NHH

Norwegian School of Economics
Bergen, Spring 2024

Effects of Hydrological Inflow on Electricity Prices

Quantile effects on electricity prices in Norway

Erlend Hallenstvedt Lid & Kristian Lystad

Supervisor: Øivind Anti Nilsen & Lars Sørgård

Master thesis, Economics and Business Administration

Major: Business Analytics & Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

Acknowledgements

First, we thank our excellent supervisors, Professor Øivind Anti Nilsen and Professor Lars Sørgård. We are grateful for their valuable insights, suggestions, and continuous feedback throughout the thesis process.

Furthermore, Nord Pool and NVE have been vital for this research. We want to express our gratitude for their efforts in managing data, which have provided the foundation for our thesis.

Lastly, we want to thank our friends, families, and significant others who have supported us.

Norwegian School of Economics

Bergen, May 2024

Erlend Hallenstvedt Lid

Kristian Lystad

Abstract

This thesis investigates the impact of hydrological inflow on electricity pricing in Norway's hydropower-dominated energy market, examining short-term and long-term effects from 2012 to 2023. Utilizing quantile regression models that span from the 10% to the 90% quantile, we control for various influences by incorporating known fundamental factors, including reservoirs and snow, soil and groundwater levels, and the capacity of subsea interconnectors.

Our results show a negative influence of inflow on electricity prices, although this effect varies across the price levels. The study also incorporates interaction terms to assess how inflow responsiveness fluctuates with market changes. The impact differs with variations in reservoir and snow reservoir levels. Additionally, the study notes altered impacts correlating with the increased capacity of subsea interconnectors. Interestingly, areas with unregulated hydropower show a greater sensitivity to short-term than long-term inflow. In contrast, regulated hydropower demonstrate opposite effects.

By highlighting the nuanced relationship between hydrological inflow and electricity prices, this study contributes valuable insights into Norway's energy market's operational and policy implications, with potential applicability to other hydro-dependent economies. The results underscore the importance of considering hydrological variables in managing and planning renewable energy resources, offering a foundation for future research on optimizing energy market stability and efficiency in the face of climatic and market variability.

Keywords – Electricity Markets, Electricity Prices, Hydropower, Hydrological Inflow, Quantile Regression, Subsea Interconnectors, Renewable Energy Management

Contents

List of Figures

List of Tables

List of Abbreviations

CET Central European Time

EMPS Multi area power-market simulator (Samkjøringsmodellen)

EUPHEMIA Pan-European Hybrid Electricity Market Integration Algorithm

GWh Gigawatt-hours

HBV Hydrologiska Byråns Vattenbalansavdelning

MAT Moving Annual Total

MPC Marginal Production Cost

NL NordLink

NO1 Norwegian price area NO1 - Østlandet

NO2 Norwegian price area NO2 - Sørlandet

NO3 Norwegian price area NO3 - Midt-Norge

NO4 Norwegian price area NO4 - Nord-Norge

NO5 Norwegian price area NO5 - Vestlandet

NSL North Sea Link

NVE Norwegian Water Resources and Energy Directorate

OLS Ordinary Least Squares

PCR Price Coupling of Regions

RD Reservoir Deviation

SDAC Single Day-Ahead Coupling

SDP Stochastic Dynamic Programming

SEC Subsea Export Capacity

SSGD Snow, Soil and Groundwater Deviation

TWh Terawatt-hours

1 Introduction

This thesis investigates the influence of water inflow on electricity pricing within Norway's predominantly renewable energy market. Given the country's reliance on hydroelectric power, understanding the pricing dynamics under varying inflow conditions is crucial for maintaining market efficiency and stability. This analysis is particularly relevant as the reliance on renewable energy sources increases due to climate change concerns and as the country moves towards an increasingly interconnected electricity market.

While extensive research has investigated the outputs of hydroelectric power generation, less attention has been paid to the role of inflow and its effects on electricity prices. Addressing this gap, this research aims to examine the short-term and long-term effects of inflow on the electricity prices in Norway and how these dynamics are shaped by the country's regional differences and growing export capabilities. The central research question is:

How does inflow impact electricity prices in Norway, across di erent market conditions and areas?

This research provides valuable insights for policymakers, energy companies, and market stakeholders by examining the impact of hydrological inflow on electricity prices in Norway's hydro-dominated market. It highlights how inflow changes affect price sensitivity, offering a deeper understanding of market dynamics and the challenges of climate change and market integration. The study emphasizes the need for flexible energy strategies to maintain market stability and efficiency, suggesting ways to enhance energy infrastructure for a sustainable future. Additionally, it offers a framework for other nations to integrate or expand hydropower within their renewable energy mixes, underlining hydropower's role in achieving a globally interconnected and sustainable energy landscape.

This thesis employs a quantile regression approach to comprehensively examine the effects of inflow on electricity prices. This approach reveals the varying effects of inflow on electricity prices across different price levels. This methodology is central to the analysis, allowing for a detailed examination of the relationships between inflow, market dynamics, and pricing in the context of hydropower reliance.

Following this introduction, the thesis initiates a literature review, assessing existing research on electricity pricing within hydro-dominant markets, followed by a theoretical exploration of the Norwegian electricity market, showcasing the systemic mechanics and the role of inflow and hydropower in price determination. The empirical approach, data sources, and the use of quantile regression are then detailed. The results and discussion section showcases the quantile-specific impacts of inflow on electricity pricing while highlighting the varying effects brought by reservoir levels, regional market dynamics, and interconnector capacities.

2 Literature Review

The relationship between inflow and electricity prices, especially across different price levels, has been an underexplored area in the literature. The impact of inflow on electricity pricing is complex, depending on factors such as precipitation and reservoir levels. Studies like Scheben et al. (2020) criticize traditional electricity price models for their inadequacy in renewable-heavy markets, noting the significant influence of inflow uncertainties on pricing. Additionally, the use of quantile regression in electricity market analysis (e.g., Nguyen, 2015, Hagfors et al., 2016, and Bunn et al., 2016) highlights how fundamental factors influence electricity prices differently across various price levels, offering a deeper understanding of market dynamics in hydro-dominated environments like Norway.

Hydropower plays a vital role in stabilizing the electricity market. The study by Owolabi et al. (2022) explores this effect, showing that hydropower modestly reduces average electricity prices and volatility but significantly impacts prices above the 70% quantile, highlighting its role in stabilizing prices amidst fluctuating renewable sources like wind. This underscores hydropower's vital contribution to market stability, especially in mitigating price volatility in renewable-rich energy mixes.

The literature also explores the strategic importance of reservoir levels in hydropower production. High reservoir levels typically lead to lower electricity prices due to increased supply. In contrast, lower levels can cause higher prices as producers strategically manage their limited water resources (Norgesenergi, 2023). This is further elaborated by Huisman et al. (2015), who demonstrate the nonlinear relationship between reservoir levels, thermal power costs, and electricity pricing, indicating how these factors affect market prices. Additionally, Bye and Bruvoll (2006) emphasizes the significant impact of variations in inflow, particularly during periods of low inflow.

The introduction and integration of export capacities, such as NordLink (NL) and North Sea Link (NSL), have significantly altered the relationship between hydropower reservoir management and electricity pricing in Norway. Døskeland et al. (2022) provides critical insights into this transformation, demonstrating that the increased export capacity significantly impacts the electricity prices within Norway. This development is pivotal in influencing market convergence and introducing new levels of price volatility. In contrast, Sapio (2019) observed a growing negative correlation between unregulated energy sources and interconnectors, suggesting a different dynamic in the broader energy market.

Furthermore, the analysis presented by Myrvoll and Undeli (2022) dives deeper into the effect of NL on the electricity markets using quantile regression. This study offers valuable insights into this aspect, highlighting how interconnectors affect electricity markets, particularly in pricing and market stability. Mauritzen (2012) introduces a strategic aspect, discussing hydroelectric power's response to wind energy dynamics. This strategy becomes pertinent in the context of Norway's fluctuating inflow and interconnected electricity grid.

An interesting counterpoint is presented by Khazal et al. (2023), who reports no direct correlation between inflow and pricing but acknowledges a significant link between prices and factors like precipitation. This finding suggests a more complex relationship than previously understood, warranting this study's investigation into the quantile-specific impacts of inflow.

The literature review sets the stage for this thesis, which seeks to look deeper into the complexities of the impacts of inflow on electricity pricing in Norway. Despite the established relationship between hydropower and electricity pricing, the literature reveals a gap in understanding inflow's quantile-specific impacts under various conditions.

3 Background

3.1 The Norwegian Electricity Market

The Norwegian electricity market, established as a market-based system in 1991, ensures the efficient use of energy resources while maintaining supply security and controlling costs. This system distinguishes between monopoly operations, like transmission and distribution, which are strictly regulated, and competitive aspects, such as electricity trading (NVE, 2023d).

3.1.1 Market Structure and Pricing Areas

The Norwegian electricity market is divided into five pricing areas: NO1 (Eastern Norway), NO2 (Southern Norway), NO3 (Central Norway), NO4 (Northern Norway), and NO5 (Western Norway) (Statnett, 2022). The pricing within these areas is affected by numerous factors, including reservoir water levels and infrastructural bottlenecks due to limitations of the power grid.

Figure 3.1: Price Areas NO1-NO5 (Statnett, 2022).

3.1.2 Role of the Power Grid

The electrical grid in Norway can be categorized into three main sectors: production, transmission, and distribution. The grid is capable of managing variations in both consumption and production. Additionally, it transfers electricity during low consumption periods and imports it during high demand. Electricity can not be stored, and a constant balance between consumption and production is necessary (Energidepartementet, 2023).

When there is enough capacity to transfer electricity between areas, electricity will flow from the low-price area to the high-price area. The flow of electricity will continue until the prices in both areas reach an equilibrium or the transmission capacity is maxed out, as shown in Figure 3.2.

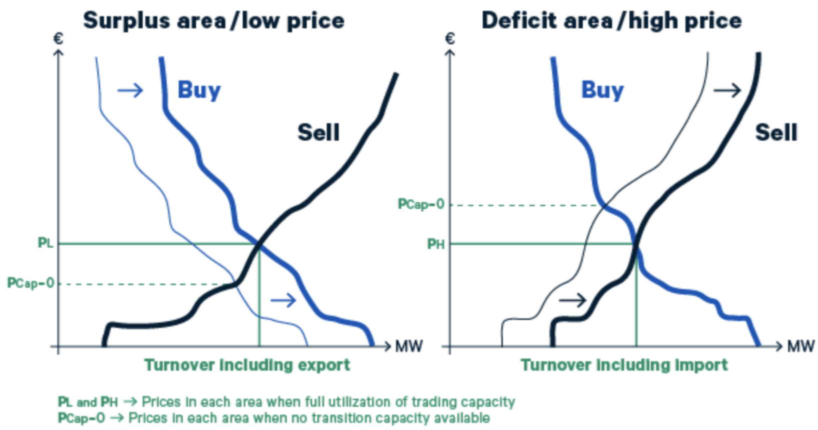


Figure 3.2: Price Convergence in Areas (NordPool, n.d.-b).

Bottlenecks and Their Effect on Price Variation

Bottlenecks, or constraints in the power grid, significantly impact electricity price variations across different areas in Norway. These bottlenecks, arising from the limited capacity of transmission cables between areas, can occur hourly. When capacity is reached, it leads to different prices between the areas (Kirkerud et al., 2023). Additionally, these bottlenecks extend beyond domestic boundaries through cross-border interconnectors. The capacity constraints in these international links can limit the efficient flow of electricity between Norway and neighboring countries, further influencing price variations and supply reliability (NVE, 2022b).

Cross-border Interconnectors

Turvey (2006) defines interconnectors, in the context of electricity, as cables or overhead lines that link two distinct market or pricing areas. Norway's interconnectors are integral to its electricity market, providing a buffer against the volatility of hydroelectric power generation. While substantial, the country's hydroelectric power production is subject to significant annual variations due to changes in the inflow to reservoirs and rivers. This variation can lead to fluctuations in electricity prices, as the availability of hydroelectric power impacts the supply side of the market equation.

The interconnectors, such as Skagerak 3 and 4, NorNed, NL, and the NSL, extend Norway's hydroelectric capacity by allowing for the import and export of electricity, thereby stabilizing the domestic market (Statnett, n.d.-a). For instance, during periods of low inflow, Norway can import electricity to meet its domestic demand, mitigating the upward pressure on prices. Conversely, during periods of high inflow and surplus production, Norway can export electricity, moderating prices both domestically and in connected markets.

3.1.3 Nord Pool and Market Dynamics

Nord Pool

Norway's electricity market is integral to Nord Pool and is the principal platform for physical electricity trading. Electricity trading was established post-1991's Energy Act. Expanding from Sweden in 1996 to Denmark and Finland by 2000, and later the Baltic states from 2010 to 2012, Nord Pool promotes efficient, competitive energy trade within a regulated grid system. Now operating across the Nordic, Baltic, and several Western European countries, Nord Pool exemplifies a market-driven approach within the interconnected European electricity network, streamlined by the Price Coupling of Regions (PCR) (Energifakta, 2023b). The wholesale electricity market is segmented into three primary markets: day-ahead, intraday, and balancing. While the day-ahead market accounts for most electricity trading, the intraday and balancing markets are essential for grid stability. For our thesis, we will narrow our focus to the day-ahead market.

Day-Ahead Market

In the day-ahead market of Nord Pool, electricity trading for the subsequent day is conducted via a blind auction, with more than 300 participants submitting over 2,000 daily bids. This market, covering 15 countries and 21 bidding areas, facilitates trading approximately 500 Terawatt-hour (TWh) annually. The auction commences with the publication of available grid capacities at 10:00 Central European Time (CET), allowing traders until noon CET to place their orders. These are then processed through the Single Day-Ahead Coupling (SDAC) using the EUPHEMIA[1] algorithm to establish the hourly prices for each area, considering network constraints. Fees are typically disclosed at 12:45 CET, followed by individual trade confirmations, setting the stage for the forthcoming 24-hour cycle, with subsequent adjustments accommodated through the intraday market (NordPool, n.d.-a).

3.2 The Norwegian Energy Mix

Hydropower is Norway's dominant energy source, positioning it as Europe's largest hydropower producer. Beyond hydropower, there is a significant expansion in wind power, which is beginning to reduce the dominance of hydropower (Energifakta, 2023c). Solar power is also being developed in Norway, though not as extensively as wind power, and currently plays a lesser role in total energy production. Additionally, thermal power accounts for approximately 2% of Norway's energy output.

Table 3.1 outlines Norway's electricity production mix, dominated by green energy sources. Furthermore, the energy sources can be categorized into two groups, regulated and unregulated energy. Regulated energy refers to energy sources where production can be adjusted in response to demand fluctuations. This typically involves water reservoirs in hydropower systems, allowing for the storage and subsequent utilization of water to generate electricity as needed. In contrast, unregulated energy depends on environmental conditions and cannot be controlled. This encompasses various renewable energy sources such as wind and solar power, as well as run-of-the-river hydropower, among others.

[1]Pan-European Hybrid Electricity Market Integration Algorithm.

Electricity Production	Percentage (%)
Hydropower	89.2
Thermal Power	1.9
Wind Power	8.9

Table 3.1: Distribution of Electricity Production as of September 2023, according to SSB (2023) and NVE (2023b).

3.2.1 Hydropower in Norway: Regulated vs Unregulated

Hydropower development has been crucial in Norway's industrial and modern evolution. Norway stands out from the rest of the world in its utilization of renewable hydropower resources. While the global reliance on fossil fuels continues, Norway's hydropower resources highlight its unique environmental and economic position.

The impact of hydropower on Norway's electricity market is largely linked to the power balance, represented by a ratio that reflects the total production capacity of the power system in relation to the total power consumption. This relationship is influenced by hydrological conditions (Kirkerud et al., 2023). Underscoring the dependence of the power balance on environmental factors in a hydropower-reliant system.

The distribution of hydropower in Norway also exhibits distinct regional variations. Table 3.2 shows that the balance between regulated and unregulated[2] production differs significantly across various areas. These differences can be attributed to factors such as geographic conditions, the availability of water resources, and the presence of infrastructure capable of regulation.

In some areas, unregulated production significantly surpasses regulated, particularly in NO1. Conversely, areas such as NO2-NO5 have a higher proportion of regulated production. These variations are crucial for understanding the flexibility and reliability of power supply in different areas of the country. Generally, hydropower is categorized into run-of-the-river power plants (unregulated), and reservoir power plants (regulated). However, when reservoir capacities reach their limits, reservoir power plants may function similarly to unregulated plants. This occurs when water is directed straight through

[2] The categorization of hydropower into regulated and unregulated is based on whether they are classified as 'Elvekraftverk' (Run-of-the-river Power Plants) or 'Magasinkraftverk' (Reservoir Power Plants). Some plants exhibit features of both river and reservoir types. For a detailed discussion, see: NVE (2023b).

the reservoirs to production facilities to prevent overflow. Such scenarios result in lower electricity prices, and society benefits from using interconnectors since the surplus can be exported instead of spilled (Blaker, 2023).

Area	Unregulated Hydropower(%)	Regulated Hydropower(%)
NO1	73.29	26.71
NO2	15.98	84.02
NO3	28.45	71.55
NO4	11.01	88.99
NO5	10.05	89.95

Table 3.2: Hydropower Distribution Across Different Areas Based on Data from NVE (2023b).

3.3 Hydrological Balance and Reservoir Management

For the Norwegian electricity market, the hydrological balance holds significant importance. NVE (2024) determine the balance with two aspects: the current state of water in reservoirs and the potential for future inflow represented by the levels in snow reservoirs, soil, and groundwater. This is measured against historical averages over the last 20 years to understand how current conditions compare to long-term norms. The balance offers an important forecast for hydropower producers as a negative value signals producers the need to conserve water, anticipating less water available for future power generation.

Snow Reservoir, Soil, and Groundwater

Snow reservoirs, soil, and groundwater are components calculated using the HBV-model[3], further discussed in subsection 3.4. Snow reservoirs serve as temporary storage for precipitation, gradually releasing water through melting processes. This release, coupled with the water in soil and groundwater, dictates the availability and timing of water flow into hydropower reservoirs. The fluctuating levels of these storages, influenced by climatic variations, directly affect hydropower plants' operational strategies based on the availability of future inflow.

[3]Hydrologiska Byråns Vattenbalanssektions model.

Reservoirs

Today the Norwegian power system is marked by its extensive reservoirs, totaling over 1000 reservoirs with a total storage capacity of 87 TWh. This capacity represents about 62% of the national power consumption, underscoring the country's scale and impact of hydropower. The regulating capability allows for adaptation to market demands, allowing efficient and flexible energy management (Energifakta, 2023c).

Area	Capacity (TWh)	Percentage (%)
NO1	6.00	6.9
NO2	34.0	38.9
NO3	9.12	10.4
NO4	20.9	23.9
NO5	17.4	19.9

Table 3.3: Reservoir Capacity. Data from 2023. Source: NVE (2023c).

Table 3.3 details reservoir capacities across the areas, showing significant geographical differences. Notably, NO2 accounts for 38.9%, whereas NO1 only accounts for 6.9%, underscoring the uneven distribution.

Although Norwegian hydropower plants operate with considerable autonomy, they must adhere to laws and specific regulations, particularly managing low reservoir volume and high reservoir volume (Jensen et al., 2010, p.26). These regulations, deciding the maximum and minimum water levels in reservoirs, are essential for operational safety and consistent energy supply. Additionally, they may also be subject to minimum flow[4] in regulated rivers requirements, ensuring minimum water flow levels for environmental protection (Halleraker & Rosvold, 2023).

According to Mæland (2018), hydroelectric producers strategically manage water resources to optimize electricity generation. They conserve water during periods of low demand and low prices, and increase production when demand and prices rise. This practice not only aims to maximize profitability, but also aligns with what is economically optimal for society, as market prices guide production decisions. In practical terms, water allocation decision in hydroelectric production depends on its value.

[4] Refers to the minimum flow as detailed by the Water Resources Act (Vannressursloven § 10), with the specific level detailed in the license conditions for the power plant.

3.4 The Dynamics of Inflow

Inflow refers to the total volume of water that enters a catchment area's precipitation field during a specific period. This measurement is essential in determining the potential energy generation from hydropower plants. Inflow is calculated from direct rainfall, surface runoff, and melting snow and ice. These factors contribute to the water supply in rivers and reservoirs utilized for energy production (NVE, 2024).

The HBV-model is a tool used for calculating inflow to hydropower stations. It uses meteorological data like precipitation and temperature to simulate critical hydrological processes that affect inflow, such as evaporation, snow storage, and moisture levels in the soil and groundwater. The model's accuracy depends on its calibration against actual hydrological data, ensuring its predictions match real-world inflow patterns. This precision is essential for managing hydropower, as it helps balance the energy power production (Holmqvist, 2017).

The variability of inflow is a significant factor in the Norwegian hydropower context. During periods of high inflow, typically in the summer when inflow is at its peak, reservoirs are filled[5]. Conversely, in the winter, when inflow decreases, the stored water is used to generate power to meet higher energy demands (NVE, 2022a). Figure 3.3 presents the trends in average weekly production and inflow from 2012 to 2023, revealing slightly higher production during winter and a decrease towards summer. Inflow reaches its peak around week 23, subsequently diminishing, with production experiencing a peak in the autumn-winter season. The mean annual production over this period stands at 142 TWh, for all energy sources, whereas the average inflow is calculated to be 135 TWh. Despite the seasonal fluctuations in inflow, the reservoirs are managed in such a way that they facilitate a steady production of electricity throughout the year.

[5] See: Appendix A1.1.

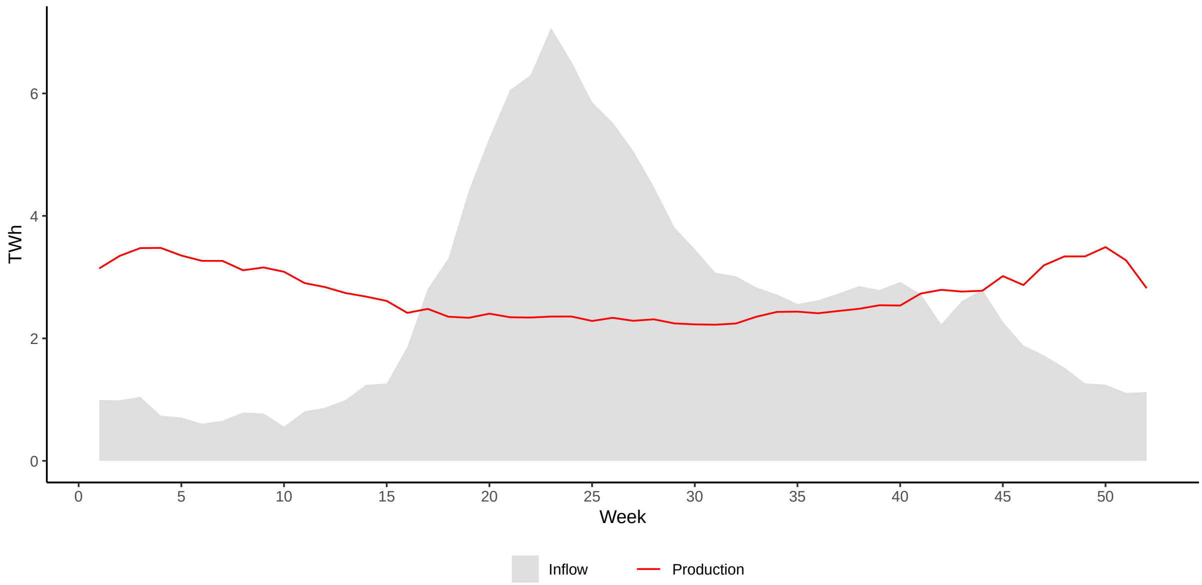


Figure 3.3: Average Weekly Production and Inflow. Data from 2012 - 2023. Source: NVE (2024) and Statnett (n.d.-b).

In addition to seasonal patterns, the Norwegian power system must contend with the unpredictability of inflow. The Norwegian Water Resources and Energy Directorate (NVE) characterizes a dry year as one where the inflow falls below 96.8 TWh, a situation that statistically occurs once every decade (Væringstad & Holmqvist, 2003). Fluctuations in inflow have notable implications, as evidenced in 2010 with its significantly low inflow compared to 2020's high productivity in electricity generation, which resulted in reduced electricity prices nationally (Statnett, 2021).

3.5 Water Value Method

The water value method is a way to manage hydroelectric power systems, particularly in optimizing reservoir operations. This method involves calculating the marginal value of water stored in a reservoir, essentially treating water as an economic commodity whose value is determined by its potential to generate electricity (Wolfgang et al., 2009). In practical terms, water value is used as the Marginal Production Cost (MPC) in hydroelectric power production and forms the basis for production planning and bidding in the Nordic electricity market (Jaehnert, 2023).

The core principle is that the value of water lies not just in its immediate use but also in its future utility, thereby necessitating a strategic approach to reservoir management (Helseth et al., 2010). This aligns with the broader concept of opportunity cost in economics, where the value of water is intrinsically linked to the foregone benefits when it is not utilized for power generation in the future (Stage & Larsson, 1961).

Jaehnert (2023) explains that the value of water is calculated based on several key factors: the uncertainty of inflow, wind, and solar variations, the limited storage capacity of water, fluctuating power demand, alternative sources of power production, and power exchange through interconnectors. Complementing this view, Kirkerud et al. (2023) underscores the vital role of the power balance as a critical parameter in the valuation process. A solution for this optimization problem is to use the Stochastic Dynamic Programming (SDP) method to minimize system costs. Wolfgang et al. (2009) demonstrates the SDP method with the EMPS-model[6], which is used as decision support by several producers in the Nordic electricity market (Jaehnert, 2023).

The variability in water value directly affects the hydropower producers MPC, more in Section 3.6. The value of water fluctuates over time – water stored in reservoirs during periods when electricity prices are low can be used later when prices increase. The ability to store and strategically utilize water directly impacts electricity pricing. When reservoir capacity is limited, so is the ability to optimize water use for periods of high prices, leading to more significant price variations. Conversely, large reservoir capacities allow for more effective management of water resources, leading to a more consistent and optimized pricing strategy in electricity markets. This dynamic shows how reservoir capacity and water value interplay significantly affect electricity pricing (Bye et al., 2010).

3.6 Demand and Supply Dynamics

3.6.1 Demand

Electricity demand exhibits short-term inelasticity, meaning consumers, including households and industries, suggest that consumers are not very sensitive to electricity prices (Csereklyei, 2020). Despite this, the market follows a predictable cyclical pattern, with a baseline level that rarely falls below and varies daily, weekly, and seasonally. Still, the supply side is the primary driver of electricity prices, especially the MPC mechanism,

[6] Multi area power-market simulator (Samkjøringsmodellen).

where the price is mainly controlled by the cost of the most expensive power plant required to meet periods of high demand. Hence, when electricity demand is moderate to high, the MPC typically corresponds to the price of fossil fuels. Consequently, natural fossil fuel prices play a crucial role in influencing the cost during periods of high demand (Kirkerud et al., 2023).

3.6.2 Supply

Fleten et al. (2010) research highlights that in supply-side economics, the impact of a single day's heavy rainfall on electricity market prices is relatively minimal if a dry spell follows it. Furthermore, high market prices are positively correlated with low reservoir inflow. For regulated hydropower, the relationship between the total inflow over an entire season or year and market prices is more significant than the correlation with weekly inflow. This significance is related to their capacity for water storage. The accumulated precipitation over a more extended period primarily affects electricity prices. For example, consistently lower-than-expected inflow over an extended period typically generates higher electricity prices. In contrast, unregulated hydropower systems tend to be more sensitive to weekly variations in inflow.

Førsund (2007) provides a theoretical framework showing how inflow changes impact electricity prices, with the demand measured in different periods and the water value adjusting to equalize prices across these periods. This relationship is depicted in Figures 3.4 and 3.5, showing market equilibrium in scenarios when there is plentiful of inflow and scarcity in inflow, respectively. The demand in period 1 (D1) is measured from left to right, and demand in period 2 (D2) from right to left. The water value, pinpointed at the intersection of D1 and D2, signifies the equilibrium price, ensuring optimal hydropower allocation across periods. This price point aligns current production with projected demand, guaranteeing electricity is priced at least to match anticipated future value.

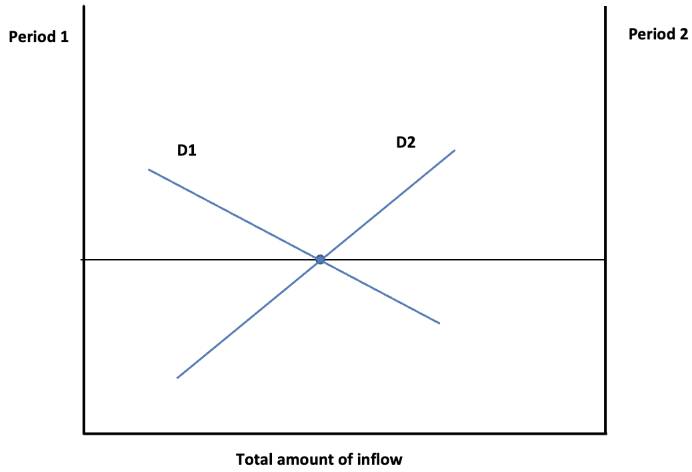


Figure 3.4: Market Equilibrium When There Is Plentiful of Water.

Conversely, during periods of scarcity of inflow, causing a shift to the left, indicating a higher water value and a corresponding increase in electricity prices, as shown in Figure 3.5. Implying that the average price over the year would be lower with plentiful of inflow than with scarcity, which aligns with basic supply and demand principles. The dotted lines in the figure illustrate the equilibrium before the reduction in inflow.

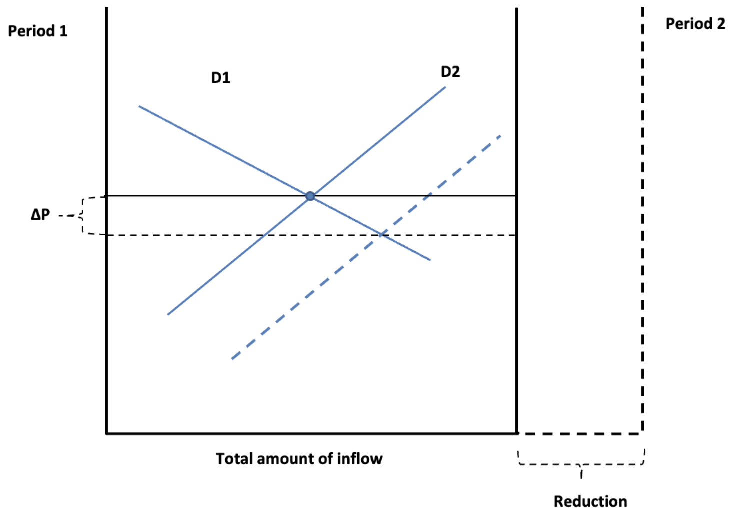


Figure 3.5: Market Equilibrium During Periods with Scarcity of Water.

3.6.3 The Merit Order

The electricity market utilizes a merit order system to order and rank electricity producers according to their MPC, thus prioritizing lower-cost sources like renewable energies (wind, solar, and hydropower). The market price at any given moment is determined by the most expensive producer needed to meet current demand, reflecting the price all buyers must pay. This mechanism promotes economic efficiency by using the most cost-effective energy sources first and adjusting prices according to the cost of the marginal producer (Bjarnes et al., 2023).

Figure 3.6 illustrates the merit order curve when there is a low water value, and each bar represents a different electricity producer, with the width of the bar indicating the amount of electricity they produce. The vertical dotted line indicates the demand that must be met. Where this line intersects with the producers' bars sets the electricity price, equal to the MPC of the last producer needed to satisfy demand. The horizontal dashed line marks this price level on the y-axis. When a producer increases its output, its bar on the merit order curve extends wider, causing a rightward shift along the demand axis. Conversely, a change in the MPC for the last producer to meet demand can raise the electricity price, reflected by a shift where the demand line and the MPC intersect. This dynamic illustrates how changes in production and MPC among different electricity sources can influence electricity prices, ensuring the most cost-effective supply meets the demand first.

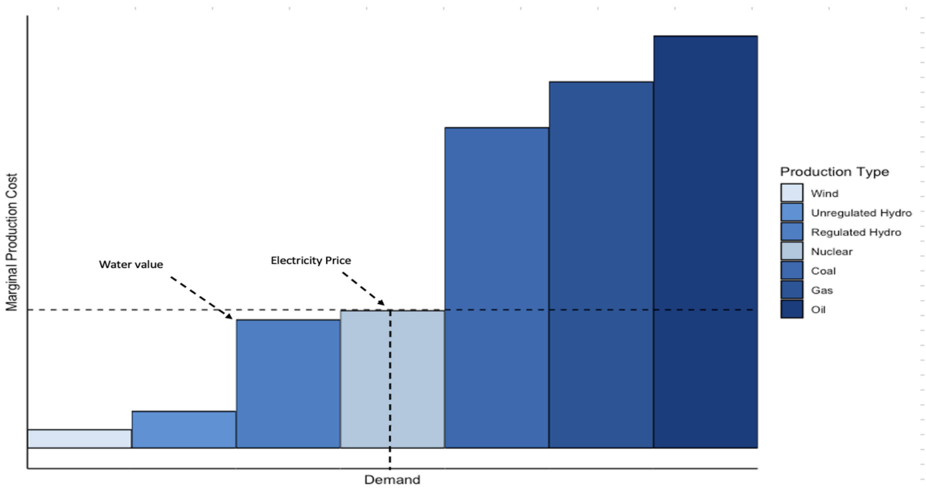


Figure 3.6: A Theoretical Illustration of Low Water Value[7].

The shift from Figure 3.6 to Figure 3.7 illustrates the dynamics when the MPC changes. For instance, increasing water value leads to a higher MPC for regulated hydropower. This change causes a rightward shift in the curve, indicating that hydropower becomes more expensive relative to other sources. As a result, it may be utilized later in the merit

[7]Note: The values used in Figure 3.6, are for illustrative purposes only and do not represent real data.

order, influencing the overall market price of electricity. This curve effectively illustrates how variations in input costs can impact the economic dynamics of electricity markets.

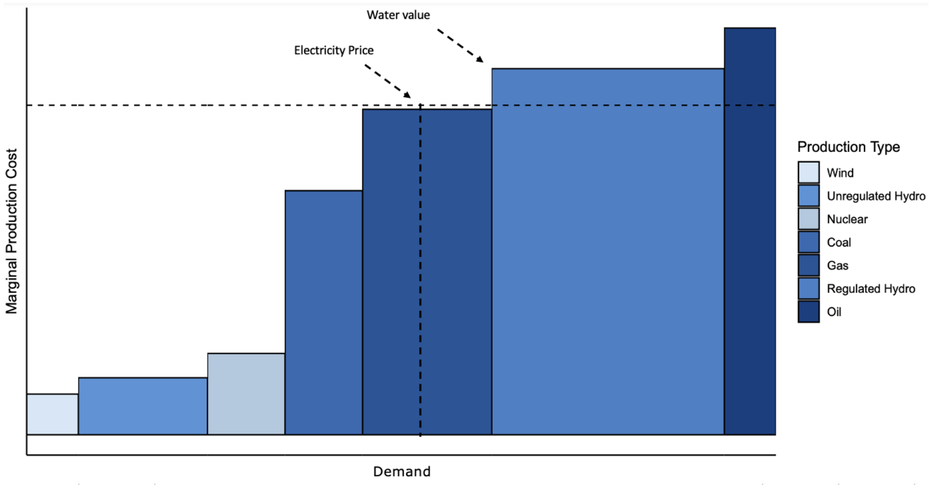


Figure 3.7: A Theoretical Illustration of High Water Value[8].

3.6.4 The Merit Order Effect

Antweiler and Muesgens (2021) describes the 'merit order effect' as when a surge in renewable energy capacity outpaces the rise in electric demand. This concept highlights the impact of increasing renewable energy sources such as solar, wind, and unregulated hydropower due to their low MPC. In contrast, traditional forms of energy production, such as gas, coal, and regulated hydropower, are subject to variable costs due to market fluctuations. Understanding the merit order and the merit order effect is essential in electricity market dynamics, particularly with increasing renewable energy sources.

Germany's ambitious energy transition is an apt example for illustrating the merit order effect. The increasing share of renewable energy in Germany's electricity mix has led to a noticeable decrease in electricity market prices (Unnerstall, 2017). Years with high inflow in Norway can be expected to cause similar effects. The increased availability of hydropower with low MPC can push more expensive producers out of the market, thus reducing the overall electricity prices as illustrated in Figure 3.8.

[8]Note: The values used in Figure 3.7, are for illustrative purposes only and do not represent real data.

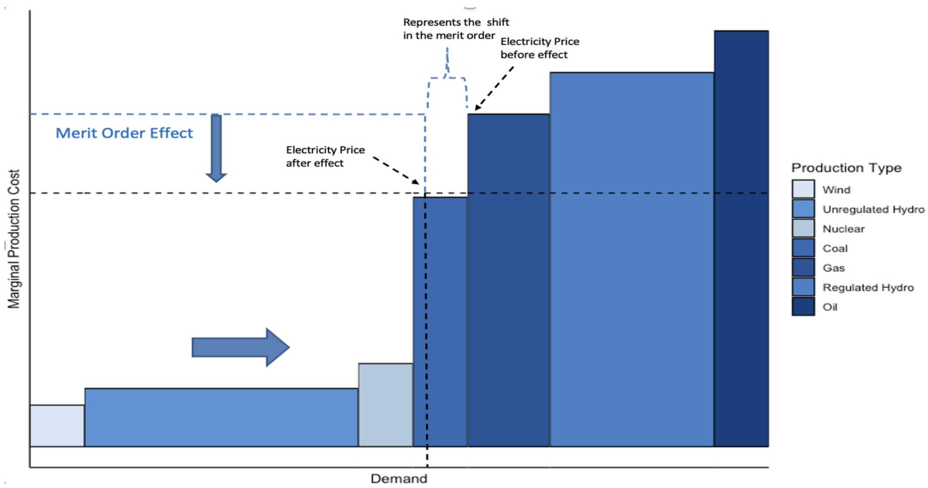


Figure 3.8: A Theoretical Illustration of the Merit Order Effect[9].

3.6.5 Impact of Inflow on Electricity Prices

Inflow significantly influences electricity pricing through its interaction with the merit order curve. In unregulated hydropower systems, an increase in inflow, which directly increases electricity production at a constant low MPC, can cause reduced prices via the merit order effect. In contrast, the placement of regulated hydropower in the merit order is decided by the water value, reflecting a balance between immediate usage and future utility, and consequently alters electricity prices. Therefore, inflow plays a key role in setting electricity prices, influencing where hydropower fits in the merit order and affecting how prices are formed in the market.

3.7 External Factors Influencing the Market

EU Carbon Permits

The EU CO2 Emission Allowances (EUAs) system is a system to reduce greenhouse gas emissions by making carbon-intensive energy production more costly. This system, part of the EU Emissions Trading System, sets and lowers emission limits yearly, compelling companies to switch from high to low CO2-emitting energy sources (Energifakta, 2023a).

Huisman et al. (2015) and Boersen and Scholtens (2014) demonstrate that fluctuations in CO2 prices significantly influence electricity prices by affecting the costs of fossil fuels.

[9]Note: The values used in Figure 3.8, are for illustrative purposes only and do not represent real data.

This relationship is particularly evident in the merit order curve, where changes in CO2 prices can increase the MPC of fossil fuel prices. Although Norway's electricity grid relies less on fossil fuels, it is still affected by CO2 price fluctuations due to its connection with the European electricity markets.

Electricity Certificate

Electricity Certificate is a scheme between Norway and Sweden that supports renewable energy production. Renewable electricity producers earn certificates for each MWh generated, which they can trade. This creates two income streams: selling electricity and trading certificates. Retailers must cover a portion of their sales with these certificates. The certificate's price reflects the cost difference between renewable and thermal energy production, potentially influencing overall electricity prices (NVE, 2023a). The research conducted by Wolfgang et al. (2015) employs a forecasting model for electricity prices that incorporates variables such as hydropower and wind production, underscoring the significance of electricity certificates as a factor influencing electricity prices.

4 Data

4.1 Variable Description

Our data have been constructed from various sources[10]. We use panel data spanning from the first week of 2012 through week 35 of 2023. This period was chosen due to the subdivision of the area into five zones that occurred in 2011[11]. Our analysis consistently employs weekly data, encompassing original weekly datasets and daily data aggregated into a weekly format. In instances where the variable isn't reported on a weekly basis, we convert it to weekly data by calculating the average for the entire week.

Each area (NO1-NO5) under study contains 609 weeks. Consequently, our panel dataset comprises a total of 3045 observations. Tables 4.1 and 4.2 present an overview of the variables employed in our models. These encompass a diverse array of continuous variables, binary dummy variables, and categorical dummies, offering the framework for our analytical exploration.

Variable	Unit	Description
Price	€/MWh	Average weekly price
Inflow_S	GWh	Short term: Weekly inflow
Inflow_L	GWh	Long term: Moving annual total inflow
Volatility	€/MWh	SD of day-ahead price using seven-day moving window
SEC	MWh	Subsea export capacity
Wind	MWh	Average weekly price
Certificate	EUR	Average weekly price
Gas	€/MWh	Average weekly price
Coal	€/1000t	Average weekly price
Eua	€/1000t CO_2	Average weekly price
Time Trend	Index	Time trend variable

Table 4.1: Continuous Variables.

[10]See Appendix A2.1 for data sources details.

[11]See: https://www.nordpoolgroup.com/4a7b04/globalassets/download-center/day-ahead/elspot-area-change-log.pdf

Variable	Dummy	Categorical	Description
D_{NE}	X		Net exchange between the areas
D_{RD}	X		Reservoir deviation
D_{SSGD}	X		Snow, soil, and groundwater deviation
Month		X	Monthly variable
Area		X	Variable indicating the area

Table 4.2: Other Variables.

4.1.1 Dependent Variable

Our research examines weekly patterns and cumulative inflows to hydropower production reported weekly. Hence, we gather daily data on day-ahead electricity prices from Nord Pool and aggregate it into weekly prices, measured in €/MWh. This approach is in sync with the weekly reporting format of our inflow data.

4.1.2 Independent Variables

We obtained weekly inflow data from NVE. The data is reported in two distinct methodologies—initially, the HBV-model was used for this purpose. Post-2015, NVE implemented another method to assess the variance between actual power generation and reservoir levels. Our study, however, concentrates on the period before and after 2015, and thus, we use data derived from the HBV-model. These inflow data are measured in Gigawatt-hours (GWh). To explore the various impacts of water availability on electricity prices, we transform this data into two distinct variables: the original weekly reported inflow ($Inflow_S$) and a derived long-term inflow variable ($Inflow_L$). The latter represents a Moving Annual Total (MAT) of inflow, providing a comprehensive view of longer-term trends in water availability. The process and rationale behind the creation and use of these variables are further detailed in the methodology section.

4.2 Control Variables

Our model incorporates a range of fundamental control variables. By integrating these variables, we aim to mitigate the influence of external factors that could confound the observed relationships within our main variables. These control variables are chosen by the supply and demand dynamics in the electricity market.

4.2.1 Continuous Variables

Price volatility

We aim to explore the effects of price uncertainty in the electricity markets not captured by other control variables. We include price volatility in line with Bunn et al. (2016). We calculated the standard deviation of the day-ahead prices using a seven-day moving window measured in €/MWh.

Subsea Export Capacity

Data on the aggregate maximum capacity of subsea interconnectors are obtained from Nord Pool and include Skagerak 3 and 4, NorNed, NL, and the NSL. While this variable does not represent real-time capacity, it is as a proxy for the highest potential capacity. We aim to control for this variable because it is expected to influence electricity prices upward (Døskeland et al., 2022).

Wind Power Production

We utilize wind power data from Nord Pool, initially collected daily and then aggregated into weekly totals, measured in Megawatt-hours (MWh). Given the increasing significance of wind power in Norway, it plays a crucial role in explaining fluctuations in electricity prices, primarily through the merit order effect. Based on insights from Westgaard et al. (2021) and foundational theoretical principles, we anticipate that increased wind power generation will exert downward pressure on electricity prices.

Electricity Certificate

We obtain weekly data on electricity certificates from Macrobond, which is reported in €. The competitive dynamics of the electricity certificate market, coupled with the principle that increased production of renewable energy generally lowers electricity prices, suggest that the availability of electricity certificates is likely to exert downward pressure on these prices. This expectation is consistent with the fundamental economic principle that an increase in renewable energy supply here typically leads to a decrease in prices, assuming demand remains constant.

Gas

We utilize Dutch TTF Natural Gas futures data sourced from Bloomberg, with prices quoted in €/MWh. Since the market is closed on weekends, we address missing values by averaging the data points immediately before and after these gaps. Natural gas significantly influences the merit order curve, impacting water values and electricity prices. According to Bunn et al. (2016), we anticipate a positive correlation between natural gas and electricity prices.

Coal

We source our data from Bloomberg and API2 Rotterdam Coal futures, with prices quoted in €/1000t. The data is then aggregated into weekly intervals. We compute the mean of the two nearest data points before aggregation to address missing values. Coal plays a significant role in influencing the merit order curve, thereby impacting the water value. Consequently, we expect coal prices to affect electricity prices positively.

Eua

We source data on EU Carbon Permits from Bloomberg, with values measured in €/1000 t CO_2 and reported every week. In cases where values are missing, we compute the mean of the two nearest data points before aggregation. CO2 prices will affect the cost of fossil fuels. Consequently, this is expected to have a positive impact on electricity prices (Kirkerud et al., 2023).

Trend

Time trending is used to adjust for external price increases in our time series analysis (Wooldridge, 2018, p. 352). This variable is included to capture any trends in the dependent variable that are not explained by the independent variables. We use a time trend variable for each area (NO1-NO5), which starts at 1 and increases sequentially by 1 for each week, up to 609. Importantly, this variable resets to 1 at the start of each new area, maintaining this pattern throughout.

4.2.2 Dummy Variables

Net Exchange

We obtain data on power exchange from Nord Pool, where electricity prices are affected by bottlenecks and transmission capacity among geographic areas. Initially, this data is collected daily. We first calculate the net balance of electricity exchange for each area[12], then aggregate these values into weekly data. A net balance with negative values indicates a prevalence of exports over imports, while positive values suggest higher imports than exports. We use a dummy variable, assigning a value of 1 in cases of net exports and 0 for net imports. Although this binary measure does not capture the immediate effects of grid bottlenecks, it is a valuable proxy to indicate the broader trade dynamics within each area and their potential impact on electricity prices.

Reservoir Deviation

Reservoir Deviation (RD) represents one of two distinct levels within the hydrological balance, with data from NVE. While the bulk of existing literature, including studies by Gjerland and Gjerde (2020) and Huisman et al. (2015), primarily focuses on reservoir levels or the broader hydrological balance, our research emphasizes the importance of the individual components of this balance. We include these variables in our study due to their significant influence on water value, arguing for a more nuanced understanding of their impacts.

We employ a binary indicator variable to account for deviations in reservoir fill levels from their historical averages. This variable is assigned a value of 1 to denote a positive deviation and 0 to indicate a negative deviation. This approach is essential for analyzing the impact of water availability in reservoirs on hydropower production capacity, as the level of water stored directly influences the potential for energy generation.

Snow Reservoir, Soil, and Groundwater Deviation

The Snow Reservoir, Soil, and Groundwater Deviation (SSGD) represents the second component of the hydrological balance. We use a binary indicator variable based on SSGD to quantify the potential for future inflow. This indicator is set to 1 if there is a positive

[12]Net balance = import - export.

deviation from historical averages across these measures, suggesting an increased potential for water availability, and 0 if there is a negative deviation. This variable is crucial as it reflects potential water resources that, while not immediately accessible, are expected to contribute to future inflow.

4.2.3 Categorical Variables

Month

We include a categorical variable for each month to evaluate the influence of seasonal fluctuations on electricity demand and supply. This addition helps us analyze these trends' inherent seasonal patterns and dynamics.

Area

We incorporate a categorical variable to represent the five areas, NO1-NO5. This approach is applied within a panel data framework encompassing all these areas.

4.3 Descriptive Statistics

4.3.1 Weekly Electricity Prices

Table 4.3 summarizes the descriptive statistics, including weekly electricity prices across various areas. The median values range from 28.7 €/MWh to 33.1 €/MWh, indicating a moderate consistency across areas. However, mean values show more variation, with the highest mean at 51.7 €/MWh and the lowest at 29.3 €/MWh, suggesting differing average levels in different areas. The standard deviation is notably high across all areas, ranging from 15.7 €/MWh to 63.8 €/MWh, highlighting the data set's volatility.

The data for all areas demonstrate high kurtosis, between 21.5 €/MWh and 50.2 €/MWh and skewness, ranging from 2.49 €/MWh to 5.12 €/MWh, suggesting non-normal distributed data. The distribution becomes clearer when observing the maximum values, which vary widely from 170.0 €/MWh to 572.0 €/MWh and the minimum values, which are relatively similar, ranging from 1.03 €/MWh to 1.62 €/MWh. These high maximum values indicate the presence of outliers, which could significantly affect the overall statistical analysis of each area.

The mean and median values differences, combined with high standard deviation, skewness, and kurtosis, indicate non-normally distributed data. This conclusion is also consistent with observations made in the work by Bunn et al. (2016).

	NO1	NO2	NO3	NO4	NO5
Median	33.1	33.1	31.3	28.7	32.6
Mean	49.6	51.7	32.8	29.3	49.3
Standard Deviation	57.7	63.8	21.6	15.7	57.7
Kurtosis	23.0	23.0	50.2	21.5	23.0
Skewness	3.87	3.95	5.12	2.49	3.86
Min	1.15	1.15	1.62	1.03	1.15
Max	552	572	279	170	552

Table 4.3: Descriptive Statistics for Different Areas.

The data in Table 4.4 represents quantile values for electricity prices across the five areas (NO1-NO5). Each row in the table corresponds to a specific quantile from 5% to 95%, showing the price at each quantile.

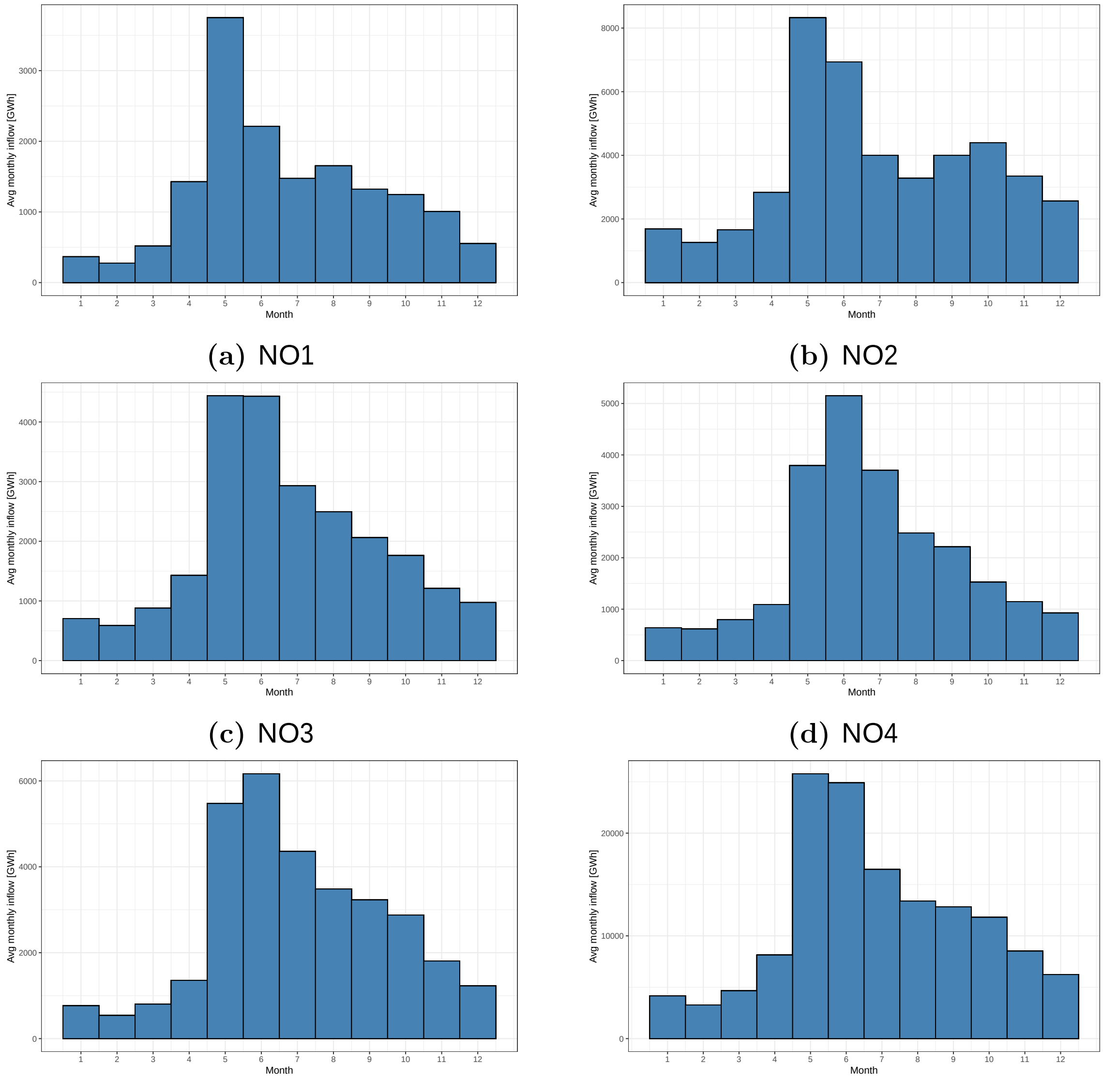
The pattern shows a clear upward trend in electricity prices across all quantiles, indicating a wide price variation rather than a concentration around the mean. This significant spread, especially between the lowest and highest quantiles, suggests high variance and the strong impact of extreme values on the overall distribution. Such characteristics make quantile regression an appropriate method, as it effectively captures these variations across different price levels.

Quantile	NO1	NO2	NO3	NO4	NO5
5 %	8.09	8.16	6.34	5.63	7.99
10 %	13.89	14.53	12.40	10.79	13.80
20 %	22.73	22.79	21.38	18.68	22.19
30 %	25.62	26.14	25.60	22.92	25.39
40 %	29.98	30.09	29.00	25.45	29.82
50 %	33.06	33.06	31.30	28.74	32.56
60 %	36.47	36.93	34.19	31.60	36.03
70 %	42.31	42.38	37.10	35.41	42.07
80 %	51.84	53.12	41.48	39.45	51.34
90 %	108.22	108.22	49.32	45.32	108.15
95 %	156.60	171.36	54.82	50.22	156.60

Table 4.4: Quantiles of Electricity Prices NO1-NO5.

4.3.2 Inflow

Figure 4.1 shows that the inflow data has a clear seasonal pattern, with higher values typically in the late spring and early summer months due to melting snow. The inflow decreases as the year progresses, with the lowest values typically in winter. Their capacity for hydropower generation influences the magnitude. NO1, characterized by its lower hydropower capacity and low storage ability, consistently experiences the most modest peak inflows. In contrast, NO3 to NO5 gradually reduces inflow as autumn progresses. NO2 is distinct, with a notable resurgence in inflow during autumn, presumably due to increased rainfall, and this area contributes significantly to the aggregated national inflow figures.



(a) NO1 (b) NO2

(c) NO3 (d) NO4

(e) NO5 (f) NO

Figure 4.1: Average Monthly Inflow Across Areas: National and Local Breakdown.

5 Methodology

We begin our methodological approach by introducing the chosen model, discussing the rationale for its selection and concluding with our hypotheses about anticipated outcomes.

5.1 Quantile Regression

Koenker and Bassett (1978) introduced quantile regression, a method that expanded upon traditional regression analysis by allowing us to examine the varying impacts at different quantiles of the response variable. This method contrasts with Ordinary Least Squares (OLS) regression, which estimates the conditional mean by considering the distribution of the dependent variable. As a result, quantile regression can reveal the varying impacts across the entire distribution of the dependent variable, capturing heterogeneity in the data that OLS, focusing on mean outcomes, might overlook. This method offers more reliable and comprehensive estimates, especially when facing non-normality or data with outliers and long tails (Hao & Naiman, 2007, pp. 1–5).

Simply put, quantile regression helps us understand how different factors influence electricity prices at various points, such as the lowest, median, and highest prices. Think of quantiles as specific points in the distribution of electricity prices – for instance, the 10% quantile (low prices), the 50% quantile (median prices), and the 90% quantile (high prices). Quantile regression allows us to see how different factors affect prices at each of these points. This is crucial in the electricity market, where prices vary widely and are impacted by several fundamental factors.

Quantile regression requires us to estimate regression coefficients through numerical optimization because it lacks a closed-form solution like OLS. The optimization typically involves linear programming to minimize the sum of weighted absolute residuals. To estimate the conditional quantile of a response variable Y given a set of explanatory variables X. For a quantile τ, where $0 < \tau < 1$. Koenker (2005) expresses the quantile regression model as follows:

$$Q_\tau(y|\mathbf{X}) = \beta_0(\tau) + \beta_1(\tau)X_1 + \beta_2(\tau)X_2 + \cdots + \beta_k(\tau)X_k \tag{5.1}$$

In this equation, $Q_\tau(y|\mathbf{X})$ represents the conditional quantile function for the dependent variable y at the τ-th quantile, given the independent variables $\mathbf{X}$. The quantile τ ranges between 0 and 1. $\beta_0(\tau)$ is the intercept for the τ-th quantile. The coefficient $\beta_k(\tau)X_k$ represents the effect of each variable $\mathbf{X}$ on the τ-th quantile of y.

Given a quantile τ, where $0 < \tau < 1$, the coefficient $\beta(\tau)$ estimation in quantile regression involves solving the following minimization problem:

$$\min_{\beta(\tau)} \sum_{i=1}^{n} \rho_\tau(y_i - x_i'\beta(\tau))$$

with the loss function $\rho_\tau(u)$ for the τ-th quantile given by:

$$\rho_\tau(u) = u(\tau - I(u < 0))$$

where u is the residual $(y_i - x_i'\beta(\tau))$, and $I(u < 0)$ is an indicator function that equals 1 if the residual u is negative and 0 otherwise. This setup ensures that approximately a τ proportion of the data points are located below the τ-th quantile regression line, while the remainder $1-\tau$ is above it. The coefficients for the quantile regression are estimated using the weighted data from the entire sample (Hao & Naiman, 2007, pp. 37–38). Unlike the squared residuals in OLS, this asymmetric loss function improves the model's robustness to outliers, which is particularly advantageous when dealing with data from electricity markets where outliers can be prevalent.

The parameters $\beta(\tau)$ are estimated by solving the minimization problem, often using linear programming methods to handle the non-differentiable nature of the absolute value function in the objective. This estimation process is conducted in programming environment where $\beta(\tau)$ are calculated for a various quantiles τ, where $0 < \tau < 1$. The environment employs linear programming techniques to address the non-differentiable minimization problem. We use the `quantreg`[13] package in R for the calculations. The package is specifically designed for quantile regression and manages the optimization challenge posed by the quantile regression loss function, $\rho_\tau(u) = u(\tau - I(u < 0))$. This function is non-differentiable due to the absolute residuals, rendering traditional

[13] Quantreg: Quantile Regression.

derivative-based optimization methods unsuitable. Instead, `quantreg` implements linear programming algorithms to efficiently estimate the coefficients, facilitating a robust and detailed exploration of the conditional quantile functions of the dependent variable.

This methodological approach is particularly advantageous in the electricity market, where distinctive attributes of electricity prices, marked by pronounced volatility, skewness, and frequent spikes, are evident (Hagfors et al., 2016). Quantile regression's ability to analyze effects across various quantiles allows for a comprehensive understanding of the impact of explanatory variables on different price levels.

The following quantiles are used in our model: 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80% and 90%. These points help to capture a wide range of outcomes, from low to high electricity prices, providing insights into different market conditions.

Base Model

We formulate a baseline quantile regression model to analyze electricity market pricing dynamics. The model focuses on the dependent variable weekly price, incorporating inflow variables and regional area. Its objective is to establish the electricity market's foundational price dynamics by isolating the effects of the inflow.

$$\begin{aligned} Q_\tau(\text{Price}|X) = \beta_0(\tau) + \beta_1(\tau) \ln \text{Inflow}_S + \beta_2(\tau) \ln \text{Inflow}_L + \\ \sum_{a=2}^{5} \gamma_a(\tau) \text{Area}_a \end{aligned} \tag{5.2}$$

The base model serves as a benchmark for the initial relationships, allowing us to explore the pure effects of inflows on price without additional complexities.

Main Model

Building upon our base model, the main model integrates all variables outlined in Table 4.1 and 4.2, controlling for a broader range of factors that may influence electricity prices.

$$
\begin{aligned}
Q_\tau(\text{Price}|X) = {} & \beta_0(\tau) + \beta_1(\tau)\ln\text{Inflow}_S + \beta_2(\tau)\ln\text{Inflow}_L + \\
& \beta_3(\tau)\ln\text{Volatility} + \beta_4(\tau)\ln\text{SEC} + \beta_5(\tau)\ln\text{Wind} + \\
& \beta_6(\tau)\ln\text{Certificate} + \beta_7(\tau)\ln\text{Gas} + \beta_8(\tau)\ln\text{Coal} + \\
& \beta_9(\tau)\ln\text{Eua} + \beta_{10}(\tau)\text{Time Trend} + \\
& \delta_1(\tau)\text{NE} + \delta_2(\tau)\text{RD} + \delta_3(\tau)\text{SSGD} + \\
& \sum_{m=2}^{12}\gamma_m(\tau)\text{Month}_m + \sum_{a=2}^{5}\gamma_a(\tau)\text{Area}_a
\end{aligned}
\tag{5.3}
$$

$\gamma_m(\tau)$ for February through December, with January used as the baseline month.

$\gamma_a(\tau)$ for the Area of NO2 through NO5, with NO1 used as the baseline area.

This comprehensive model allows us to evaluate the robustness of our base model's findings and to assess the explanatory power of additional variables. It also facilitates a deeper exploration of the quantile-specific effects of various market drivers, providing a richer understanding of the market.

We obtain standard errors with bootstrapping. Bootstrapping, first introduced by Efron (1979), is a resampling technique often used in statistical analysis, mainly when standard error formulas are complex to derive or are not reliable approximations of the actual sampling variation of an estimator (Wooldridge, 2018, p. 219). This method has been widely used in quantile regression to estimate the variance of the quantile regression estimator and construct confidence intervals, and several papers support this, including Hahn (1995). Bootstrapped quantile regression combines the robustness of bootstrapping with the flexibility of quantile regression to provide reliable statistical inference.

5.1.1 Interaction Terms

Interaction terms in regression models are a tool for understanding how the relationship between a dependent variable and an independent variable may vary depending on the level of another variable. This can give insights into models where variables often interact in complex ways (Wooldridge, 2018, pp.192-194). Specifically, in the context of examining electricity prices, including an interaction term enables the investigation of whether the influence of hydropower energy on electricity prices changes across various market conditions. This approach is particularly relevant for addressing the research question of how the impact of inflow on electricity pricing may differ under different market scenarios.

5.1.2 Timing of Data

Standard practice in modeling day-ahead prices involves using explanatory variables lagged by one day to maintain their exogeneity, ensuring they are known to the market before the closure of power exchanges (Hagfors et al., 2016). Our study, however, focuses on weekly electricity prices. Adhering to this convention might be less crucial for weekly data, yet we still chose to lag these variables by one day before aggregating them into weekly values.

5.1.3 Functional Form of the Data

Conejo et al. (2005) utilized a log transformation on their dataset to stabilize the variance. Similarly, Westgaard et al. (2021) applied log transformation to their data to smooth out fluctuations and interpret coefficients as elasticities. On the other hand, Karakatsani and Bunn (2010) contested the suitability of logarithmic shifts in the electricity market context. They cautioned that such transformations might obscure crucial statistical details and introduce inaccuracies. This consideration is especially pertinent since logarithmic transformations apply to positive numbers, and electricity price data can sometimes contain negative values. However, in our dataset, there are no instances of negative values. The pronounced divergence between peak and mean electricity prices in Norway's market justifies the logarithmic transformation of price data, aligning with Do et al. (2019) who contend that such a transformation is justified when the highest prices exceed the average or median levels in order of several magnitudes. Furthermore, we want to interpret the coefficients as elasticities, and we will transform our data using the natural logarithm[14].

5.1.4 Methodological Strategy for the Inflow Variables

Our methodology leverages weekly inflow data from NVE to analyze its impact on electricity prices, using two variables. The first, weekly reported inflow ($Inflow_S$), captures effects

[14] In cases where weeks have zero values, a constant is added to the variable to calculate ln(X). See: SSRN Paper.

primarily from unregulated hydropower and, to a lesser extent, regulated hydropower. The second variable, the Moving Annual Total (MAT) inflow ($Inflow_L$), is a dynamic measure representing the rolling yearly sum of the past 52 weeks. This MAT inflow provides a long-term view crucial for understanding trends in regulated hydropower, contrasting with the approach in Førsund (2007) that focuses on average price dynamics during periods of water abundance or scarcity.

Originally, we tried using the methodology from Førsund (2007) with annual aggregation from 2012 to 2023, yielding 12 data points. However, this led to statistically insignificant outcomes. We thus shifted to a methodology closer to Fleten et al. (2010), using a 52-week rolling sum after finding that this period optimally captures the correlation between inflow and electricity prices, incorporating significant seasonal variations.

5.2 Expected Results

We present our hypothesis exploring the impact of inflow on electricity prices. We investigate short-term and long-term effects across various market conditions, considering the differences between areas where regulated and unregulated hydropower production dominates.

5.2.1 Overall National Impact

We hypothesize that energy sources with lower MPC tend to dominate the market, particularly in lower price ranges. As hydropower production increases with more available inflow, we expect a significant downward pressure on prices, particularly in these lower quantiles. Our hypothesis predicts that all coefficients will display a negative effect, implying that increased supply leads to lower electricity prices, a trend consistent in both short-term and long-term perspectives. Furthermore, since most of the areas are dominated by regulated hydropower, we expect the magnitude of the coefficients to be higher in the long-term inflow variable.

However, in higher-priced market segments, dynamics may differ. Here, electricity prices are more influenced by energy sources with higher MPC. During high-demand periods or reduced availability of renewable energy sources, even substantial inflows may have a limited effect on lowering prices, as the market is influenced more by expensive energy sources.

Tables 5.1 and 5.2 are presented to illustrate our hypotheses on how short-term and long-term inflow influences electricity prices across different quantiles in various areas, where β^q represents the coefficient estimates of inflow impact.

Effect	Result
Inflow$_S$ reduces price	$\beta^q < 0$ for all quantiles
Reduced effect at higher quantiles	β^q increasing for higher quantiles

Table 5.1: Hypothesis for the Influence of Short-Term Inflow on Price Across Quantiles.

Effect	Result
Inflow$_L$ reduces price	$\beta^q < 0$ for all quantiles
Reduced effect at higher quantiles	β^q increasing for higher quantiles

Table 5.2: Hypothesis for the Influence of Long-Term Inflow on Price Across Quantiles.

5.2.2 Interaction with Market Conditions

This hypothesis examines the expected outcomes of interaction terms, exploring how the effects of inflow vary with fundamental market conditions. We will interact Reservoir Deviation (RD), Snow, Soil, and Groundwater Deviation (SSGD), and the Subsea Export Capacity (SEC) with the inflow variables.

When RD is above average, it signals higher-than-average reservoir levels and usually a low water value (Jaehnert, 2023). Since the water value is already low, the influence of inflow on electricity prices is expected to diminish. In such scenarios, the additional impact of inflow on electricity production and pricing is expected to become less pronounced.

In the case of SSGD, when there is significant snow in the mountains, it can be anticipated that there will be considerable future inflow due to melting. This expectation tends to decrease the water value, as producers expect ample water supply for future electricity generation (Koestler, 2020). Therefore, in scenarios of high SSGD, the effect of inflow on electricity prices is likely to be reduced.

The study by Døskeland et al. (2022) suggests that as the SEC's capacity expands, the influence of inflows on electricity prices is likely to diminish. Conversely, Sapio (2019) indicates that for unregulated renewables, this increase in capacity could lead to more downward pressure on prices from these energy sources. Hence, we expect different effects from the two inflow variables.

5.2.3 NO1 vs NO2-NO5

The expected results from inflow in Areas NO1 and NO2-NO5 are summarized in Tables 5.3 and 5.4, where β^q represents the coefficient estimate of inflow.

Effect	Result
Inflow$_{S,NO1}$ reduces price	$\beta^q < 0$ for all quantiles
Reduction diminishes at higher quantiles	β^q increasing for higher quantiles

Table 5.3: Hypothesis for Area NO1.

Effect	Result
Inflow$_{S,NO2-NO5}$ reduces price	$\beta^q < 0$ for all quantiles
Inflow$_{L,NO2-NO5}$ reduces price	$\beta^q < 0$ for all quantiles
Reduction diminishes at higher quantiles	β^q increasing for higher quantiles

Table 5.4: Hypothesis for Areas NO2-NO5.

In Area NO1, characterized by unregulated hydropower, short-term inflow fluctuations are expected to significantly influence electricity prices. This is reflected in the hypothesis that $Inflow_{S,NO1}$ leads to a reduction in prices, with the effect diminishing at higher quantiles.

In contrast, Areas NO2-NO5 feature regulated hydropower, which includes water storage capabilities. This configuration allows for a more pronounced impact from long-term inflow variations ($Inflow_L$). Therefore, both short-term ($Inflow_S$) and long-term ($Inflow_L$) inflows are considered in the hypothesis for these areas. Although both types of inflow are expected to reduce prices, the impact of long-term inflow ($Inflow_L$) is anticipated to be more substantial. Despite the significant role of $Inflow_L$, the influence of short-term inflow ($Inflow_S$) should not be overlooked, as it still contributes to price variations in these areas.

6 Empirical Results

Our quantile regression analysis explains how different factors influence the electricity price at various points in its distribution. The analysis is visualized through a series of plots, each depicting the coefficient estimates of our independent variables across distinct price quantiles. These plots highlight each variable's effect at different price levels.

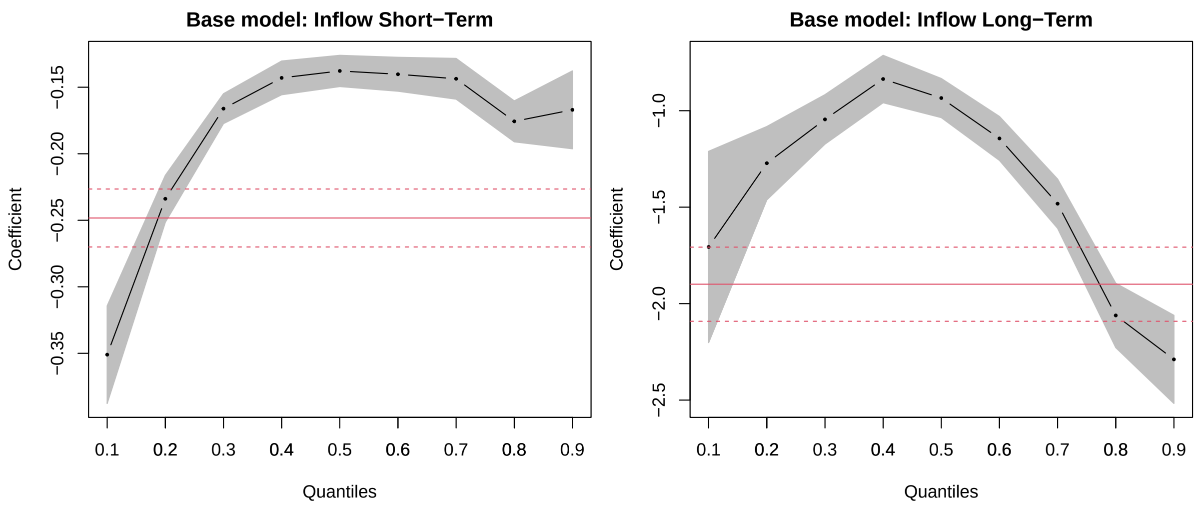
The y-axis shows the coefficient values for our independent variables. The x-axis, meanwhile, represents the quantiles of the price levels, ranging from the 10% to the 90% quantiles. The core of each graph is the line representing the coefficient estimates for a given variable across price quantiles. The line visually illustrates how the variable's influence changes from one quantile to another. Surrounding these estimates is a shaded area depicting the bootstrapped 95% confidence intervals.

Additionally, for comparative purposes, each plot includes the OLS estimates depicted as solid red lines consistent across all quantiles and their respective confidence intervals shown through dotted red lines. While these OLS lines provide a benchmark for comparing the average effects captured by OLS and the detailed effects revealed in the quantile regression, detailed discussions on these estimates will be omitted. This decision aligns with the conclusions drawn in the methodology section.

We'll discuss the quantile regression results in more detail, examine how different factors might interact, and investigate how the results differ in areas with predominantly unregulated and regulated hydropower production. Given the log-log structure of our quantile regression models, we can interpret the coefficients as elasticities. This interpretation allows us to understand the proportional relationship between the dependent and independent variables.

6.1 Base Model

Our analysis initiates with the base model specified in Equation 5.2, which includes critical inflow measures and area dummy variables. Coefficients from the quantile regression are presented in Figure 6.1, detailing the influence of short-term and long-term inflow variables on electricity pricing.



(a) Short-Term (b) Long-Term

Figure 6.1: Short-Term and Long-Term Effects of Inflow on Electricity Prices.

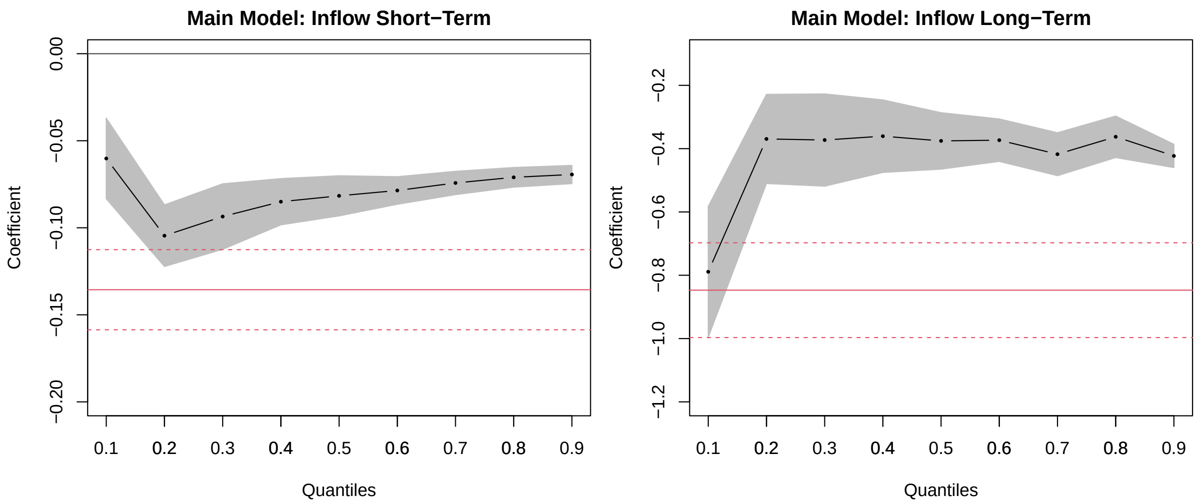
Figure 6.1a reveals the short-term impact on electricity prices. The results demonstrate a distinct negative correlation between increases in short-term inflow and electricity prices, supporting our hypothesis. There is a noticeable diminishing effect up to the median (50% quantile). After the 50% quantile, the coefficients flatten but have a more significant impact in higher quantiles. For instance, at the 10% quantile, a 1% increase in weekly inflow correlates with a decrease of 0.351% in electricity prices. In contrast, at the 90% quantile, this effect is moderated, with the same 1% increase in inflow leading to a minor price reduction of 0.167%. This variation in impact, from -0.351% to -0.167% across different quantiles, highlights a more pronounced effect at the lower end of the price levels.

The coefficients in Figure 6.1b illustrate the long-term effects. The downward pressure decreases from the lower quantiles up to the 40% quantile. The effect shows a shift beyond this point. The influence of inflow on driving prices downwards becomes more significant again. This pattern is pronounced at the extremes of the quantile range, underscoring a more impactful role of inflow on both the lower and higher ends of the price. The magnitude of the coefficients is higher than the short-term coefficients and ranges from -1.706 in the 10% quantile to -2.289 in the 90% quantile, with the lowest effect in the 40% quantile.

The analysis reveals that the coefficients are statistically significant at the 1% level across all quantiles, covering both short-term and long-term periods. Notably, short-term and long-term coefficients are negative, aligning with our hypothesis and suggesting a price decrease. However, the larger absolute values at the 80% and 90% quantile in the short term and the increasing trend in higher quantiles over the long term were unexpected. These unexpected results suggest the necessity to integrate additional fundamental factors into our model. A likely explanation is the overestimation of inflow effects by our current model. Given this complexity, drawing meaningful conclusions without including fundamental factors is inadvisable. Consequently, the following subsection will introduce a more complex model that provides for essential control variables.

6.2 Main Model

Building on our base model, the main model includes all the variables displayed in Tables 4.1 and 4.2. This model controls for additional factors affecting price, offering a more detailed exploration of the impact inflow has on electricity prices, as further quantified in the regression coefficients. Table A3.2 in the Appendix presents the quantile regression results, while Figure 6.2 illustrates the coefficients derived from the inflow variables.



(a) Short-Term (b) Long-Term

Figure 6.2: Comparative Analysis of Short-Term and Long-Term Inflow Coefficients.

Figure 6.2a presents the coefficients corresponding to the short-term variable. The coefficients vary slightly across the quantiles but remain stable between -0.060 and -0.105, indicating that the impact of inflow on price is somewhat uniform across the distribution. The larger absolute values at specific quantiles (like 20%) could suggest a more pronounced inflow effect on price at those particular points.

For example, a 1% increase in short-term inflow is associated with a 0.060% decrease in the 10% quantile of electricity prices. Notably, the 20% quantile represents the most magnitude coefficient observed with a 1.05% decrease for a 1% increase in inflow. At the 90% quantile, the coefficient is -0.069, suggesting that a 1% rise in inflow leads to a 0.069% reduction in the corresponding electricity price quantile.

However, it is essential to recognize that this effect consists of two components, each with its mechanisms influencing market prices, aligning with the theoretical framework presented earlier in the paper.

Firstly, there is the direct impact of inflow from unregulated hydropower. Increased water availability for these hydropower plants might increase production, which can induce a rightward shift in the merit order curve, resulting in lower electricity prices. This relationship underscores the immediate linkage between inflow and electricity generation and its effect on the dynamics of the merit order curve.

Secondly, the inflow to reservoirs imparts a less direct but essential effect on prices. By increasing reservoir levels, inflow increases the power balance—potentially leading to a decrease in the water value. The water value, determining the regulated hydropower Marginal Production Cost (MPC), can be influenced by the physical increase in reservoir capacity and the expectations surrounding future inflow. Such expectations can alter the strategic release of water, thus affecting current and future electricity prices. Moreover, heightened production caused by increased inflow to reservoirs can also lead to a rightward shift in the merit order curve.

Contrary to the short-term inflow coefficients, the coefficients in Figure 6.2b related to long-term inflow demonstrate excellent stability across different quantiles. The most substantial negative impact is observed at the 10% quantile, where the effect of reducing electricity prices is most pronounced. Beyond this point, there is a noticeable decrease in the magnitude of this effect at the 20% quantile, followed by a consistent trend in higher quantiles. This pattern indicates that the influence of long-term inflow in lowering electricity prices is significantly noticeable at the 10% quantile. It further implies that during periods of high long-term inflow, the price-reducing effect tends to be less variable and more uniform across different electricity price levels.

The long-term coefficients exhibit varying magnitude, ranging from -0.789 at the 10% quantile to -0.361 at the 40% quantile. This variation indicates that a 1% increase in inflow over the previous year corresponds to a 0.789% decrease in price at the 10% quantile. In contrast, at the 40% quantile, where the coefficient is -0.361, the same 1% inflow increase results in a 0.361% reduction in price. Furthermore, at the highest quantile analyzed, a 1% increase in inflow is associated with a 0.423% decrease in price.

Consistent with the base model, the coefficients are negative and statistically significant at the 1% level across all quantiles. In contrast to the base model, which exhibited coefficients ranging from -0.351 to -0.140 in the short term and -1.706 to -2.289 in the long term, the full model reveals a more moderate effect. This moderation underscores the impact of fundamental factors, seasonality, and time trends, which, when unaccounted for, may overestimate the effect of inflow.

The results align with expectations in the short term, except for the lowest quantile, where inflow exerts a less significant downward pressure on prices. This finding supports the hypothesis that at higher electricity prices, typically driven by the MPC of generation, the effect of increased inflow is less pronounced. Such an outcome aligns well with the principles of the merit order. In contrast, the long-term estimates present unexpected findings. Here, inflow significantly impacts price reduction, especially when electricity prices are at their minimum. Beyond this specific point, across the rest of the distribution, the impact of inflow on prices demonstrates a nearly uniform effect.

6.3 Interaction Terms

After our model exploration, we focus on the interaction terms within our quantile regression analysis to reveal the interactions between inflow and different market conditions. The coefficients for interaction terms are shown in Table A3.3 in the Appendix.

6.3.1 Reservoir Deviation

We aim to analyze the impact of inflow on electricity prices, particularly when reservoir levels exceed their historical average. Reservoir deviation indicate whether there is more or less water available than usual for hydropower production. This availability is a crucial determinant of both the water value and, consequently, electricity prices. Our focus is on an interaction term designed to explore how the effect of inflow varies depending on the volume of water available for hydropower production. Essentially, it investigates if the influence of inflow on electricity prices alters when there's a positive deviation in reservoir fill levels. For instance, a negative coefficient in the interaction term would suggest that reservoir levels higher than average amplify the reducing effect of inflow on electricity prices, as opposed to scenarios where reservoir levels are below average.

(a) Reservoir Short-Term

(b) Reservoir Long-Term

Figure 6.3: Comparative Analysis of RD Interaction with Short-Term and Long-Term Inflow.

In Figure 6.3a, we depict the short-term dynamics of coefficient values. These coefficients measure the extra impact when reservoir levels exceed the historical average. A key observation is that all negative coefficients signify a heightened inflow effect under these conditions. The magnitude of these coefficients is most pronounced in the lower quantiles, gradually diminishing as the quantiles rise, ranging from -0.099 at the 10% quantile to -0.022 at the 90% quantile. This trend implies a more substantial downward pressure on electricity prices when reservoir levels exceed the historical average.

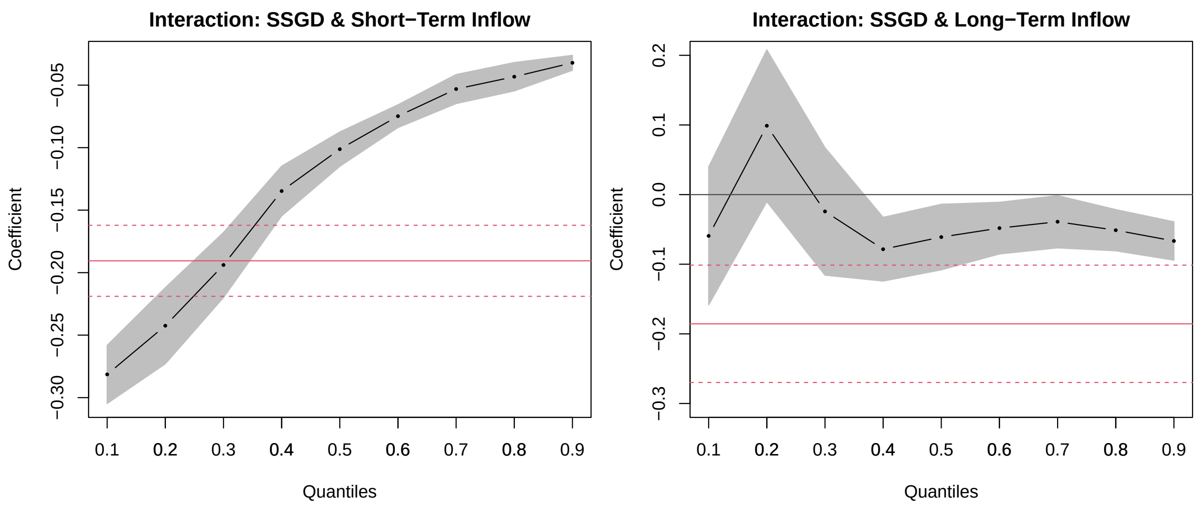
In Figure 6.3b, the analysis concentrates on the relationship between long-term inflow and variations in reservoir levels. As anticipated, the coefficients are positive. However, significance is observed only at the 20% quantile, which suggests no significant relationship exists between the increased effect from inflow and reservoir levels when they exceed the historical average.

Another point of interest is the relatively high Standard Errors (SE) associated with these coefficients. For instance, at the 10% quantile, the SE is 0.086, which is quite substantial relative to the coefficient of 0.071. High SE indicates a lower level of precision in the estimates, suggesting that the actual effect of this interaction could vary widely. This lack of accuracy could be due to variability in the data, or it could reflect that other unobserved factors influence the relationship between long-term inflow, reservoir levels, and electricity prices.

The unexpected negative coefficients found in the short-term analysis could be explained by situations where flooding leads to high reservoir levels and extremely low and sometimes even negative, electricity prices due to supply exceeding demand (Statnett, 2023). The additional effect from inflow in these scenarios could account for the coefficients observed, suggesting that the short-term variable is particularly relevant for run-of-the-river energy production, an impact that reservoirs and water values do not influence. In contrast, long-term observations show no significant correlation, which is consistent with our initial hypothesis.

6.3.2 Snow, Soil and Groundwater Deviation

In the previous subsection, we explored the interaction between inflow and electricity prices in the context of reservoir-level fluctuations. Extending this approach, we now examine the impact of deviations in the Snow, Soil, and Groundwater (SSGD) levels from their historical average. A notable distinction is potential future inflow, distinct from reservoir deviations. This interaction term is included to analyze whether inflow effects vary when producers anticipate significant future inflow from snow, soil, and groundwater.



(a) Inflow and SSGD Short-Term (b) Inflow and SSGD Long-Term

Figure 6.4: Comparative Analysis of SSGD Interaction with Short-Term and Long-Term Inflow.

Figure 6.4a presents estimates for the interplay between weekly inflow and SSGD. The interaction coefficients are uniformly negative across all quantiles and exhibit statistical significance at the 1% level. This consistent pattern underscores the intensified impact of short-term inflow on electricity prices, mainly when there's an above-average forecast for future reservoir inflow.

A closer examination reveals that the interaction's influence on the price levels varies significantly. This variation is most evident in the differential magnitude of coefficients at different quantiles. For instance, the interaction's negative impact on price is markedly more substantial at lower quantiles, diminishing progressively at higher quantiles. Quantitatively, the coefficients at different quantiles are as follows: -0.281 at the 10% quantile, -1.101 at the median (50% quantile), and -0.032 at the 90% quantile. To provide context, consider the median impact: when the SSGD is above its historical average, a 1% increase in inflow correlates with a 1.101% increase in the downward pressure on electricity prices.

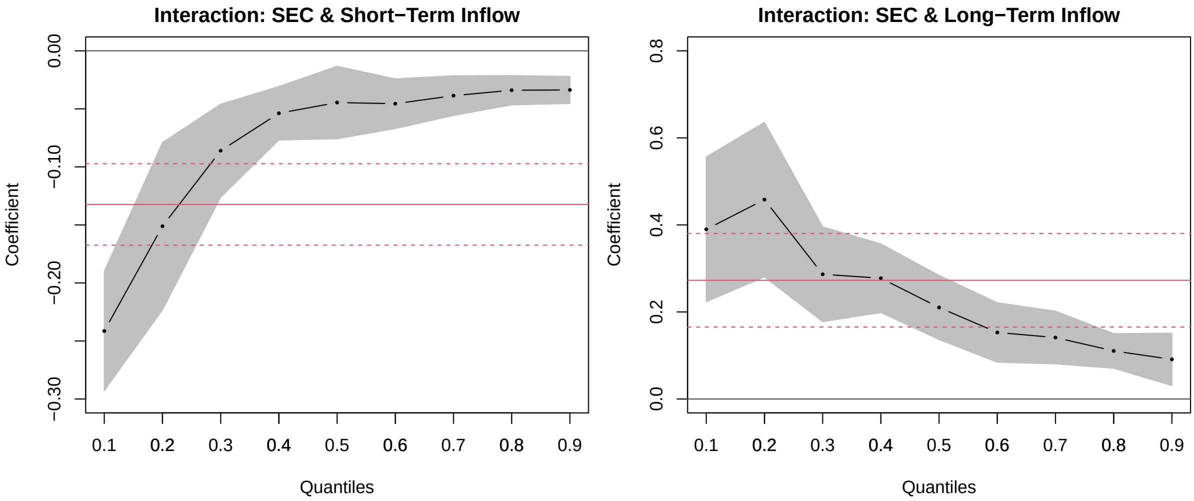
In the long-term analysis, we observe a persistent negative relationship, illustrated in Figure 6.4b. Notably, this relationship becomes statistically significant at and beyond the 40% quantile. This pattern is distinct from the short-term analysis, where more substantial variability is evident. The relatively consistent coefficients across higher quantiles in the long-term data suggest a more stable relationship. This stability indicates that the factors influencing this relationship are less volatile in the long term. The estimates range from -0.061 at the 40% quantile to -0.067 at the 90% quantile, indicating that a 1% increase in inflow results in a rise in 0.061% in the downward pressure on electricity prices at the 40% quantile and an increase of 0.067% at the 90% quantile.

The interaction terms indicate the combined effects of current inflow and anticipated future inflow, with high expected future inflow amplifying the impact of current inflow. This dynamic is likely related to an increased water supply, enhancing hydropower production. Koestler (2020) observe that anticipated high snowmelt inflow prompts water release from reservoirs, boosting hydropower production. This positive hydrological balance and heightened hydropower production correlate with lower electricity prices, which supports our findings.

6.3.3 Subsea Export Capacity

This subsection explores the impact of increased interconnector capacity between Norway and the European electricity market on price dynamics. The expansion of these interconnectors is expected to modify the traditional influence of water inflow on electricity prices (Døskeland et al., 2022). Historically, variations in precipitation directly affected prices due to changes in hydroelectric power availability. However, with the new interconnectors, these relationships may shift. Low precipitation levels may not lead to the sharp price increases seen in the past, and similarly, high precipitation might not cause the usual price declines. This subsection examines the evolving influence of inflow on electricity pricing following the integration of increased Subsea Export Capacity (SEC).

In Figure 6.5a, the coefficients are negative and statistically significant at the 1% level, except at the 50% quantile, where the significance is at the 5% level. These negative coefficients suggest that an increase in capacity enhances the price-reducing effect of inflow, particularly in the lower tail of the data distribution. This finding is unexpected. The varying magnitudes of these coefficients across different quantiles indicate that the interaction between short-term inflow and SEC affects electricity prices differently at various price levels. The impact is more substantial at lower quantiles (e.g., -0.241 at the 10% quantile) and diminishes at higher quantiles (e.g., -0.034 at the 90% quantile).



(a) SEC Short-Term (b) SEC Long-Term

Figure 6.5: Comparative Analysis of SEC with Short-Term and Long-Term Inflow.

A potential explanation for the negative coefficients observed in our analysis could be the increased production from unregulated hydropower, which contributes to the merit order effect during specific periods (Blaker, 2023). Additionally, the expansion of unregulated hydropower capacity supports this finding (AFGruppen, n.d.). Our results are consistent with those of Sapio (2019), who identified a strengthened negative correlation between electricity prices and unregulated energy sources, amplified by interconnectors.

Figure 6.5b presents the long-term coefficient estimates, which are statistically significant at the 1% level across all quantiles, except at the 90% quantile, where the significance drops to 5%. This consistent pattern suggests that the negative impact of inflow on electricity prices diminishes as the capacity of subsea interconnectors increases. The effect consistently weakens across all quantiles, with the magnitude of the impact decreasing from 0.458 at the lowest quantile to 0.091 at the highest. These results highlight the moderating influence of subsea interconnector capacity on the relationship between inflow and electricity prices across various price levels.

The positive interaction coefficients between long-term inflow and SEC indicate that as SEC increases, the price-reducing impact of long-term inflow diminishes. Norway can manage its reservoir levels more strategically with greater export capacity. Rather than driving down domestic prices by increasing supply, the electricity can be stored and potentially sold at higher prices to neighboring countries when demand peaks. This approach leads to a more moderated reduction in domestic electricity prices. This moderated effect of inflow on pricing is especially evident at the lower quantiles.

This might suggest that with more capacity, the Norwegian market will be more integrated with neighboring markets. Hence, the price effects are more moderated by the regional balance of supply and demand over the long term. In other words, increased capacity allows for better-balancing electricity supply and demand across borders, stabilizing prices.

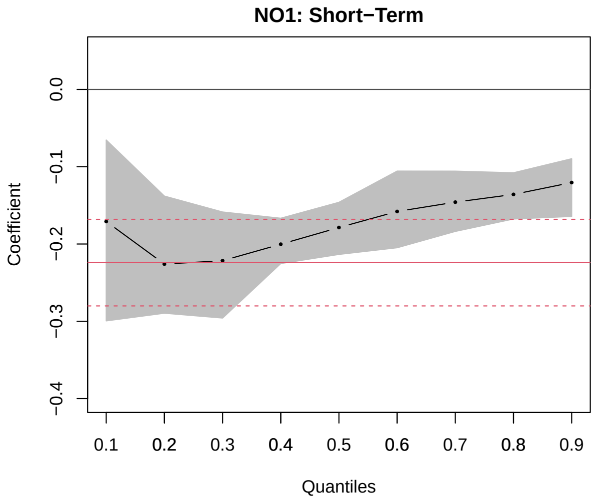
6.4 NO1 vs NO2-NO5

In addition to analyzing the electricity market in Norway, this subsection aims to look into the impacts across different areas. Although our primary results encompass Norway, an area-specific analysis presents an interesting perspective, especially considering the diversity in hydropower regulation.

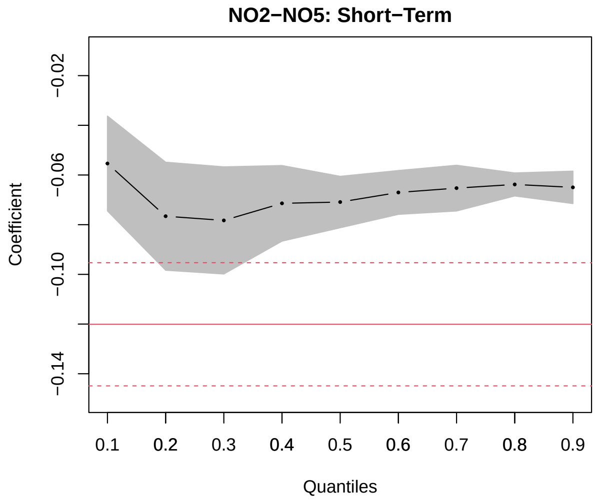
We will focus on contrasting the effects of NO1 vs NO2-NO5. NO1 is notable for its substantial unregulated hydropower capacity, influenced more by short-term inflow variations. Meanwhile, NO2-NO5 predominantly features regulated hydropower, making long-term inflow more relevant. Quantile regression results for NO1 and NO2-NO5 are presented in A3.4 and A3.5 in the Appendix, respectively.

6.4.1 Short-Term

Figure 6.6 compares the effects of short-term inflow electricity prices between Area NO1 and Areas NO2-NO5. In Area NO1, the coefficients are significantly negative across all quantiles, ranging from -0.171 to -0.120. This consistent negative trend indicates that increased short-term inflow leads to decreased electricity prices. The magnitude of the coefficients, along with their statistical significance, underscores the strong influence of short-term inflow in this area. Furthermore, the diminishing absolute value of coefficients at higher quantiles suggests that while short-term inflow is a significant price determinant, its influence decreases at higher price levels.



(a) NO1



(b) NO2-NO5

Figure 6.6: Area Effects from Short-Term Inflow on Electricity Prices.

Conversely, in Areas NO2-NO5, the coefficients are also negative across all quantiles but with smaller magnitudes, ranging from -0.055 to -0.065. The consistent negative values across quantiles indicate a decrease in electricity prices with increased short-term inflow, similar to Area NO1. However, the smaller magnitude of these coefficients than NO1 suggests that short-term inflow has a less pronounced effect in these areas.

The more substantial coefficients in NO1 highlight the greater sensitivity of electricity prices to short-term inflow variations in predominately unregulated hydropower production. This is likely due to the rapid response of unregulated systems to fluctuations in water inflow. In contrast, the regulated systems in NO2-NO5, with their ability to store water in reservoirs, exhibit a more muted response to short-term inflow changes.

Both areas show a consistent negative impact across all quantiles, but the effect is more pronounced in NO1. This suggests that short-term inflow is critical in unregulated and regulated areas, but its relative importance is higher where hydropower is unregulated.

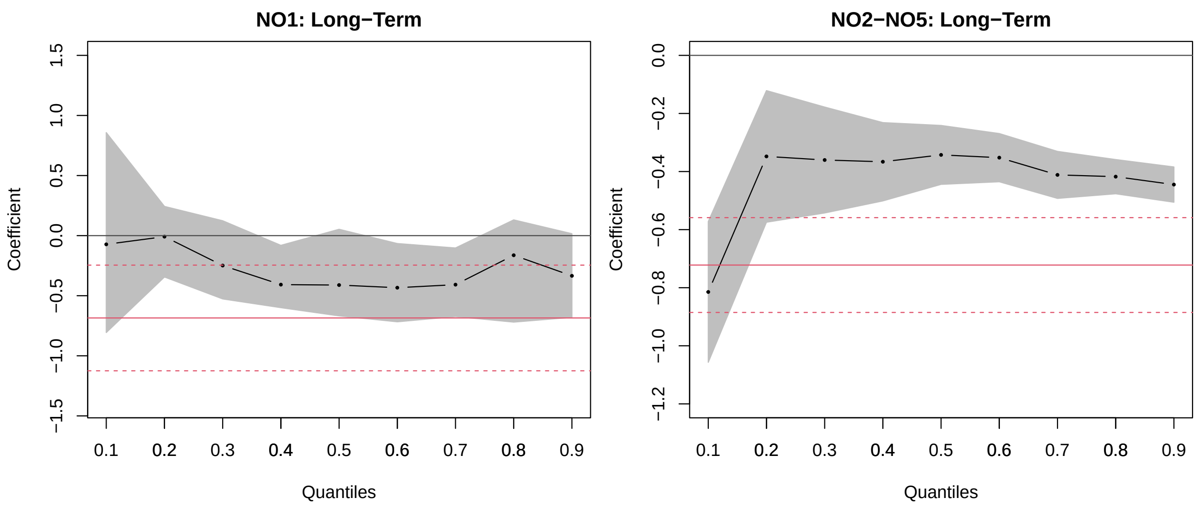
The difference in the magnitude of coefficients confirms our hypothesis. Unregulated systems in NO1 react more directly to inflow variations, influencing prices more significantly. In contrast, regulated systems in NO2-NO5 have mechanisms to buffer against short-term inflow variability, leading to a lesser immediate impact on prices. Moreover, these regulated systems allow producers to adapt to price changes strategically. Since producers can control the release of water, they tend to sell when prices are high, aligning with the higher water value. This regulation enables them to maximize profits based on the value of water. Such a strategy can then be effective in regulated environments where the ability to control water release impacts market prices.

In addition to the observed differences between unregulated and regulated hydropower systems in response to short-term inflow, it's essential to consider specific scenarios such as flood conditions. In periods of high reservoir levels or extreme inflow, regulated hydropower systems in areas like NO2-NO5 might temporarily operate similarly to unregulated systems. This situation occurs when the power plants might need to release water to avoid flooding, effectively making them 'unregulated' during these periods. This aspect adds another layer to our understanding of the dynamics in regulated areas.

During such high inflow events, the distinction between regulated and unregulated systems diminishes, as both types of systems may be compelled to release water regardless of current electricity demand, potentially leading to a more pronounced decrease in electricity prices as observed in unregulated systems under normal conditions. Therefore, while regulated systems generally exhibit a buffered response to short-term inflow variability, extreme conditions such as potential flooding can temporarily align behavior with unregulated systems, reinforcing our observations of negative coefficients in electricity price response across NO1 and NO2-NO5.

6.4.2 Long-Term

In the context of long-term inflow in Figure 6.7, the dynamics between Areas NO1 and NO2-NO5 exhibit a significant variance, aligning with our hypothesis. For Area NO1, characterized predominantly by unregulated hydropower, the impact of inflow on electricity prices is less pronounced compared to the short-term estimates. NO1 reacts quickly to short-term inflow changes but is less sensitive to long-term variations. Consequently, in NO1, the coefficients are relatively minor and less consistent, indicating a weaker correlation between long-term inflow and electricity prices.



(a) NO1 (b) NO2-NO5

Figure 6.7: Area Effects from Long-Term Inflow on Electricity Prices.

We observe a pronounced effect in areas NO2-NO5, where regulated hydropower is prevalent. The significant coefficients in these areas highlight the advantages of regulated hydropower in water resource management over extended periods. These areas exhibit a strong and consistent negative correlation between long-term inflow and electricity prices, confirming our hypothesis that regulated hydropower in NO2-NO5 is more influenced by long-term inflow conditions compared to the unregulated hydropower in NO1.

The regression analysis reinforces this hypothesis, showing that long-term inflow significantly impacts electricity prices in areas with regulated hydropower. This impact underscores the importance of storage and regulation capabilities in these systems, especially for managing variations in long-term inflow. Additionally, the RD variable, which represents reservoir deviation, yields significant results in NO2-NO5, further emphasizing the importance of reservoir levels in these regulated areas. In contrast, its negligible effect in NO1 supports the observation of limited reservoir management influence in unregulated hydropower.

7 Discussion

7.1 Effect on Electricity Prices

The outcomes of the study, highlighting both short-term and long-term effects of inflow on electricity prices in Norway, resonate with the theoretical framework. The negative relationship between increased inflow and electricity prices, observed in the quantile regression analysis, aligns with Norway's hydropower-dominated energy mix, reflective of both the effect of unregulated hydropower and regulated hydropower's flexibility, which increases with inflow, exerting downward pressure on electricity prices due to the merit order effect.

Our findings align with those of Owolabi et al. (2022), who reported a diminished impact on electricity prices with higher hydropower production, particularly in upper quantiles. However, their research, focusing only on renewable sources like hydropower, wind, and solar, needs a comprehensive scope as it excludes critical factors such as fossil fuels. This limitation makes a direct comparison less applicable. Interestingly, we observe a magnified effect in the upper quantiles when contrasting our results with a base model incorporating only inflow variables. Nonetheless, caution is advised when drawing direct comparisons, given the significant difference in the energy mix between Norway and England in their study, where hydropower is not as predominant.

In our study, we observed significant results contrasting those reported by Khazal et al. (2023), who found no significant correlation between inflow and electricity prices. Unlike our approach, Khazal et al. (2023) incorporated the water content available in reservoirs and inflow data. They attributed the lack of significant findings to this methodological difference, noting that increased water levels, equivalent to increased inflow, tend to lower prices. This observation aligns with our findings. However, Khazal et al. (2023) mentioned that inflow alone did not significantly impact prices when controlling for reservoir contents, a conclusion divergent from ours. This discrepancy might be explained by the fact that our analysis includes reservoir deviation, but not actual reservoir levels due to the seasonal fluctuation. Additionally, their study's time-related and geographical scope, covering data from 2008 to 2013 across areas (NO1-NO4), differs from ours, which could further account for the variation in results.

The area-specific analyses reveal the impact of inflow on prices across different Norwegian areas, resonating with the geographical differences in reservoir capacities and hydropower capabilities. Further, interaction terms highlight the intricate relationship between inflow and other market dynamics. These variations illustrate the effect of inflow on overall electricity prices, especially at higher quantiles. This effect aligns with the merit order's role in setting electricity prices.

7.2 Unexpected Findings

One unexpected finding was the interaction between subsea export capacity and short-term inflow on electricity prices. Contrary to initial expectations, the coefficients were negative and statistically significant, indicating that increasing export capacity amplifies the price-reducing impact of inflow. This finding is counterintuitive since expanded export capacity typically leads to higher electricity prices (Døskeland et al., 2022). Further integrating Norway into the European market, potentially mitigating the influence of inflow on prices. A plausible explanation could be found in the production dynamics of run-of-the-river energy and its role in the merit order effect during specific periods (Sirin & Yilmaz, 2020). Additionally, the dominance of unregulated hydropower in NO1 and NO2, which are most affected by the subsea interconnectors, might contribute to this phenomenon. Consequently, it is NO1 that primarily drives this significant effect.

Additionally, the increased capacity following the introduction of NSL and NL could have played a role. Sapio (2019) noted a strengthened negative correlation between prices and unregulated energy sources due to interconnectors[15]. These factors suggest a complex interplay between export capacity and inflow. While the cables initially raise prices, they also increase the price-reducing impact of additional inflow. Even with a higher baseline price due to cables, the relative reduction caused by inflow seems more substantial, indicative of the complex interplay between renewable energy, market, and infrastructure developments like increased cable capacity.

[15] Sapio (2019) also observed that the interaction between cables and renewable energy sources generally showed a negative correlation with electricity prices in Italy, indicating a strengthening of the merit order e□ect. However, this e□ect varied across areas, with some showing positive or non-significant impacts.

7.3 Implications of Quantile Regression Model

Our findings emphasize the advantage of quantile regression over OLS, highlighted by significant disparities in their estimates. These variations across different electricity price levels confirm quantile regression's suitability for our dataset, supporting the choice through other studies like Hagfors et al. (2016) and Bunn et al. (2016).

7.4 Limitations

Our study examines the overall impact of water inflow on electricity prices, combining the effects of unregulated and regulated hydropower without distinction. It's important to note that our regression analysis does not separate these effects; instead, it considers the total impact of inflow. A limitation of our current model is its inability to distinguish between the contributions of hydropower from run-of-the-river and reservoirs. Future research should address this gap.

Additionally, the uncertainty of weekly water inflow affects the valuation of water and, consequently, the electricity market prices. This is because the models used to calculate water value can adapt in real time to fluctuations in weekly inflow. Therefore, variations in water inflow each week can lead to changes in the outputs of these models. However, determining the specific impact of these fluctuations on market prices is not addressed within the scope of our current analysis.

Lastly, the study does not account for the role of infrastructure bottlenecks, such as transmission and distribution capacity limitations, which are critical drivers of price formation in electricity markets. Future research would benefit from integrating more granular, possibly hourly, market data to comprehensively understand how these bottlenecks impact prices, especially under high supply or demand conditions. The 10-year period of our long-term analysis may need to sufficiently capture the full range of dry and wet years, potentially limiting the understanding of the actual long-term effects of inflow variability. Extending the analysis period in future research could yield insights into how extreme hydrological conditions impact electricity prices over more extended times periods.

8 Conclusion

This study contributes to renewable energy research, with a particular focus on electricity markets heavily reliant on hydropower. Amidst escalating global concerns over climate change, increasing electricity demands, and the push for market interconnectivity, our study underscores the critical impact of inflow on electricity prices in Norway, a country predominantly powered by hydroelectric resources. We present the complex, nonlinear relationship between inflow and electricity prices through quantile regression analysis, revealing a predominantly negative correlation with notable variability across the different price levels.

Our analysis underscores the dynamic interplay between hydrological inflow and electricity pricing within Norway's market, which is distinguished by its heavy reliance on regulated and unregulated hydropower sources. Through quantile regression, we find a consistently negative impact of inflow on electricity prices, a trend that persists across the various price levels. Notably, we observed that short-term inflow has a pronounced effect on lowering prices when reservoirs hold more water than their historical average, accentuating the importance of hydrological conditions in price formation. Additionally, when snow, soil, and groundwater levels surpass their historical averages, the effect of reducing electricity prices is further increased. Contrary to initial assumptions, short-term inflow's influence on price does not appear to diminish with the expansion of transmission cable capacity; instead, the long-term inflow positively correlates with such infrastructural developments, suggesting a nuanced relationship between market mechanisms and infrastructure. Notably, markets with a predominance of unregulated hydropower exhibit a higher sensitivity to short-term inflow variations than those influenced by long-term inflow, underscoring the strategic use of water in regulated systems for electricity generation over extended periods.

These findings underline the intricate dynamics between hydrological inflow and electricity market operations in a hydro-dominated energy system, highlighting the importance of adaptive resource management to ensure market stability and efficiency.

Policymakers and market operators can leverage our findings to enhance hydropower resource management, aiming for stability and efficiency in the energy market despite changing environmental and market conditions. Specific policy measures could include more effectively integrating new renewable energy sources with other hydropower to mitigate the impacts of hydrological variability.

Understanding the dynamics between hydrological factors and electricity pricing becomes increasingly crucial as we move towards a sustainable and interconnected energy future. Our research contributes to this understanding, offering a robust framework for addressing the complexities of hydro-dominated electricity markets.

Declaration on the use of AI tools

Name (and version) of the AI tool: ChatGPT, 4.0.

Purpose of using the tool: AI-based tools were used for aid in structuring and organizing content. The use of AI was strictly as a supportive tool, and all content and analyses were independently conducted.

We are aware that we are responsible for all content of this master's thesis, including the parts where AI tools are used. We are responsible for ensuring that the thesis complies with ethical rules for privacy and publication.

References

AFGruppen. (n.d.). *Vamma Kraftverk*. https://afgruppen.no/prosjekter/anlegg/vamma-kraftverk/

Antweiler, W., & Muesgens, F. (2021). On the long-term merit order effect of renewable energies. *Energy Economics*, *99*, 105275. https://doi.org/10.1016/j.eneco.2021.105275

Bjarnes, A., Ursin, L., Paarup Michelsen, L.-H., & Skaugen, H. (2023, November 1). *Håndbok til energidebatten* (Temanotat 1/2023). Klimastifelsen. https://www.klimastiftelsen.no/publikasjoner/handbok-til-energidebatten

Blaker, M. (2023, August 30). *Norge eksporterte en nesten ufattelig mengde strøm i forrige uke.* https://www.nettavisen.no/strom/strompriser/nve/nve-nar-full-eksport-pa-alle-stromkabler-fra-sor-norge/s/5-95-1296505

Boersen, A., & Scholtens, B. (2014). The relationship between European electricity markets and emission allowance futures prices in phase II of the EU (European Union) emission trading scheme. *Energy*, *74*, 585–594. https://doi.org/10.1016/j.energy.2014.07.024

Bunn, D., Andresen, A., Chen, D., & Westgaard, S. (2016). Analysis and Forecasting of Electricity Price Risks with Quantile Factor Models. *The Energy Journal*, *37*(1), 101–122. https://doi.org/10.5547/01956574.37.1.dbun

Bye, T., Bjørndal, M., Doorman, G., Kjølle, G., & Riis, C. (2010, November 30). *Flere og riktigere priser -Et mer e ektivt kraftsystem*. Energidepartementet. https://www.regjeringen.no/globalassets/upload/oed/rapporter/2010_1130_flere_og_riktigere_priser_et_mer_effektivt_kraftsystem.pdf?id=2200911

Bye, T., & Bruvoll, A. (2006, September 14). *Tilsigssvikt – konsekvenser for produksjon og priser*. SSB. https://www.ssb.no/a/publikasjoner/pdf/oa_200604/bye.pdf

Conejo, A. J., Contreras, J., Espínola, R., & Plazas, M. A. (2005). Forecasting electricity prices for a day-ahead pool-based electric energy market. *International Journal of Forecasting*, *21*(3), 435–462. https://doi.org/10.1016/j.ijforecast.2004.12.005

Csereklyei, Z. (2020). Price and income elasticities of residential and industrial electricity demand in the European Union. *Energy Policy*, *137*, 111079. https://doi.org/10.1016/j.enpol.2019.111079

Do, L. P. C., Lyócsa, Š., & Molnár, P. (2019). Impact of wind and solar production on electricity prices: quantile regression approach. *Journal of the Operational Research Society*, *70(10)*, 1752–1768.

Døskeland, I. H., Kringstad, A., & Bøhnsdalen, E. T. (2022, March). *Prisvirkning av NordLink og NSL*. Statnett. https://www.statnett.no/contentassets/

489321f1ecf74728b0d8e376921bf39c/prisvirkning-av-nordlink-og-nsl---metode-og-oppdatert-estimat-mars-2022.pdf

Efron, B. (1979). Bootstrap Methods: Another Look at the Jackknife. *The Annals of Statistics*, *7*(1). https://doi.org/10.1214/aos/1176344552

Energidepartementet. (2023, December 29). *Straumforsyning og straumnettet.* Retrieved January 5, 2023, from https://www.regjeringen.no/no/tema/energi/strom/stromforsyning-og-stromnettet/id2353792/

Energifakta. (2023a, November 29). *Avgifter og kvoteplikt.* Retrieved January 10, 2024, from https://energifaktanorge.no/et-baerekraftig-og-sikkert-energisystem/avgifter-og-kvoteplikt/

Energifakta. (2023b, November 29). *Kraftmarkedet.* Retrieved January 10, 2024, from https://energifaktanorge.no/norsk-energiforsyning/kraftmarkedet/

Energifakta. (2023c, November 30). *Kraftproduksjon.* Retrieved September 1, 2024, from https://energifaktanorge.no/norsk-energiforsyning/kraftforsyningen/

Fleten, S.-E., Seim, T. O., & Thorsnes, O. R. (2010). The Relationship Between Prices and Inflow in Hydroelectric Scheduling. *2010 Modern Electric Power Systems, Wroclaw, Poland, 2010, pp. 1-7.*

Førsund, F. R. (2007). *Hydropower Economics*. Springer Science & Business Media.

Gjerland, C. F., & Gjerde, M. (2020). *Wind Power Production and Electricity Price Volatility* [Masterthesis, NHH]. Brage. https://openaccess.nhh.no/nhh-xmlui/handle/11250/2679448

Hagfors, L. I., Bunn, D., Kristoffersen, E., Staver, T. T., & Westgaard, S. (2016). Modeling the UK electricity price distributions using quantile regression. *Energy*, *102*, 231–243. https://doi.org/10.1016/j.energy.2016.02.025

Hahn, J. (1995). Bootstrapping Quantile Regression Estimators. *Econometric Theory*, *11*(1), 105–121. https://doi.org/10.1017/S0266466600009051

Halleraker, J. H., & Rosvold, K. A. (2023, January 25). Minstevannføring. In *Store norske leksikon*. https://snl.no/minstevannf%C3%B8ring

Hao, L., & Naiman, D. (2007). *Quantile Regression*. SAGE Publications, Inc. https://doi.org/10.4135/9781412985550

Helseth, A., Mo, B., & Warland, G. (2010). Long-term scheduling of hydro-thermal power systems using scenario fans. *Energy Systems*, *1*(4), 377–391. https://doi.org/10.1007/s12667-010-0020-7

Holmqvist, E. (2017). *Norges vannbalanse i TWh basert på HBV-modeller.* (No. 87-2017). Norges vassdrags- og energidirektorat. https://publikasjoner.nve.no/rapport/2017/rapport2017_87.pdf

Huisman, R., Michels, D., & Westgaard, S. (2015). Hydro reservoir levels and power price dynamics. Empirical insight on the nonlinear influence of fuel and emission cost on Nord Pool day-ahead electricity pricesjae. *Journal of Energy and Development*, *40 (1-2)*, 149–187.

Jaehnert, S. (2023, January 31). *Hvorfor vannverdi er viktig for strømpris og forsyningssikkerhet*. Retrieved November 16, 2023, from https://blogg.sintef.no/sintefenergy-nb/vannverdi-er-viktig-for-strompris-og-forsyningssikkerhet/

Jensen, C., Brodtkorb, E., Stokker, R., Sørensen, J., & Gakkestad, K. (2010, November). *Konsesjonshandsaming av vasskraftsaker* (No. 3/2010). NVE. https://www.nve.no/media/1831/rettleiar_3_2010_web.pdf

Karakatsani, N. V., & Bunn, D. W. (2010). Fundamental and Behavioural Drivers of Electricity Price Volatility. *Studies in Nonlinear Dynamics & Econometrics*, *14*(4). https://doi.org/10.2202/1558-3708.1657

Khazal, A., Risa, E., & Johansen, M. (2023). Determinants of Norwegian Electricity Prices. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4424521

Kirkerud, J. G., Haukeli, I. E., & Grytli Tveten, Å. (2023, September 14). *Sammenhengen mellom kraftbalanse og kraftpris*. NVE. https://www.nve.no/media/14441/notat_kraftbalanser.pdf

Koenker, R. (2005). *Quantile Regression*. Cambridge University Press. https://doi.org/10.1017/CBO9780511754098

Koenker, R., & Bassett, G. (1978). Regression Quantiles. *Econometrica*, *46*(1), 33. https://doi.org/10.2307/1913643

Koestler, V. (2020, August 28). *Høy hydrologisk balanse og historisk lave priser i andre kvartal.* https://www.nve.no/nytt-fra-nve/nyheter-energi/hoy-hydrologisk-balanse-og-historisk-lave-priser-i-andre-kvartal/

Mæland, A. (2018). *Myteknusing: "Kraftselskapene tenker bare på profitt!".* https://www.statkraft.no/nyheter/nyheter-og-pressemeldinger/2018/myteknusing-kraftselskapene-tenker-bare-pa-profitt/

Mauritzen, J. (2012). Dead Battery? Wind Power, the Spot Market, and Hydro Power Interaction in the Nordic Electricity Market. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2045493

Myrvoll, T., & Undeli, P. (2022). *Assessing the Impact of NordLink on Day-Ahead Prices in NO2 and Germany: A Quantile Regression Approach* [Masterthesis, NHH]. Brage. https://openaccess.nhh.no/nhh-xmlui/handle/11250/3023471

Nguyen, M. T. (2015). *Modeling the Nord Pool System Price: A Quantile Regression Approach* [Masterthesis, NTNU]. Institutt for samfunnsøkonomi.

NordPool. (n.d.-a). *Day-ahead market.* https://www.nordpoolgroup.com/en/the-power-market/Day-ahead-market/

NordPool. (n.d.-b). *Price calculation.* https://www.nordpoolgroup.com/en/trading/Day-ahead-trading/Price-calculation/

Norgesenergi. (2023, September 20). *Slik påvirkes strømprisen.* https://norgesenergi.no/stromsmart/dette-pavirker-stromprisen/

NVE. (2022a, October 8). *Om kraftmarkedet og det norske kraftsystemet.* https://www.nve.no/reguleringsmyndigheten/kunde/om-kraftmarkedet-og-det-norske-kraftsystemet/

NVE. (2022b, October 25). *Hva er budområder og flaskehalser?* https://www.nve.no/reguleringsmyndigheten/slik-fungerer-kraftsystemet/hva-er-budomraader-og-flaskehalser/

NVE. (2023a). *Elsertifikater - NVE*. Retrieved November 29, 2023, from https://www.nve.no/energi/virkemidler/elsertifikater/

NVE. (2023b). *Hvor stor andel av vannkraften i Norge er fleksibel?* (No. 1/2023). https://publikasjoner.nve.no/fakta/2023/fakta2023_01.pdf

NVE. (2023c). *Magasinstatistikk*. Retrieved December 13, 2023, from https://www.nve.no/energi/analyser-og-statistikk/magasinstatistikk/

NVE. (2023d, July 11). *Slik fungerer kraftsystemet*. Retrieved November 17, 2023, from https://www.nve.no/reguleringsmyndigheten/slik-fungerer-kraftsystemet/

NVE. (2024, February 1). *Hydrologiske data til kraftsituasjonsrapporten.* https://www.nve.no/energi/analyser-og-statistikk/hydrologiske-data-til-kraftsituasjonsrapporten/

Owolabi, O. O., Lawson, K., Sengupta, S., Huang, Y., Wang, L., Shen, C., Getmansky Sherman, M., & Sunter, D. A. (2022). A robust statistical analysis of the role of hydropower on the system electricity price and price volatility. *Environmental Research Communications*, *4*(7), 075003. https://doi.org/10.1088/2515-7620/ac7b74

Sapio, A. (2019). Greener, more integrated, and less volatile? A quantile regression analysis of Italian wholesale electricity prices. *Energy Policy*, *126*, 452–469. https://doi.org/10.1016/j.enpol.2018.10.017

Scheben, H., Klempp, N., & Hufendiek, K. (2020). Impact of Long-Term Water Inflow Uncertainty on Wholesale Electricity Prices in Markets with High Shares of Renewable Energies and Storages. *Energies*, *13*(9), 2347. https://doi.org/10.3390/en13092347

Sirin, S. M., & Yilmaz, B. N. (2020). Variable renewable energy technologies in the Turkish electricity market: Quantile regression analysis of the merit-order effect. *Energy Policy*, *144*, 111660. https://doi.org/10.1016/j.enpol.2020.111660

SSB. (2023, October 19). *Elektrisitet.* Retrieved November 2, 2023, from https://www.ssb.no/energi-og-industri/energi/statistikk/elektrisitet

Stage, S., & Larsson, Y. (1961). Incremental Cost of Water Power. *Transactions of the American Institute of Electrical Engineers. Part III: Power Apparatus and Systems*, *80*(3), 361–364. https://doi.org/10.1109/AIEEPAS.1961.4501045

Statnett. (n.d.-a). *Mellomlandsforbindelser.* Retrieved November 17, 2023, from https://www.statnett.no/vare-prosjekter/mellomlandsforbindelser/

Statnett. (n.d.-b). *Tall og data fra kraftsystemet.* Retrieved January 3, 2024, from https://www.statnett.no/for-aktorer-i-kraftbransjen/tall-og-data-fra-kraftsystemet/

Statnett. (2021). *Kraftproduksjonsrekord i 2020*. Retrieved November 18, 2023, from https://www.statnett.no/om-statnett/nyheter-og-pressemeldinger/nyhetsarkiv-2021/kraftproduksjonsrekord-i-2020/

Statnett. (2022, March 10). *Derfor har vi prisområder*. https://www.statnett.no/om-statnett/bli-bedre-kjent-med-statnett/om-strompriser/fakta-om-prisomrader/

Statnett. (2023). *Negative markedspriser - Årsaker og konsekvenser*. https://www.statnett.no/globalassets/for-aktorer-i-kraftsystemet/marked/negative-markedspriser-arsaker-og-konsekvenser.pdf

Turvey, R. (2006). Interconnector economics. *Energy Policy*, *34*(13), 1457–1472. https://doi.org/10.1016/j.enpol.2004.11.009

Unnerstall, T. (2017). How expensive is an energy transition? A lesson from the German Energiewende. *Energy, Sustainability and Society*, *7*(1), 38. https://doi.org/10.1186/s13705-017-0141-0

Væringstad, T., & Holmqvist, E. (2003). *Tørrårsberegninger.* https://publikasjoner.nve.no/oppdragsrapportA/2003/oppdragsrapportA2003_10.pdf

Westgaard, S., Fleten, S.-E., Negash, A., Botterud, A., Bogaard, K., & Verling, T. H. (2021). Performing price scenario analysis and stress testing using quantile regression: A case study of the Californian electricity market. *Energy*, *214*, 118796. https://doi.org/10.1016/j.energy.2020.118796

Wolfgang, O., Haugstad, A., Mo, B., Gjelsvik, A., Wangensteen, I., & Doorman, G. (2009). Hydro reservoir handling in Norway before and after deregulation. *11th Conference on Process Integration, Modelling and Optimisation for Energy Saving and Pollution Reduction*, *34* (10), 1642–1651. https://doi.org/10.1016/j.energy.2009.07.025

Wolfgang, O., Jaehnert, S., & Mo, B. (2015). Methodology for forecasting in the Swedish–Norwegian market for el-certificates. *Energy*, *88*, 322–333. https://doi.org/10.1016/j.energy.2015.05.052

Wooldridge, J. M. (2018). *Introductory Econometrics* (7th ed.). South-Western College Publishing.

Appendix

A1 Background

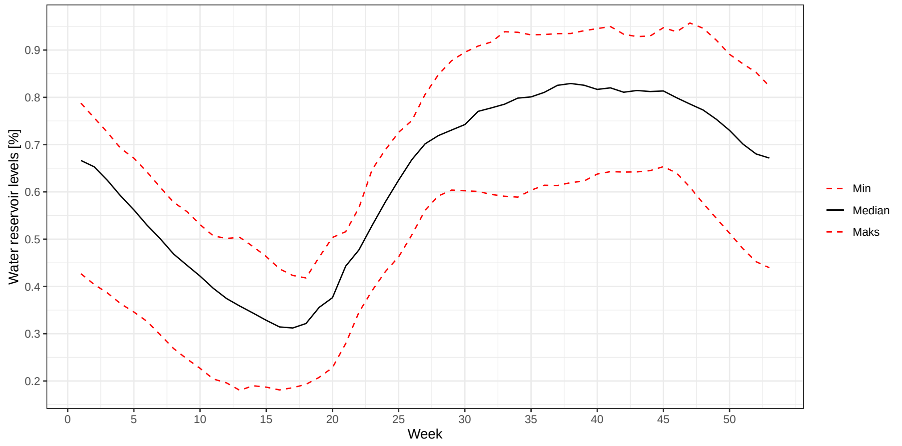


Figure A1.1: Average Observations from the last 20 years.

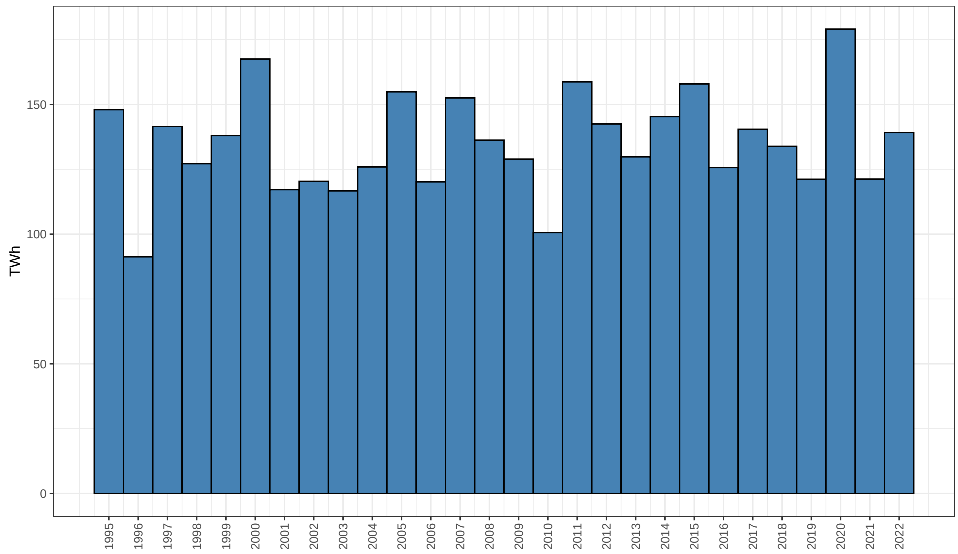


Figure A1.2: Water Inflow from 1995 - 2022.

A2 Data

Variable	Unit	Frequncy	Source
Electricity Price	EUR/MWh	Daily	Nord Pool[a]
Inflow	GWh	Weekly	NVE[b]
Export Capacity	MW	Daily	Nord Pool[c]
Volatility	EUR/MWh	Daily	Nord Pool[b]
Wind Production	MW	Daily	Nord Pool[d]
Power Exchange	MW	Daily	Nord Pool[e]
Electricity Certificate Price	EUR	Daily	Macrobond[f]
Reservoir Deviation	GWh	Weekly	NVE[a]
SSG Deviation	GWh	Weekly	NVE[a]
Coal Price	EUR/1000t	Daily	Bloomberg, Ticker: API21MON OECM Index
Gas Price	EUR/MWh	Daily	Bloomberg, Ticker: EGTHDAHD OEthe CM Index
Eua Price	EUR/1000t CO_2	Daily	Bloomberg, Ticker: DBRST3PA Index

[a] Available upon request. See: Day-ahead prices
[b] See: Hydrological data for the power situation (Norwegian)
[c] Available upon request. See: Day-ahead capacities
[d] Available upon request. See: Wind power
[e] Available upon request. See: Exchange
[f] Available upon request. See: Macrobond

Table A2.1: Summary of Data Sources.

A3 Results

Quantile regression: Base Model

	Dependent variable:								
					ln Price				
	10%	20%	30%	40%	50%	60%	70%	80%	90%
ln Inflow$_S$	-0.351^{***}	-0.234^{***}	-0.166^{***}	-0.143^{***}	-0.138^{***}	-0.140^{***}	-0.144^{***}	-0.176^{***}	-0.167^{***}
	(0.022)	(0.011)	(0.007)	(0.008)	(0.007)	(0.008)	(0.009)	(0.009)	(0.018)
ln Inflow$_L$	-1.706^{***}	-1.272^{***}	-1.045^{***}	-0.836^{***}	-0.934^{***}	-1.144^{***}	-1.482^{***}	-2.061^{***}	-2.289^{***}
	(0.302)	(0.116)	(0.078)	(0.075)	(0.062)	(0.069)	(0.078)	(0.101)	(0.139)
Observations	3,045	3,045	3,045	3,045	3,045	3,045	3,045	3,045	3,045
Area Control Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Note:									*p<0.1; **p<0.05; ***p<0.01

Table A3.1: Quantile Regression: Base Model.

Quantile regression: Main Model

	Dependent variable:								
					ln Price				
	10%	20%	30%	40%	50%	60%	70%	80%	90%
ln Inflow$_S$	-0.060^{***}	-0.105^{***}	-0.094^{***}	-0.085^{***}	-0.082^{***}	-0.079^{***}	-0.074^{***}	-0.071^{***}	-0.069^{***}
	(0.014)	(0.011)	(0.011)	(0.008)	(0.007)	(0.005)	(0.004)	(0.003)	(0.003)
ln Inflow$_L$	-0.789^{***}	-0.369^{***}	-0.373^{***}	-0.361^{***}	-0.376^{***}	-0.373^{***}	-0.418^{***}	-0.363^{***}	-0.423^{***}
	(0.125)	(0.086)	(0.089)	(0.070)	(0.054)	(0.041)	(0.041)	(0.040)	(0.022)
ln Volatility	0.026^{***}	0.020^{***}	0.015^{***}	0.014^{***}	0.013^{***}	0.014^{***}	0.014^{***}	0.016^{***}	0.017^{***}
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
ln SEC	0.822^{***}	0.931^{***}	0.773^{***}	0.723^{***}	0.542^{***}	0.429^{***}	0.356^{***}	0.251^{***}	0.212^{***}
	(0.098)	(0.080)	(0.087)	(0.052)	(0.053)	(0.046)	(0.045)	(0.040)	(0.026)
ln Wind	0.041^{***}	0.071^{***}	0.050^{***}	0.032^{***}	0.025^{***}	0.018^{***}	0.015^{***}	0.012^{***}	0.009^{***}
	(0.013)	(0.010)	(0.007)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
ln Certificate	0.458^{***}	0.505^{***}	0.445^{***}	0.528^{***}	0.474^{***}	0.376^{***}	0.249^{***}	0.171^{***}	0.108^{***}
	(0.085)	(0.079)	(0.064)	(0.036)	(0.038)	(0.032)	(0.027)	(0.021)	(0.013)
ln Gas	0.625^{***}	0.501^{***}	0.448^{***}	0.435^{***}	0.428^{***}	0.370^{***}	0.340^{***}	0.343^{***}	0.328^{***}
	(0.063)	(0.067)	(0.042)	(0.027)	(0.028)	(0.024)	(0.021)	(0.017)	(0.009)
ln Coal	0.075	0.397^{***}	0.456^{***}	0.482^{***}	0.471^{***}	0.476^{***}	0.405^{***}	0.325^{***}	0.289^{***}
	(0.066)	(0.061)	(0.053)	(0.034)	(0.031)	(0.028)	(0.029)	(0.023)	(0.016)
ln Eua	0.009	0.095^{**}	0.179^{***}	0.263^{***}	0.265^{***}	0.257^{***}	0.248^{***}	0.219^{***}	0.210^{***}
	(0.051)	(0.041)	(0.037)	(0.023)	(0.015)	(0.012)	(0.010)	(0.009)	(0.006)
Time Trend	-0.002^{***}	-0.001^{***}	-0.001^{***}	-0.0005^{***}	-0.0001	-0.0001	-0.0002^{*}	-0.0001	-0.0001
	(0.0003)	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
NE	0.056	-0.079	-0.108^{**}	-0.058	-0.045^{**}	-0.018	0.016	0.012	0.006
	(0.040)	(0.067)	(0.049)	(0.036)	(0.021)	(0.025)	(0.020)	(0.014)	(0.010)
RD	-0.131^{***}	-0.144^{***}	-0.131^{***}	-0.105^{***}	-0.077^{***}	-0.079^{***}	-0.081^{***}	-0.083^{***}	-0.072^{***}
	(0.025)	(0.017)	(0.018)	(0.014)	(0.010)	(0.008)	(0.006)	(0.007)	(0.004)
SSGD	-0.432^{***}	-0.403^{***}	-0.313^{***}	-0.240^{***}	-0.200^{***}	-0.170^{***}	-0.147^{***}	-0.120^{***}	-0.090^{***}
	(0.024)	(0.025)	(0.023)	(0.015)	(0.011)	(0.009)	(0.008)	(0.008)	(0.005)
Observations	3,045	3,045	3,045	3,045	3,045	3,045	3,045	3,045	3,045
Area Control Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Control Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Note:									*p<0.1; **p<0.05; ***p<0.01

Table A3.2: Quantile Regression: Main Model.

Quantile regression: Interaction terms

	Dependent variable:								
					ln Price				
	10%	20%	30%	40%	50%	60%	70%	80%	90%
ln Inflow$_S$ * RD	-0.099^{***}	-0.072^{***}	-0.060^{***}	-0.063^{***}	-0.049^{***}	-0.048^{***}	-0.034^{***}	-0.026^{***}	-0.022^{***}
	(0.020)	(0.018)	(0.015)	(0.010)	(0.007)	(0.006)	(0.006)	(0.005)	(0.004)
ln Inflow$_L$ * RD	0.071	0.112^{**}	0.069^{*}	0.035	0.013	0.0001	0.0002	0.016	-0.001
	(0.086)	(0.052)	(0.040)	(0.029)	(0.026)	(0.018)	(0.017)	(0.015)	(0.013)
ln Inflow$_S$ * SSGD	-0.281^{***}	-0.242^{***}	-0.194^{***}	-0.135^{***}	-0.101^{***}	-0.075^{***}	-0.053^{***}	-0.043^{***}	-0.032^{***}
	(0.014)	(0.019)	(0.016)	(0.012)	(0.008)	(0.006)	(0.007)	(0.007)	(0.004)
ln Inflow$_L$ * SSGD	-0.059	0.099	-0.024	-0.078^{***}	-0.061^{**}	-0.048^{**}	-0.039^{*}	-0.051^{***}	-0.067^{***}
	(0.060)	(0.066)	(0.056)	(0.028)	(0.029)	(0.023)	(0.023)	(0.018)	(0.017)
ln Inflow$_S$ * SEC	-0.241^{***}	-0.151^{***}	-0.086^{***}	-0.054^{***}	-0.045^{**}	-0.046^{***}	-0.039^{***}	-0.034^{***}	-0.034^{***}
	(0.031)	(0.044)	(0.024)	(0.014)	(0.019)	(0.013)	(0.010)	(0.008)	(0.007)
ln Inflow$_L$ * SEC	0.390^{***}	0.458^{***}	0.287^{***}	0.278^{***}	0.210^{***}	0.153^{***}	0.141^{***}	0.110^{***}	0.091^{**}
	(0.101)	(0.108)	(0.066)	(0.048)	(0.045)	(0.042)	(0.037)	(0.024)	(0.037)
Observations	3,045	3,045	3,045	3,045	3,045	3,045	3,045	3,045	3,045
Area Control Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Control Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Note:									*p<0.1; **p<0.05; ***p<0.01

Table A3.3: Quantile Regression: Interaction Terms.

Quantile regression: NO1

	Dependent variable:								
					ln Price				
	10%	20%	30%	40%	50%	60%	70%	80%	90%
ln Inflow$_S$	-0.171^{***}	-0.226^{***}	-0.222^{***}	-0.200^{***}	-0.179^{***}	-0.158^{***}	-0.146^{***}	-0.136^{***}	-0.120^{***}
	(0.056)	(0.017)	(0.026)	(0.036)	(0.026)	(0.016)	(0.012)	(0.013)	(0.016)
ln Inflow$_L$	-0.072	-0.008	-0.249	-0.408^{**}	-0.411^{**}	-0.433^{***}	-0.408^{***}	-0.163	-0.334^{***}
	(0.425)	(0.186)	(0.209)	(0.184)	(0.160)	(0.150)	(0.126)	(0.133)	(0.101)
ln Volatility	0.001	0.002^{**}	0.002	0.005^{***}	0.004^{***}	0.005^{***}	0.008^{***}	0.011^{***}	0.016^{***}
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
ln SEC	0.870^{***}	0.907^{***}	0.715^{***}	0.482^{***}	0.346^{***}	0.181^{*}	0.076	0.148^{**}	0.119^{*}
	(0.266)	(0.108)	(0.149)	(0.147)	(0.108)	(0.097)	(0.075)	(0.073)	(0.062)
ln Wind	-0.008	-0.013^{**}	0.004	0.012	0.010^{*}	0.008	0.005	0.007	0.008^{**}
	(0.020)	(0.006)	(0.010)	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.003)
ln Certificate	0.301^{**}	0.465^{***}	0.479^{***}	0.357^{***}	0.276^{***}	0.234^{***}	0.204^{***}	0.195^{***}	0.189^{***}
	(0.140)	(0.070)	(0.108)	(0.107)	(0.068)	(0.050)	(0.037)	(0.037)	(0.019)
ln Gas	1.100^{***}	0.968^{***}	0.836^{***}	0.668^{***}	0.615^{***}	0.518^{***}	0.490^{***}	0.431^{***}	0.466^{***}
	(0.111)	(0.066)	(0.074)	(0.073)	(0.053)	(0.050)	(0.039)	(0.042)	(0.028)
ln Coal	0.342^{**}	0.388^{***}	0.451^{***}	0.406^{***}	0.345^{***}	0.338^{***}	0.282^{***}	0.361^{***}	0.286^{***}
	(0.164)	(0.056)	(0.093)	(0.088)	(0.074)	(0.069)	(0.049)	(0.056)	(0.051)
ln Eua	-0.197	-0.037	0.066	0.153^{**}	0.194^{***}	0.250^{***}	0.265^{***}	0.241^{***}	0.259^{***}
	(0.125)	(0.080)	(0.069)	(0.066)	(0.048)	(0.047)	(0.039)	(0.034)	(0.025)
Time Trend	-0.00001	0.0004	0.0004	0.0002	0.0003	0.0003	0.0004^{*}	0.0004	0.0002
	(0.001)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
NE	-0.237^{*}	0.0005	-0.007	0.072	0.030	0.086^{*}	0.103^{***}	0.078^{*}	0.034
	(0.129)	(0.154)	(0.084)	(0.095)	(0.052)	(0.046)	(0.027)	(0.041)	(0.022)
RD	0.071	0.104^{***}	0.082^{**}	0.053	0.052^{**}	0.011	-0.028^{*}	-0.019	-0.037^{**}
	(0.070)	(0.032)	(0.033)	(0.037)	(0.025)	(0.024)	(0.017)	(0.016)	(0.015)
SSGD	-0.150^{***}	-0.154^{***}	-0.193^{***}	-0.159^{***}	-0.115^{***}	-0.103^{***}	-0.059^{***}	-0.035^{**}	-0.003
	(0.057)	(0.027)	(0.025)	(0.032)	(0.020)	(0.019)	(0.019)	(0.017)	(0.012)
Observations	609	609	609	609	609	609	609	609	609
Monthly Control Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Note:									*p<0.1; **p<0.05; ***p<0.01

Table A3.4: Quantile Regression: NO1.

Quantile regression: NO2-NO5

	Dependent variable:								
	ln Price								
	10%	20%	30%	40%	50%	60%	70%	80%	90%
ln Inflow$_S$	-0.055^{***}	-0.077^{***}	-0.078^{***}	-0.071^{***}	-0.071^{***}	-0.067^{***}	-0.065^{***}	-0.064^{***}	-0.065^{***}
	(0.012)	(0.013)	(0.013)	(0.009)	(0.006)	(0.005)	(0.006)	(0.003)	(0.004)
ln Inflow$_L$	-0.815^{***}	-0.348^{**}	-0.360^{***}	-0.366^{***}	-0.343^{***}	-0.352^{***}	-0.412^{***}	-0.418^{***}	-0.445^{***}
	(0.147)	(0.138)	(0.111)	(0.082)	(0.062)	(0.050)	(0.049)	(0.036)	(0.037)
ln Volatility	0.028^{***}	0.024^{***}	0.020^{***}	0.018^{***}	0.018^{***}	0.017^{***}	0.017^{***}	0.017^{***}	0.017^{***}
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
ln SEC	1.084^{***}	1.130^{***}	0.849^{***}	0.758^{***}	0.560^{***}	0.521^{***}	0.417^{***}	0.338^{***}	0.195^{***}
	(0.114)	(0.107)	(0.097)	(0.070)	(0.055)	(0.048)	(0.061)	(0.036)	(0.031)
ln Wind	0.037^{***}	0.091^{***}	0.072^{***}	0.048^{***}	0.038^{***}	0.028^{***}	0.021^{***}	0.013^{***}	0.011^{***}
	(0.014)	(0.014)	(0.012)	(0.008)	(0.007)	(0.008)	(0.006)	(0.004)	(0.004)
ln Certificate	0.597^{***}	0.581^{***}	0.431^{***}	0.492^{***}	0.435^{***}	0.405^{***}	0.296^{***}	0.197^{***}	0.090^{***}
	(0.093)	(0.079)	(0.082)	(0.047)	(0.037)	(0.038)	(0.036)	(0.024)	(0.020)
ln Gas	0.573^{***}	0.434^{***}	0.313^{***}	0.322^{***}	0.322^{***}	0.329^{***}	0.300^{***}	0.295^{***}	0.292^{***}
	(0.061)	(0.069)	(0.053)	(0.038)	(0.026)	(0.030)	(0.029)	(0.017)	(0.017)
ln Coal	-0.019	0.354^{***}	0.436^{***}	0.446^{***}	0.471^{***}	0.476^{***}	0.431^{***}	0.344^{***}	0.308^{***}
	(0.073)	(0.069)	(0.069)	(0.040)	(0.029)	(0.033)	(0.040)	(0.020)	(0.022)
ln Eua	0.115^{**}	0.201^{***}	0.229^{***}	0.278^{***}	0.262^{***}	0.266^{***}	0.262^{***}	0.233^{***}	0.201^{***}
	(0.051)	(0.036)	(0.041)	(0.026)	(0.018)	(0.014)	(0.013)	(0.010)	(0.010)
Time Trend	-0.002^{***}	-0.002^{***}	-0.001^{***}	-0.001^{***}	-0.0004^{**}	-0.0002^{*}	-0.0003^{**}	-0.0002^{**}	-0.0001
	(0.0003)	(0.0004)	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
NE	0.065	-0.063	-0.138^{***}	-0.085^{***}	-0.074^{***}	-0.034	-0.023	-0.013	-0.038^{*}
	(0.080)	(0.071)	(0.042)	(0.025)	(0.028)	(0.023)	(0.019)	(0.011)	(0.020)
RD	-0.185^{***}	-0.179^{***}	-0.173^{***}	-0.138^{***}	-0.108^{***}	-0.101^{***}	-0.095^{***}	-0.094^{***}	-0.071^{***}
	(0.025)	(0.024)	(0.020)	(0.017)	(0.013)	(0.009)	(0.009)	(0.007)	(0.006)
SSGD	-0.552^{***}	-0.465^{***}	-0.356^{***}	-0.285^{***}	-0.223^{***}	-0.192^{***}	-0.162^{***}	-0.137^{***}	-0.109^{***}
	(0.030)	(0.028)	(0.029)	(0.018)	(0.015)	(0.011)	(0.011)	(0.007)	(0.007)
Observations	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436
Area Control Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Control Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Note:									*p<0.1; **p<0.05; ***p<0.01

Table A3.5: Quantile Regression: NO2-NO5.