, the positive and significant γ_1 coefficients observed in all models confirm the presence of an "inverse leverage effect" in the Norwegian electricity market, indicating that volatility increases more with positive shocks than negative ones. This is especially interesting in the context of the Norwegian market, where unexpected dry periods impacting hydropower generation lead to substantial volatility due to immediate supply effects. Although Norway's storage capacity can buffer some fluctuations, it may not fully mitigate extended or intense supply constraints. Conversely, negative shocks, such as unexpected reduction in demand, do not result in comparable volatility. This is because hydropower systems are flexible and can store excess water in the reservoirs, thereby stabilizing the market.

However, the increasing integration of wind generation, being intermittent and lacking strategic storage options, is less capable of responding to market imbalances. Consequently, it is reasonable to assume that wind generation reacts similarly to both positive and negative shocks. This characteristic could potentially diminish this effect observed as the Norwegian market becomes less reliant on hydropower and more exposed to the unpredictability of wind electricity. Therefore, the extent of an "inverse leverage effect" may vary depending on the proportion of wind generation in the market, and its interplay with hydrological conditions and market demand.

7.2 Historical Control Period

To examine potential shifts in market responses to external variables over time, a comparing analysis using a historical control period will be conducted. While traditional literature uses a 30-year benchmark to determine climatic variations, data limitations and market structure changes constrain the start of the historical analysis to 2010[3]. Recent findings from the Norwegian Meteorological Institute, however, suggests that a 10-year window may be sufficient, reflecting the accelerated rate of climate change in recent years (Steiro, 2023). Thus, the period from 2010 to 2014 has been chosen as the control period, balancing data constraints and relevance. Deviations in the model's outputs across the main and control periods could reveal shifts in the market structure, potentially attributable to climatic factors.

[3]Price area NO5, established in 2010, marks the earliest instance of the current price area structures. Load data limited post-2010.

The control period analysis employs a slightly simplified model relative to the main period spanning 2018-2023, reflecting the market's greater stability and lower impact of external influences. In accordance with the methodology described in Chapter 6, the most fitting model is determined to be ARMA(7,0)-EGARCH(1,1). A detailed model output of the control period is presented in Appendix B.

In the context of climate change, it is crucial to remember that when examining the differing outputs from the control and main periods, the potential impact of climatic phenomena such as El Niño and La Niña should not be overlooked. These events are acknowledged as triggers for natural, annual weather cycles (NOAA, 2023). An understanding of these phenomena is important when analyzing the changes in weather patterns and their impacts, especially because the identified trends might extend beyond or differ from those explainable by natural variations alone. While these cycles indeed contribute to weather condition variability, including temperature fluctuations, the persistent rise in global temperatures suggests the influence of additional factors beyond these natural cycles (NOAA, 2023). It is important to clarify that this thesis does not constitute a causal study and does not test for statistical differences between coefficients. Such analysis falls outside the scope of this thesis and are left for further research.

7.2.1 Model Comparison Hydrological Balance

In the conditional mean equation a comparison of the hydrological balance coefficients in two periods demonstrate consistent and significant effects; increased hydrological balance are associated with a decrease in average area prices. A notable observation in the mean equation is the pronounced impact of hydrological balance in NO1. Where, the coefficient is -75.45 during the control period, compared to -48.70 in the main period. The introduction of wind generation into NO1's portfolio in the main period might suggest that diversifying the generation mix by incorporating wind, could result in lower price sensitivity to changes in hydrological balance. In contrast, in areas such as NO2 and NO3, where the generation mix has remained more consistent, there is a notable increase in absolute terms of the coefficient for hydrological balance. This observation suggests that a similar change in hydrological balance currently has a more substantial impact on average prices than it did during the control period.

Table 7.3: Model Comparison Hydrological Balance Mean Equation

	NO1	NO2	NO3	NO4	NO5
b_t Peak Hours					
Control	-75.4538***	-42.6711***	-59.5142***	-45.1651***	-84.3075***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Main	-48.6953***	-84.7086***	-95.9825***	-51.6897***	-19.9572***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
b_t Off-Peak Hours					
Control	-17.5172**	-29.4846***	-35.5999***	-33.7197***	-31.6523***
	(0.0230)	(0.0009)	(0.0009)	(0.0027)	(0.0001)
Main	-64.1197***	-85.4438***	-67.9909***	-49.2885***	-68.9300***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Statistical significance: *** 1% level, ** 5% level, and * 10% level

In the conditional variance equation, the hydrological balance consistently reduces price volatility in both periods. However, the hydrological balance was not statistically significant during the control period. The empirical results reveal that fluctuations in the hydrological balance now exert a more pronounced influence on price volatility. This could suggest an increase in the risk associated with hydrological levels, potentially a consequence of evolving precipitation patterns, and more frequent and rapid changes in the hydrological balance over the past decade. An example of this trend may be identified in NO1, where a noticeable shift appears around 2017-18, as illustrated in Figure 7.2. These observations support the argument that the market has been experiencing more rapid changes and larger deviations from the "normal" levels in recent years.

Table 7.4: Model Comparison Hydrological Balance Variance Equation

	NO1	NO2	NO3	NO4	NO5
b_t Peak Hours					
Control	-0.0040	-0.0108	-0.0017	-0.0034	-0.0090
	(0.7821)	(0.4667)	(0.8928)	(0.8073)	(0.4540)
Main	-0.0109***	-0.0099***	-0.0121*	-0.0091*	-0.0089**
	(0.0078)	(0.0099)	(0.0665)	(0.0566)	(0.0228)
b_t Off-Peak Hours					
Control	0.0066	0.0094	-0.0093	0.0015	0.0043
	(0.6893)	(0.5451)	(0.6020)	(0.9319)	(0.7789)
Main	-0.0145**	-0.0136**	-0.0142**	-0.0201**	-0.0093
	(0.0285)	(0.0113)	(0.0435)	(0.0200)	(0.1304)

Statistical significance: *** 1% level, ** 5% level, and * 10% level

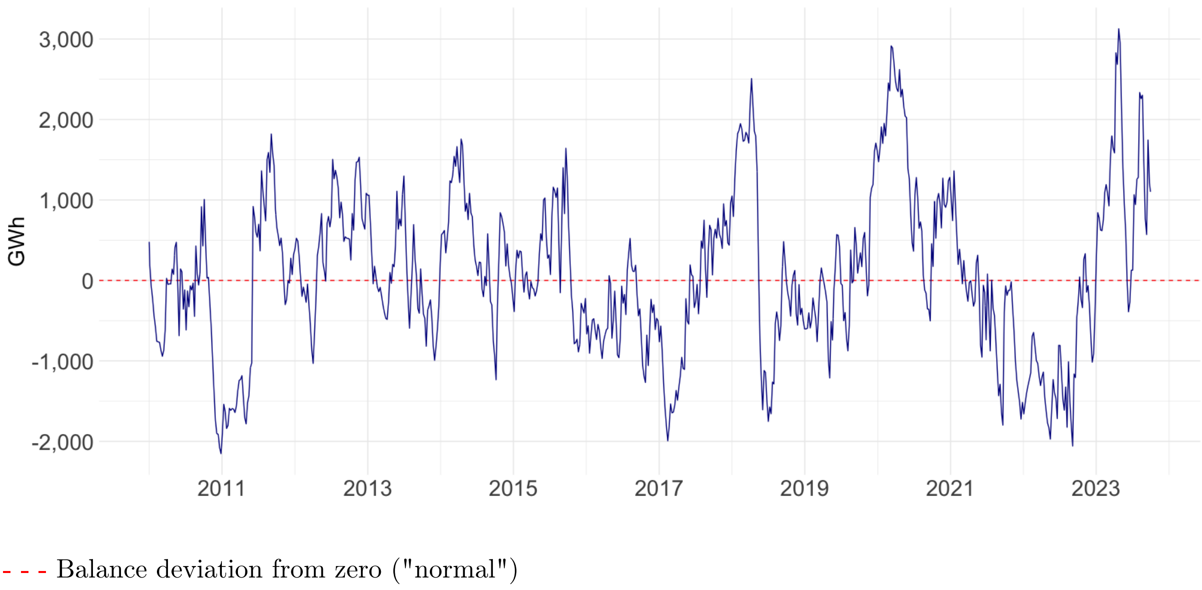


Figure 7.1: Hydrological Balance NO1 2010-2023

The accelerated changes in Norway's hydrological balance can be associated with changing precipitation patterns and increasing temperatures. A warmer climate typically results in more intense precipitation events, as warmer air holds more moisture. When this releases, it results in substantial precipitation, causing precipitation patterns to become more concentrated. This leads to extended periods of drought and increased instances of heavy rainfall, as evidenced in climate studies(Hanssen-Bauer et al., 2017). This emerging pattern, characterized by the climate becoming simultaneously drier and wetter, introduces greater unpredictability and instability into the hydrological balance.

This pattern is particularly observed in the summer months, due to higher temperatures. The summer of 2023 serves as an extreme example, starting with drought conditions and ending with significant flooding by August, illustrating this emerging pattern of prolonged droughts periods followed by heavy rainfall. These climatic changes carry profound implications for the electricity sector. Increased flooding risk in reservoirs heightens the potential for generation loss, as facilities may not fully utilize their resources due to insufficient storage capacity. Additionally, the increased risk of drought and uncertain precipitation patterns create a strong incentive to conserve resources during periods when the hydrological balance falls below zero, particularly in case of long lasting dry period. Such significant and unforeseen deviations from normal levels are likely to have a more pronounced impact on average price levels and volatility.

In the analysis comparing the coefficients of the main and control periods in the variance equation, a notable pattern emerges. Although the control period coefficients were not significant, a greater change in the coefficients is observed in NO1, NO3, and NO4 compared to NO2 and NO5, where impacts remain relatively stable. The increased sensitivity to hydrological imbalances in NO1, NO3, and NO4 points to a potential evolution in water availability fluctuations in these areas. Such varying changes across different price areas between the two periods underscore the heterogeneous nature of climate change impacts, indicating that risk exposure is region specific. This aligns with observations from the NVE, which states that the impacts of climate change are geographically diverse (Kirkerud et al., 2023). Specifically, the region NO1 has experienced shifts in precipitation patterns while maintaining consistent precipitation volumes. In contrast, NO5 has witnessed increased rainfall but without significant changes in its patterns. This differential development is mirrored in the results: NO1 shows a higher and significant coefficient in the main period, while NO5 exhibits a significant yet consistent coefficient. The larger coefficient in NO1, relative to NO5, may suggest an increased weather volatility in NO1.

7.2.2 Model Comparison Wind Generation

The coefficients for the main and control models are compared in the Table 7.5 and 7.6. In the conditional mean equation, wind generation is associated with a decrease in average prices, showing significant and consistent effects.

Table 7.5: Model Comparison Wind Generation Mean Equation

	NO1	**NO2**	**NO3**	**NO4**	**NO5**
w_t Peak Hours					
Control		-1.7478***	-2.1183***	-1.1198***	
		(0.0000)	(0.0000)	(0.0083)	
Main	-5.5534***	-4.9439***	-14.0151***	-7.1976***	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
w_t Off-Peak Hours					
Control		-0.2469*	-0.4953*	-0.9030***	
		(0.0729)	(0.0667)	(0.0001)	
Main	-5.4258***	-6.7368***	-13.5122***	-6.4163***	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

Statistical significance: *** 1% level, ** 5% level, and * 10% level

In areas with wind generation during the control period in 2010-2014 (NO2, NO3, and NO4), the mean equation shows negative coefficients, indicating that wind generation contributes to a reduction in average electricity prices. This is equivalent with findings from the main period, reflecting the principle that increased supply leads to reduced average price levels. However, a noteworthy observation is the higher wind coefficient in the main period compared to the control period, indicating that changes in wind generation in the main period exert a more substantial influence on average prices. Throughout the combined analysis period, there has been a notable escalation in integration of wind electricity, which could account for its expanding influence on the mean equation. As the supply and dependence on wind electricity grow, this would correspondingly lead to a more substantial influence on the overall price levels.

Table 7.6: Model Comparison Wind Generation Variance Equation

	NO1	**NO2**	**NO3**	**NO4**	**NO5**
w_t Peak Hours					
Control		-0.0272	-0.0859***	-0.0414**	
		(0.1470)	(0.0001)	(0.0423)	
Main	0.0201***	0.0340***	0.0177*	0.0234**	
	(0.0020)	(0.0000)	(0.0973)	(0.0028)	
w_t Off-Peak Hours					
Control		0.0076	-0.0485*	-0.0736***	
		(0.6572)	(0.0623)	(0.0051)	
Main	0.0299***	0.0680***	0.0300***	0.0232**	
	(0.0007)	(0.0000)	(0.0047)	(0.0505)	

Statistical significance: *** 1% level, ** 5% level, and * 10% level

Whereas, the effect in the variance equation notably changes from negative in the control period to positive in the main period, with significant coefficients observed in the control period for NO3 and NO4. This shift suggests that wind generation initially contributed to price stabilization during the control period, but later in 2018 to 2023 increases price volatility. This change might be interpreted as an initial diversification effect, where wind added stability to the overall generation mix in the control period. However, increased wind penetration seems to introduce more risk and volatility. This diversification, while beneficial in theory due to more generation channels, can introduce complexity to the market.

The growing reliance on wind, an inherently unpredictable electricity source, seems to have introduced a higher degree of uncertainty. The electricity market becomes more susceptible to the unpredictability of wind availability, leading to greater uncertainty in day-ahead market predictions. The heightened likelihood of supply and demand mismatches, arising from the unpredictability of wind generation, amplifies market fluctuations, reflected in the observed increase in price volatility in the main period.

To support the diversification argument, NO1's performance in the main period should correspond with this effect after introducing wind generation in 2019. However, this effect is only found evident in the mean equation as previously discussed. A possible explanation for this observation could be that the strengthening of interconnections among price areas might diminish NO1's ability to benefit from diversification through wind fluctuations. This scenario suggests that the complex interactions between the areas could potentially offset some of the region-specific risk exposures.

Higher wind penetration during the main period compared to the control period increases the impact on electricity prices, reflecting the sensitivity to wind when it constitutes a larger portion of the total electricity generation. The results indicate a more pronounced effect of wind in the main period compared to the control period, through the larger presented coefficients. The increased relative contribution of wind electricity makes the overall electricity supply more susceptible to fluctuations in wind. High wind generation can notably decrease electricity prices and vice versa. This phenomenon of wind penetration affecting prices and volatility mirrors the observations made in studies of the German and Spanish markets by Ketterer (2014) and Pereira et al. (2017), respectively.

Overall, the wind coefficients have exhibited different influence in the mean and variance equations from the control to the main period. It has been argued that the higher wind penetration alters market structures, thereby exerting a more pronounced influence in the main period. Furthermore, the enhanced impact of wind on pricing, compared to the control period, may be linked to more extreme weather conditions, which can be favorable for wind electricity. Factors such as temperature shifts and changing precipitation patterns, especially in recent years, have led to these extreme conditions, potentially contributing to the rise in wind generation. Overall there has been identified a marginal increase in wind speed in Norway during til last 50 years, but exhibit large annually and geographically variations (Hanssen-Bauer et al., 2017). However, the limited research on the historical evolution of wind patterns and their market risk implications makes it challenging to ascertain whether the observed increase in volatility and larger price impacts are due to climate change or simply higher wind penetration. Nevertheless, this topic remains interesting for future research. It is important to understand how shifts in wind patterns, whether caused by natural variability or climate change, affect electricity price volatility, as this reflects the changing dynamics of the electricity market.

7.3 Future Forecasts

Moving into the discussion about future forecasts in the light of climatic and structural changes, the discussion proceeds under the assumption that the model is precise and the differences identified between the control and main periods are reliable. While historical development does not guarantee future development, they can provide valuable insights into the relationship between the variables of interest. This exploration seeks to unravel how the relationships, identified and discussed, might contribute to future development and impacts in the context of an evolving electricity market.

The future impact of climate change will depend on global greenhouse gas emissions (Jackson, 2023). With the current situation of increasing greenhouse gas emissions, there is expected that Norway is facing rising temperatures year-round. Notably, the most significant change for Norway in the future is anticipated to be in precipitation patterns. Overall, precipitation is projected to rise, but will more often occur as intense rainfall episodes. This will lead to larger and more frequent rain floods, while frequency and size of snowmelt floods will decrease. Changes in snow patterns are also anticipated; in coastal and low-lying areas, snowfall is expected to decrease, whereas in mountainous regions, it may increase (Hanssen-Bauer et al., 2017).

Table 7.7 details the proportions of hydropower and wind power generation as a percentage of the total load in the price areas for the years 2022 and 2040, as forecasted.

Table 7.7: Percentage of Total Load

% of Load	NO1	NO2	NO3	NO4	NO5
2022					
Hydro	50%	132%	73%	125%	186%
Wind	4%	14%	26%	20%	0%
2040					
Hydro	40%	82%	63%	81%	142%
Wind	9%	62%	39%	16%	12%

Calculations based on NVE (Kirkerud et al., 2023)

7.3.1 Hydrological Balance Forecasts

The expected continuing changes in climate patterns are, in line with previously discussion, expected to increase the instability and occurrence of extreme values in the hydrological balance. This development is consistent with meteorological and climate research, which forecasts a rise in both the annual water inflow to reservoirs and the variability of this inflow annually and within the year (Gran et al., 2023, p. 149). Additionally, the changes in snow patterns will reduce snow volume and bring forward the timing of snowmelt. This shift is projected to result in diminished spring floods, which have historically been essential for refilling reservoirs and balancing the high electricity generation volumes during the winter months.

According to NVE's 2023 forecast, total hydropower generation in Norway is expected to increase modestly by 12% by 2040 compared to 2022, but will only constitute 70% of the national generation mix (Kirkerud et al., 2023). As shown in Table 7.7, the proportion of hydro generation relative to the total load is predicted to decrease in all areas. From the 2022 baseline, the share of hydropower in total load is anticipated to drop by 10 percentage points in NO1 and NO3, and nearly 50 percentage points in NO2, NO4, and NO5.

The reduction in hydro's share of the electricity mix leads to greater reliance on and sensitivity to fluctuations in hydrological levels, as discussed in the main model. The increased vulnerability arises because wind power, to a lesser extent, can offset hydropower. Both technologies are needed to maximize generation output and to meet total demand. Particularly, NO2 and NO4 are forecast to transition from having a hydro surplus to being unable to meet their own demand solely through hydro generation. To illustrate, in NO2, hydro generation is expected to reduce from covering 132% to only 82% of the total demand by 2040. This shift indicates a growing dependence on alternative electricity sources, especially wind, to compensate for the diminishing hydro surplus. Consequently, this could make these areas more internally affected by variations in the hydrological balance, as they become more reliant on the total hydro generation.

In 2022, NO5 demonstrated significant self-sufficiency in hydropower generation, with output reaching 190% of its total load. This surplus has led to suggestions that the area is internally less affected by fluctuations in the hydrological balance. However, future projections indicate that NO5's hydropower generation will align more closely with its internal load levels. This shift could expose NO5 to greater risks related to hydrological fluctuations, potentially resulting in increased price sensitivity. On the other hand, the Norwegian Meteorological Institute predicts that NO5 will experience an increase in precipitation, though with consistent patterns, which might lessen the adverse effects on the future electricity prices. In a contrasting scenario, NO1 is expected to encounter increasingly volatile precipitation patterns, maintaining a steady volume (Steiro, 2023). This increased precipitation volatility in NO1 can consequently lead to more uncertainty in electricity prices.

7.3.2 Wind Generation Forecasts

The future impact of climate change on wind patterns remains uncertain. Nonetheless, there is a direct relationship between wind speed and electricity generation, where higher wind speeds yield increased electricity output. The efficiency of wind power depends on the temperature differences between cold polar and warm tropical regions (Robbins, 2022). The progressive impact of global warming, notably in Norway (Rommetveit et al., 2021), is gradually reducing these temperature contrasts. This trend could pose a challenge to wind electricity: as temperature differentials diminish, a potential decline in wind speeds may become apparent. Consequently, the effectiveness of wind-based electricity generation could diminish, and the variability of wind patterns may increase, leading to heightened uncertainty in this electricity sector.

The hypothesis that climate change will alter wind patterns, especially given the increasing frequency of extreme weather events, is plausible. However, the NVE has forecasted that wind patterns, including speed and frequency, are expected to remain stable in the coming decades (Kirkerud et al., 2023). This projection is particularly noteworthy as it contradicts the expectation of increased variability associated with rapid climate changes. In light of these forecasts, market dynamics are likely to evolve more due to structural changes and the associated uncertainties in demand fulfillment, rather than direct climatic influences. However, climate change's potential to alter wind patterns may become increasingly relevant over an extended timeframe.

Wind power generation, encompassing both onshore and offshore technologies, is expected to see a dramatic 250% increase according to NVE projections (Kirkerud et al., 2023). This significant rise is poised to transform the current generation mix, moving from the stabilizing effects of hydropower to a future marked by greater reliance on intermittent resources. As wind technology becomes more integrated into the market, its impact on electricity prices – affecting both average levels and volatility – is expected to increase.

By 2040, an expansion in wind penetration is forecasted across all Norwegian pricing areas, with the exception of NO4. Historically, increased wind penetration has been linked to heightened price volatility. Specifically, NO1 and NO3, which are already facing power shortages, are likely to see more significant effects on pricing and volatility, especially during peak hours. This underscores the importance of analyzing data for both peak and off-peak periods (Kirchner et al., 2022, p. 5). While the combined wind and hydro generation is expected to remain at the same level, the reliance will lean more towards wind generation. Furthermore, NO4 is anticipated to experience a shortfall in meeting its 2040 demand with its current hydro and wind capacities, likely requiring the addition of other electricity sources. The future scenario of power deficit across NO1, NO3, and NO4 points to increased sensitivity in prices and volatility.

Furthermore, heightened wind penetration, as Ketterer (2014) suggests, could eventually decrease price volatility, if wind electricity becomes a substantial component of the electricity mix. This effect was found evident in Denmark's electricity market, which heavily relies on wind power. However, in contrast to Denmark, Norway's future electricity landscape is expected to continue being predominantly hydro-based. Despite the rapid growth of wind power, it is not projected to become the primary electricity source. This scenario raises questions about whether the rise of wind electricity in Norway will be substantial enough to stabilize the market.

In Denmark, the wind penetration in the market reached 44% in 2021 (Fernández, 2023). Comparatively, forecasts for Norway suggest that NO2 and NO3 will attain wind penetrations of 62% and 39%, respectively. Such levels are close to or surpass Denmark's. Consequently, in the Norwegian market, the combination of hydro and increasing wind penetration could potentially contribute to reduced volatility. This indicates a scenario where both hydro and wind generation may collectively foster a more stable electricity pricing environment, especially where wind penetration will become notably high.

7.3.3 Extended Market Implications

The forecasted regional developments can indicate a growing divergence among Norwegian areas, potentially leading to heightened market uncertainty. Interestingly, NVE's Long-Term Power Market Analysis predicts more uniform electricity prices between Northern and Southern Norway by 2040, a notable shift from the significant price variations recently observed. If future developments exhibit regional variations, this could further drive price differences. However, NVE attributes this projected uniformity to enhanced transmission networks with Northern and Southern Sweden, expected to mitigate bottlenecks (Kirkerud et al., 2023). While these improvements could reduce price disparities, achieving complete price alignment may be improbable due to the existing market structure. In this scenario, network enhancements are expected to distribute risk more uniformly across different price areas. However, the overall risk from climatic and structural changes will remain pertinent, likely affecting future electricity prices.

In the Norwegian electricity market, increased generation is important to meet future demand levels. On the other hand, the anticipated rise in market uncertainty poses a potential challenge for future investments in the Norwegian electricity market. This scenario, as supported by financial theory, suggests that heightened risk from market instability could prompt investors to seek higher returns, further leading to lower investment levels. This trend is particularly concerning, given Norway's need to expand its electricity generation capacity both to meet growing demands and to achieve climate goals. Additionally, the electricity sector's investments typically require a long horizon to become profitable, adding to the investment challenge. This is particularly applicable to wind electricity, as the difficulty in adjusting generation to price fluctuating makes it a less appealing option for investors (Gran et al., 2023, p. 163). Ketterer (2014) also argues that low and volatile prices for renewable electricity can make investors hesitant to invest in the market.

Understanding the implications of heightened market risk involves considering Norway's challenges in achieving its 2030 and 2050 climate targets. The Energy Transition Outlook 2023 report from DNV (2023) highlights Norway's shortfall in achieving these climate objectives. Projections show that at the current emissions reduction pace, Norway could be three decades behind schedule in reaching its 2030 target, emphasizing the need for increased investment in the electricity sector (Rommetveit et al., 2021). Reducing greenhouse gas emissions are important to slow down future climate changes and increased market risks (Hanssen-Bauer et al., 2017). Norway's capability of achieving its climate objectives and lower emissions are critically dependent on heightened investment levels. This creates a paradox: investment can stabilize the market and slow down climate change, but uncertainties might inhibit these investments. Overcoming this barrier is important for Norway's electricity market stability and progress towards climate targets.

7.4 Impact of International Dynamics

The scope of this thesis encompasses national variables within the Norwegian electricity market. Nonetheless, it is imperative to highlight the broader implications of an increasingly interconnected market on the Norwegian price levels and market volatility. The traditional electricity market, previously defined by national supply and demand dynamics, is undergoing a significant transformation. Interconnectors such as NordLink and North Sea Link not only expand the market's geographical scope, but they also incorporate a new layer of complexity. The market is now integrated into the broader European network.

Norway's integration into a broader market allows for a more diversified electricity portfolio, mitigating risks tied to dominated hydro generation. As a result of a broader dependence on technologies and different weather-dependent renewable generation, varied market reactions emerge across Europe. For example, a dry year in Norway might escalate electricity prices due to reduced hydrological balance. For contrast, in Germany, these weather conditions can result in an abundance of solar and wind electricity, potentially lowering German prices.

The heightened need for flexibility and stability in the power system, especially with the shift towards intermittent renewable energy sources, elevates the significance of international electrical cables (Kustani, n.d.). Constructing power networks between Norway and European neighbors is important for enhancing the flexibility and balancing the Norwegian electricity supply's dependency on local weather variations and the often mismatched geographical locations of demand and supply. The Norwegian electricity market will at times have significant surplus capacity useful for export, while during other periods the market may need to import electricity to fulfill national demand (Gran et al., 2023). Resulting in reduction of volatility sourced from domestic fluctuations.

However, while these interconnected networks add flexibility to renewable electricity markets, research indicates that increased reliance on cross-border electricity resources could potentially lead to more than just elevated average electricity prices, but also intensify market volatility (DNV, 2023). The integration introduces Norway to the inherent volatility of the European electricity market, influenced by geopolitical factors, supply chain issues, and the intermittent nature of renewable electricity sources.

Norway's renewable-dominated landscape contrasts sharply with Europe's varied electricity mix, which includes a significant portion of gas, coal, and nuclear energy. This disparity significantly alters the merit order. While renewable technology, with their negligible marginal costs, typically lower the merit order, the inclusion of higher-cost non-renewables in Europe introduce steeper merit order curves and thus higher price volatility. Ketterer (2014) sheds light on this concept by illustrating the effects of Germany's nuclear phase-out, which leads to a flattening of the merit order curve and, subsequently, affects how increased wind electricity influences prices.

As Europe continues its green transition, the merit order curve is likely to flatten further, resulting from the phase-out of non-renewables. Conversely, unlike Norway, with feasible storage capabilities to store renewable electricity, Europe's lack of similar storage capabilities on the supply side could perpetuate higher volatility, suggesting a lasting impact on Norway due to high volatility in Europe.

Despite Norway's diversified risk profile due to international market integration, climate change poses additional uncertainties. As the Norwegian market becomes more susceptible to external factors, it faces increased exposure to climate risk. The heightened interdependency on continental dynamics may exacerbate the market's vulnerability to global climate phenomena, leading to greater overall risk.

Looking ahead, the internationalization of the electricity market poses critical questions about the adequacy of relying solely on national climate variables to capture the entire effect of influential factors. Norway's intensifying dependence on the European continent might suggest that the actual impacts of climate conditions might extend beyond the scope of national climate development alone. This scenario indicates that the Norwegian electricity market could face even more significant and complex climate risks. These aspects have not been fully addressed and fall outside the scope of the thesis.

8 Conclusion

This thesis aimed to explore the effect of hydro and wind generation on both the mean and volatility of electricity prices in the Norwegian electricity market, particularly from a climate change perspective. This involved analyzing the risks associated with weather-dependent hydro and wind generation, segmented into historical and future developments. The study underscores distinct market dynamics and risk exposures across various Norwegian price areas, influenced by their unique electricity generation mixes and geographical traits. The interaction of wind and hydro resources, compounded by regional dependencies and interconnections, offers an extensive insight into the electricity market's functioning and its financial implications.

The methodology employed was an ARMA(7,7)-EGARCH(1,1) model with hydrological balance, wind generation, and total load as external regressors in both the mean and variance equations. Key findings from Chapter 7.1 indicate that an increase in hydrological balance and wind generation typically lowers the average price due to augmented supply. An increase in hydrological balance is found to reduce volatility explained by its stabilizing characteristics, whereas wind generation exacerbates volatility due to its intermittent nature. Furthermore, market shocks is found to have a prolonged effect on prices, indicating persistent volatility in the dataset.

Intrestingly, all price areas demonstrated "inverse leverage effects", where positive market shocks have a more significant impact on volatility. Implying that the market dynamics are more resilient in handling the negative shocks. The empirical findings demonstrate the ARMA-EGARCH model's robustness in accurately capturing the conditional mean and variance of the price process, providing estimations that are easily interpretable and align with economic reasoning.

Continuing discussions in Chapter 7.2 and 7.3 explore the potential impact of climate change, climate risk, and international dynamics. The comparing analysis reveals that hydrological balance and wind generation now exert a greater and more significant influence on price levels and volatility, relative to the control periods. A coefficient shift in the hydrological balance could be linked to more unstable precipitation patterns. Conversely, the findings regarding wind generation present a complex picture; the growth and integration of wind electricity make it challenging to attribute changes exclusively to climatic factors. Instead, the observed shifts might be explained by the rising wind penetration in the Norwegian market. Projected market developments are expected to result in heightened volatility in the Norwegian market, driven by factors such as rising temperatures, changing precipitation patterns, increased wind penetration, and a growing power deficit. These elements not only add to market uncertainty but also pose challenges in meeting climate targets and reducing climate emissions.

The findings in this thesis can offer interesting insights into the influence of hydro and wind generation and their consequential effects on the price dynamics and risk profile within the Norwegian electricity market. A market that is notably susceptible to climatic and structural shifts. In a broader context, these findings can contribute to an improved understanding of the complex nature and evolving electricity markets.

A further extension of this thesis should include structural breaks analysis to better grasp the impact of renewables on electricity prices. The increasing wind penetration over the sample period and potential shifts in hydrological variability, may reveal structural breaks in the model. To enhance the precision of capturing climate-related impacts on the electricity market, an expanded model could incorporate a causal analysis and adopt an international perspective, thereby offering insights into how international climate dynamics affect market operations.

Further research could involve replicating this study with updated datasets to gain insights into the ongoing evolution of the Norwegian electricity market. The inclusion of publicly available data enhances the transparency and reproducibility of the study, facilitating future investigations to build upon these findings and explore emerging developments in the dynamic electricity landscape.

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Appendices

A Data Analysis

A.1 Unit Root and Stationarity

Table A.1: Unit Root and Stationarity Tests Peak Series

Variable	**ADF**	**DF-GLS**	**PP**	**KPSS**
Price				
NO1	-5.7299*	-6.8843*	-140.68*	2.0064
NO2	-5.7148*	-7.4751*	-160.29*	2.6409
NO3	-6.2981*	-10.6377*	-226.67*	0.82795
NO4	-5.9403*	-11.8983*	-363.61*	1.0419
NO5	-5.7842*	-6.8118*	-134.93*	2.0302
Hydrological Balance				
NO	-5.0514*	-4.4142*	-62.06*	1.6371
Wind				
NO1	-8.9500*	-19.6886*	-1414.8*	11.985
NO2	-11.895*	-23.3819*	-1474.3*	10.301
NO3	-8.6828*	-19.2974*	-1229.8*	13.472
NO4	-10.164*	-18.8321*	-1147.6*	13.974
NO5	NA	NA	NA	NA
Load				
NO1	-7.3832*	-5.5677*	-162.43*	2.097
NO2	-6.388*	-5.9263*	-152.44*	1.4208
NO3	-7.6684*	-6.1772*	-198.5*	1.1804
NO4	-6.7705*	-5.6903*	-163.66*	0.72797
NO5	-6.7705*	-5.6903*	-163.66*	0.72797

** Stationary at the 5% level*

Table A.2: Unit Root and Stationarity Tests Off-Peak Series

Variable	**ADF**	**DF-GLS**	**PP**	**KPSS**
Price				
NO1	-5.14*	-5.4748*	-89.552*	2.0627
NO2	-4.963*	-5.6114*	-90.195*	2.8347
NO3	-6.5544*	-9.998*	-141.27*	0.76206
NO4	-5.4579*	-8.6732*	-128.76*	1.7758
NO5	-5.1845*	-5.4323*	-87.046*	2.1126
Hydrological Balance				
NO	-5.0514*	-4.4142*	-62.06*	1.6371
Wind				
NO1	-8.6535*	-19.2181*	-855.2*	13.923
NO2	-11.001*	-21.891	-990.94*	10.97
NO3	-8.7179*	-18.2396*	-760.56*	13.543
NO4	-9.9583*	-18.8203*	-695.35*	14.261
NO5	NA	NA	NA	NA
Load				
NO1	-7.291*	-5.453*	-139.80*	1.3128
NO2	-6.386*	-5.7268	-131.72*	0.9079
NO3	-7.5152*	-6.0089*	-178.84*	1.6719
NO4	-6.5184*	-5.8751*	-142.58*	1.085
NO5	-6.5184*	-5.8751*	-142.58*	1.085

** Stationary at the 5% level*

A.2 Multicollinearity

Table A.3: Correlation Matrices for Independent Variables Peak

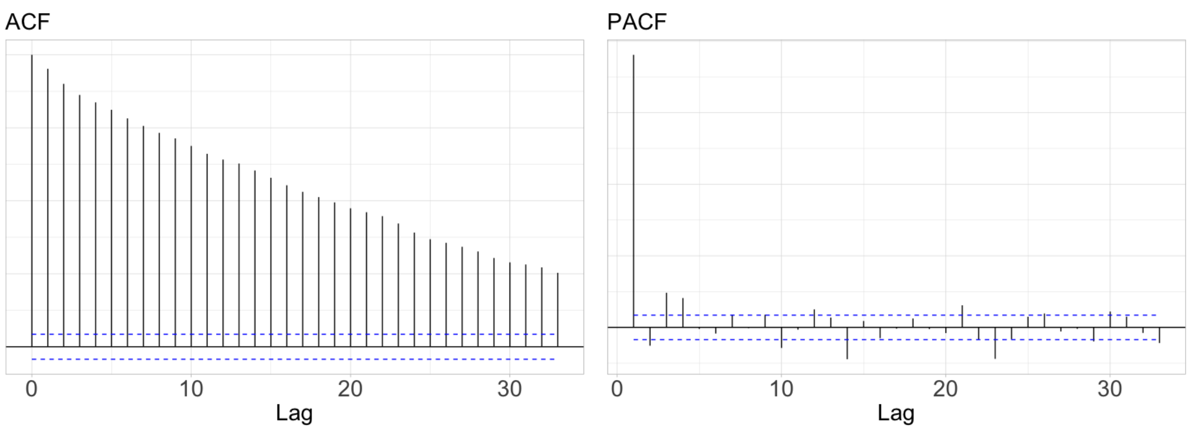
Peak NO1			
	Hydrological Balance	Wind	Load
Hydrological Balance	1.00	0.065	0.017
Wind	0.065	1.00	0.038
Load	0.017	0.038	1.00
Peak NO2			
	Hydrological Balance	Wind	Load
Hydrological Balance	1.00	0.074	0.043
Wind	0.074	1.00	0.152
Load	0.043	0.152	1.00
Peak NO3			
	Hydrological Balance	Wind	Load
Hydrological Balance	1.00	0.047	0.019
Wind	0.047	1.00	0.318
Load	0.019	0.318	1.00
Peak NO4			
	Hydrological Balance	Wind	Load
Hydrological Balance	1.00	0.059	0.007
Wind	0.059	1.00	0.285
Load	0.007	0.285	1.00
Peak NO5			
	Hydrological Balance	Wind	Load
Hydrological Balance	1.00		0.007
Wind			
Load	0.007		1.00

Table A.4: Correlation Matrices for Independent Variables Off-Peak

Off-Peak NO1			
	Hydrological Balance	Wind	Load
Hydrological Balance	1.00	0.066	0.025
Wind	0.066	1.00	0.005
Load	0.025	0.005	1.00
Off-Peak NO2			
	Hydrological Balance	Wind	Load
Hydrological Balance	1.00	0.064	0.056
Wind	0.064	1.00	0.182
Load	0.056	0.182	1.00
Off-Peak NO3			
	Hydrological Balance	Wind	Load
Hydrological Balance	1.00	0.050	0.021
Wind	0.050	1.00	0.307
Load	0.021	0.307	1.00
Off-Peak NO4			
	Hydrological Balance	Wind	Load
Hydrological Balance	1.00	0.053	0.018
Wind	0.053	1.00	0.298
Load	0.018	0.298	1.00
Off-Peak NO5			
	Hydrological Balance	Wind	Load
Hydrological Balance	1.00		0.018
Wind			
Load	0.018		1.00

A.3 Autocorrelation Price Series

Figure A.1: Autocorrelation Plots Off-Peak NO1



A.4 Information Criteria ARMA Models

Table A.5: ARMA Model Results Peak NO1

Model	LL	AIC	BIC
ARMA(0,0)	-16383.94	32771.88	32783.18
ARMA(1,0)	-14435.73	28877.45	28894.40
ARMA(2,0)	**-14430.74**	**28869.48**	**28892.08**
ARMA(3,0)	-14411.53	28833.07	28861.32
ARMA(4,0)	-14400.80	28813.61	28847.50
ARMA(5,0)	-14400.76	28815.52	28855.06
ARMA(6,0)	-14380.18	28776.36	28821.55
ARMA(7,0)	**-14379.53**	**28777.06**	**28827.90**
ARMA(0,1)	-15493.51	30993.03	31009.97
ARMA(0,2)	-15013.65	30035.31	30057.90
ARMA(0,3)	-14892.27	29794.55	29822.79
ARMA(1,1)	-14428.54	28865.07	28887.67
ARMA(2,2)	-14399.70	28811.40	28845.30
ARMA(3,3)	-14387.97	28791.94	28837.14
ARMA(4,4)	-14381.56	28783.12	28839.62
ARMA(5,5)	-14363.18	28750.37	28818.16
ARMA(6,6)	-14339.74	28707.47	28786.56
ARMA(7,7)	**-14339.38**	**28710.76**	**28801.15**
ARMA(2,5)	-14387.84	28793.68	28844.53
ARMA(2,7)	-14373.13	28768.26	28830.40

Table A.6: ARMA Model Results Off-Peak NO1

Model	LL	AIC	BIC
ARMA(0,0)	-16045.29	32094.58	32105.88
ARMA(1,0)	-13555.08	27116.15	27133.10
ARMA(2,0)	**-13550.78**	**27109.56**	**27132.16**
ARMA(3,0)	-13535.15	27080.30	27108.55
ARMA(4,0)	-13523.88	27059.76	27093.66
ARMA(5,0)	-13523.85	27061.71	27101.25
ARMA(6,0)	-13523.36	27062.72	27107.91
ARMA(7,0)	**-13521.36**	**27060.72**	**27111.56**
ARMA(0,1)	-14967.73	29941.47	29958.42
ARMA(0,2)	-14391.93	28791.85	28814.45
ARMA(0,3)	-14107.71	28225.43	28253.67
ARMA(1,1)	-13549.50	27107.00	27129.59
ARMA(2,2)	-13530.18	27072.37	27106.26
ARMA(3,3)	-13542.50	27101.00	27146.19
ARMA(4,4)	-13510.49	27040.99	27097.48
ARMA(5,5)	-13508.88	27041.76	27109.55
ARMA(6,6)	-13509.29	27046.59	27125.68
ARMA(7,7)	**-13488.87**	**27009.74**	**27100.12**
ARMA(2,5)	-13517.21	27052.42	27103.26
ARMA(2,7)	-13517.08	27056.15	27118.29

A.5 Ljung-Box Test

Table A.7: Ljung-Box Test Q-Statistic

Model	NO1	NO2	NO3	NO4	NO5
ARMA(0,0)	12269	12188	8875.4	7222	12346
ARMA(1,0)	117.16	226.34	107.21	133.49	116.53
ARMA(2,0)	**116.79**	**229.64**	**97.05**	**109.58**	**117.39**
ARMA(3,0)	83.99	144.45	92.878	89.341	83.715
ARMA(4,0)	67.864	136.87	94.642	86.814	70.384
ARMA(5,0)	68.164	135.16	80.077	86.028	70.087
ARMA(6,0)	18.665*	57.609	80.924	87.941	30.158
ARMA(7,0)	**16.372***	**41.913**	**66.733**	**79.169**	**26.921**
ARMA(0,1)	7078.2	6850.1	4491.8	3207.8	7165.9
ARMA(0,2)	3318.9	3066.7	2341.8	1586.7	3422.4
ARMA(0,3)	2153.1	2058.9	1113.6	822.02	2186.8
ARMA(1,1)	115.93	228.95	95.992	102.04	117.42
ARMA(2,2)	57.817	112.94	76.338	70.912	59.437
ARMA(3,3)	43.244	90.313	75.708	68.887	50.452
ARMA(4,4)	26.042	57.074	46.072	58.623	28.883
ARMA(5,5)	21.623	30.4	32.066	55.622	30.423
ARMA(6,6)	8.9653*	46.863	30.596	31.399	9.2105*
ARMA(7,7)	**9.9801***	**17.916***	**2.9672***	**4.2884***	**10.992***
ARMA(2,5)	35.457	99.989	57.257	68.111	51.292
ARMA(2,7)	1.3915*	8.1421*	45.408	32.237	1.6979*

** No autocorrelation at the 5% level. Df = 10*

A.6 Autocorrelation AR(7)

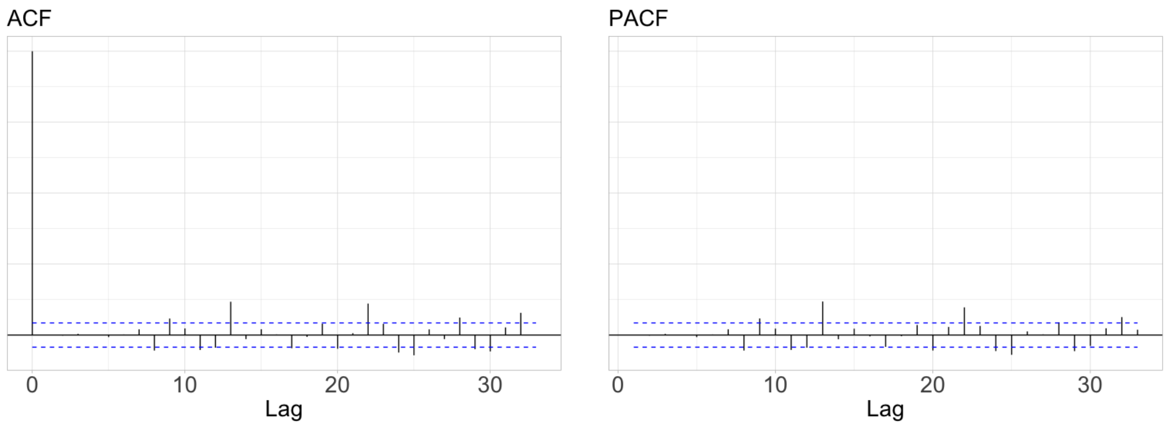


Figure A.2: Autocorrelation AR(7) Off-Peak NO1

A.7 Autocorrelation ARMA(7,7)

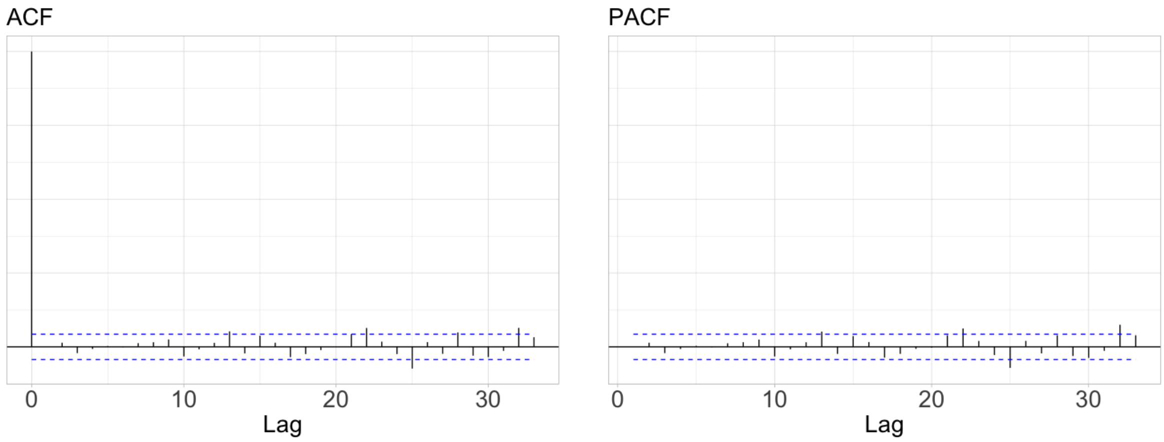


Figure A.3: Autocorrelation ARMA(7,7) Off-Peak NO1

A.8 Autocorrelation Squared Residuals ARMA

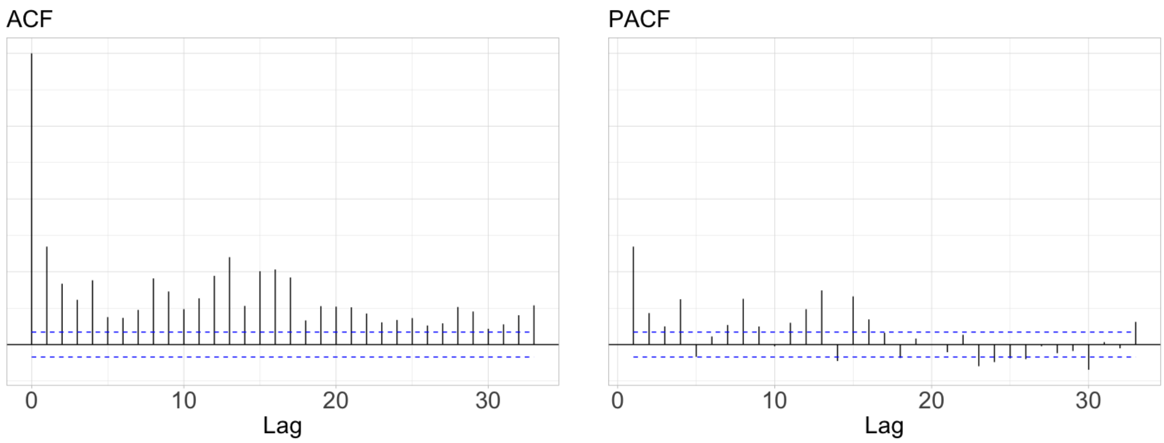


Figure A.4: Autocorrelation Squared Residuals ARMA(7,7) Off-Peak NO1

A.9 ARCH Test Heteroskedasticity

Table A.8: ARCH Test Heteroskedasticity (LM-test) Peak

Model	Lags	NO1	NO2	NO3	NO4	NO5
ARMA(7,7)	4	207.16*	182.67*	477.04*	137.14*	197.25*
	8	239.00*	238.86*	669.15*	248.56*	228.2*
	16	308.11*	306.79*	685.63*	298.67*	301.34*
	32	407.38*	368.86*	707.61*	308.60*	401.3*

**Significant at the 1% level*

Table A.9: ARCH Test Heteroskedasticity (LM-test) Off-Peak

Model	Lags	NO1	NO2	NO3	NO4	NO5
ARMA(7,7)	4	310.28*	202.84*	222.31*	447.48*	316.94*
	8	365.83*	270.10*	441.95*	561.66*	378.66*
	16	524.82*	372.74*	475.66*	623.11*	529.39*
	32	564.76*	433.66*	495.44*	676.63*	564.09*

**Significant at the 1% level*

A.10 Autocorrelation Residuals ARMA-EGARCH

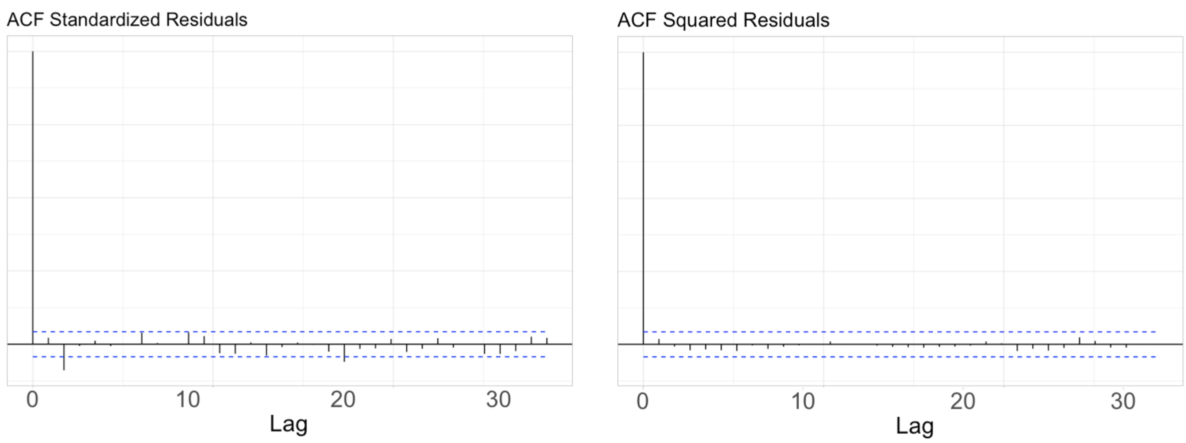


Figure A.5: Autocorrelation Residuals ARMA(7,7)-EGARCH(1,1) Off-Peak NO1

B Results

B.1 Detailed Model Output 2018-2023

Table B.1: EGARCH Model Fit Peak Hours (2018-2023)

	NO1	NO2	NO3	NO4	NO5
A. Conditional Mean Equation					
μ	255.0869	255.3865	351.4498	318.0996	223.3969
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	-0.0008	0.0013	-0.0128	-0.0123	-0.0024
	(0.0000)	(0.0139)	(0.0153)	(0.0030)	(0.0000)
ϕ_2	-0.0010	0.0023	0.0065	0.0137	0.0016
	(0.0000)	(0.0004)	(0.0000)	(0.0033)	(0.0000)
ϕ_3	-0.0031	0.0009	0.0239	0.0198	-0.0016
	(0.0000)	(0.0483)	(0.0000)	(0.0050)	(0.0000)
ϕ_4	-0.0009	0.0008	0.0254	0.0128	-0.0002
	(0.0001)	(0.0393)	(0.0000)	(0.0000)	(0.4106)
ϕ_5	-0.0039	-0.0003	-0.0085	-0.0107	-0.0021
	(0.0000)	(0.1047)	(0.0036)	(0.0032)	(0.0000)
ϕ_6	0.0007	0.0021	-0.0209	-0.0183	-0.0004
	(0.0000)	(0.0000)	(0.0000)	(0.0087)	(0.1008)
ϕ_7	1.0016	1.0022	0.9647	0.9585	1.0052
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_1	0.8011	0.8196	0.8074	0.7333	0.8431
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_2	0.7864	0.7623	0.7323	0.6285	0.7920
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_3	0.7404	0.7352	0.5523	0.5394	0.7613
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_4	0.7199	0.7339	0.4382	0.5039	0.7402
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_5	0.7132	0.6938	0.4600	0.4917	0.7018
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_6	0.7398	0.7090	0.5943	0.5421	0.7178
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

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Table B.1 – continued from previous page

	NO1	NO2	NO3	NO4	NO5
θ_7	-0.1963	-0.1779	-0.2297	-0.2396	-0.1636
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
b_t	-48.6953	-84.7086	-95.9825	-51.6897	-19.9572
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
w_t	-5.5534	-4.9439	-14.0151	-7.1976	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
l_t	14.9124	9.5307	11.5453	14.0528	2.0377
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
B. Conditional Variance Equation					
ω	0.0774	0.0569	0.2646	0.2057	0.0247
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
α_1	0.0473	0.0818	0.0902	0.0397	0.0236
	(0.0250)	(0.0007)	(0.0000)	(0.0711)	(0.3188)
β_1	0.9913	0.9938	0.9696	0.9743	0.9976
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_1	0.3195	0.2798	0.5132	0.3160	0.3575
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
b_t	-0.0109	-0.0099	-0.0121	-0.0091	-0.0089
	(0.0078)	(0.0099)	(0.0665)	(0.0566)	(0.0228)
w_t	0.0201	0.0340	0.0177	0.0234	NA
	(0.0020)	(0.0000)	(0.0973)	(0.0028)	NA
l_t	-0.0254	-0.0151	-0.0026	-0.0007	-0.0109
	(0.0000)	(0.0036)	(0.7698)	(0.9166)	(0.0600)
ν	2.6232	2.6235	2.4899	2.5656	2.4931
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
C. Model Fit Statistics					
AIC	11.297	11.356	10.902	10.390	11.187
BIC	11.367	11.426	10.972	10.460	11.252
Shibata	11.297	11.355	10.902	10.389	11.187
Hannan-Quinn	11.323	11.381	10.928	10.415	11.211
Log Likelihood	-11830.5	-11891.7	-11416.14	-10878	-11716.89
Q(30) p-value	0.0001	0.1962	0.0518	0.4351	0.0886
$Q(30)^2$ p-value	1.0000	1.0000	0.9794	1.0000	1.0000

Table B.2: EGARCH Model Fit Off-Peak Hours (2018-2023)

	NO1	NO2	NO3	NO4	NO5
A. Conditional Mean Equation					
μ	325.3454	317.0026	319.5105	306.9518	337.1040
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	1.6280	0.9344	1.4845	1.9323	1.6251
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_2	-1.3735	-0.6017	-1.3453	-0.3471	-1.3534
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_3	0.8466	0.1462	0.8133	-1.7791	0.8129
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_4	-0.1511	0.3328	-0.0248	1.1369	-0.1113
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_5	-0.5757	-0.7537	-0.6163	1.2750	-0.6144
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_6	1.1877	1.0181	0.9817	-1.7100	1.2167
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_7	-0.5611	-0.0858	-0.2928	0.4921	-0.5751
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_1	-0.7263	-0.0364	-0.4799	-1.0048	-0.6743
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_2	0.7126	0.5671	0.6633	-0.6618	0.6636
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_3	-0.1347	0.4011	0.0543	1.2971	-0.0973
	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0000)
θ_4	-0.0502	0.0328	-0.1073	0.0856	-0.0663
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_5	0.6387	0.8362	0.6057	-1.3357	0.6403
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_6	-0.6762	-0.2137	-0.3262	0.5088	-0.6515
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_7	0.0551	-0.0616	-0.1392	0.1096	0.0168
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
b_t	-64.1197	-85.4438	-67.9909	-49.2885	-68.9300
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
w_t	-5.4258	-6.7368	-13.5122	-6.4163	

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Table B.2 – continued from previous page

	NO1	NO2	NO3	NO4	NO5
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
l_t	12.3907	7.0253	10.3045	10.3933	7.6461
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
B. Conditional Variance Equation					
ω	0.1699	0.1957	0.2714	0.3544	0.1144
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1	0.0023	-0.0290	0.0087	-0.0670	-0.0041
	(0.9162)	(0.3186)	(0.7567)	(0.0018)	(0.8493)
β_1	0.9786	0.9777	0.9678	0.9507	0.9857
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_1	0.4473	0.4100	0.5906	0.5894	0.4383
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
b_t	-0.0145	-0.0136	-0.0142	-0.0201	-0.0093
	(0.0285)	(0.0113)	(0.0435)	(0.0200)	(0.1304)
w_t	0.0299	0.0680	0.0300	0.0232	
	(0.0007)	(0.0000)	(0.0047)	(0.0505)	
l_t	-0.0051	-0.0135	-0.0138	0.0051	0.0020
	(0.5506)	(0.0494)	(0.1609)	(0.6284)	(0.8057)
ν	3.0906	2.4740	2.3528	2.6645	3.0602
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
C. Model Fit Statistics					
AIC	10.273	10.545	9.9748	9.3986	10.256
BIC	10.343	10.615	10.0447	9.4685	10.321
Shibata	10.272	10.544	9.9745	9.3983	10.256
Hannan-Quinn	10.298	10.570	10.0004	9.4242	10.280
Log Likelihood	-10755.18	-11040.59	-10442.52	-9837.793	-10739.85
Q(30) p-value	0.0001	0.0001	0.0549	0.5208	0.0001
$Q(30)^2$ p-value	0.9988	1.0000	0.0001	0.9967	0.9993

B.2 Detailed Model Output 2010-2014

Table B.3: EGARCH Model Fit Peak Hours (2010-2014)

Parameter	NO1	NO2	NO3	NO4	NO5
A. Conditional Mean Equation					
μ	143.0725	350.9030	302.3828	296.1962	319.7932
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.9233	0.9008	0.7678	0.7802	0.9134
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_2	-0.0701	-0.1042	-0.1663	-0.1472	0.0015
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.8473)
ϕ_3	-0.0111	0.0765	0.0690	0.0659	-0.0694
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_4	-0.0085	-0.0024	0.0218	0.0366	0.0321
	(0.0000)	(0.5523)	(0.0043)	(0.4019)	(0.1951)
ϕ_5	0.0275	-0.0317	-0.0411	-0.0662	0.0195
	(0.0000)	(0.0000)	(0.0000)	(0.0101)	(0.0358)
ϕ_6	0.1111	0.1043	0.1696	0.1696	0.0716
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_7	0.0294	0.0521	0.1368	0.1244	0.0242
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1578)
b_t	-75.4538	-42.6711	-59.5142	-45.1651	-84.3075
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
w_t	NA	-1.7478	-2.1183	-1.1198	
	NA	(0.0000)	(0.0000)	(0.0083)	
l_t	19.2090	5.3352	5.5069	4.9270	8.8499
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ω	0.7561	0.5516	0.5941	0.6452	0.5619
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0049)
B. Conditional Variance Equation					
α	0.1171	-0.1833	-0.0227	-0.0309	0.0767
	(0.0005)	(0.0000)	(0.5008)	(0.4125)	(0.0154)
β	0.8779	0.9072	0.9147	0.9075	0.9048
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.5999	0.6699	0.5279	0.6196	0.5074
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

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Table B.3 continued from previous page

	NO1	NO2	NO3	NO4	NO5
b_t	-0.0040	-0.0108	-0.0017	-0.0034	-0.0090
	(0.7821)	(0.4667)	(0.8928)	(0.8073)	(0.4540)
w_t	NA	-0.0272	-0.0859	-0.0414	
	NA	(0.1470)	(0.0001)	(0.0423)	
l_t	0.0531	0.0341	0.0243	0.0071	-0.0002
	(0.0177)	(0.0280)	(0.0950)	(0.6454)	(0.9910)
ν	2.9361	2.8447	3.1500	2.8910	3.1620
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
C. Model Fit Statistics					
AIC	8.6041	8.3413	9.5281	9.4137	8.4582
BIC	8.6554	8.3986	9.5855	9.4710	8.5095
Hannan-Quinn	8.6230	8.3624	9.5493	9.4348	8.4771
LL	-7838.515	-7596.569	-8680.186	-8575.703	-7705.343
Shibata	8.6039	8.3410	9.5279	9.4135	8.4580
Q(30) p-value	1.221e-12	2.2e-16	$<$ 2.2e-16	2.2e-16	6.001e-13
$Q(30)^2$ p-value	0.9912	1.0000	0.9977	0.5871	0.3681

Table B.4: EGARCH Model Fit Off-Peak Hours (2010-2014)

	NO1	NO2	NO3	NO4	NO5
A. Conditional Mean Equation					
μ	257.2353	337.1102	328.4497	321.0539	325.7683
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	1.0171	1.0423	0.9260	0.9361	1.0450
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_2	-0.0942	-0.1145	-0.1531	-0.1601	-0.1149
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_3	0.0565	0.0384	0.0997	0.0967	0.0390
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_4	-0.0377	-0.0214	-0.0195	-0.0254	-0.0092
	(0.0000)	(0.0000)	(0.0447)	(0.0001)	(0.0005)
ϕ_5	0.0184	0.0409	0.0437	0.0359	0.0224
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
ϕ_6	0.0336	0.0306	0.0610	0.0717	0.0276

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Table B.4 continued from previous page

Parameter	NO1	NO2	NO3	NO4	NO5
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_7	0.0021	-0.0212	0.0316	0.0321	-0.0158
	(0.0345)	(0.0000)	(0.0774)	(0.0000)	(0.0000)
b_t	-17.5172	-29.4846	-35.5999	-33.7197	-31.6523
	(0.0230)	(0.0009)	(0.0009)	(0.0027)	(0.0001)
w_t	NA	-0.2469	-0.4953	-0.9030	
	NA	(0.0729)	(0.0667)	(0.0001)	
l_t	8.9837	4.6109	3.9946	2.6365	1.5079
	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0001)
B. Conditional Variance Equation					
ω	0.8205	0.4723	0.9956	1.0009	0.6052
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
α	-0.2922	-0.1433	-0.1441	-0.1466	-0.1186
	(0.0013)	(0.0000)	(0.0002)	(0.0004)	(0.0009)
β	0.8960	0.9103	0.8396	0.8377	0.8898
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	1.6357	0.5967	0.6865	0.6957	0.6832
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
b_t	0.0066	0.0094	-0.0093	0.0015	0.0043
	(0.6893)	(0.5451)	(0.6020)	(0.9319)	(0.7789)
w_t	NA	0.0076	-0.0485	-0.0736	
	NA	(0.6572)	(0.0623)	(0.0051)	
l_t	0.0546	0.0016	-0.0198	-0.0364	-0.0040
	(0.0147)	(0.9049)	(0.3235)	(0.0827)	(0.8162)
ν	2.1000	3.2705	2.8997	2.8491	3.0650
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
C. Model Fit Statistics					
AIC	8.0807	7.8984	8.6926	8.6040	8.0104
BIC	8.1319	7.9557	8.7499	8.6613	8.0617
Shibata	8.0805	7.8982	8.6924	8.6038	8.0102
Hannan-Quinn	8.0996	7.9195	8.7137	8.6251	8.0293
Log Likelihood	-7360.635	-7192.238	-7917.324	-7836.435	-7848.435
Q(30) p-value	2.2e-16	2.2e-16	2.2e-16	6.661e-16	2.2e-16
$Q(30)^2$ p-value	0.0035	1.731e-05	1.0000	1.0000	8.616e-11