The influence of renewable energy generation on electricity price fluctuations, a case study of The Netherlands

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Preface

Completing this thesis marks the culmination of months of challenging yet rewarding work. My fascination with the energy sector found its expression in this research, an opportunity I am grateful for, courtesy of APPM. I am very grateful to my first supervisor, Enno Schöder, whose positive guidance and precise feedback were invaluable. Special thanks to my second supervisor, Zofia Lukszo, for her assistance in clarifying the research's purpose. My colleagues at APPM, especially Mirthe Meijer and Jeroen Veger, who provided energy, support and knowledge, making my journey more enriching.

This project brought both professional and personal growth. Navigating the complexities of this multifaceted field was challenging, but the passivity and friendly advice from Enno, energy and fun from colleagues, and the friends among MOT students helped me overcome hurdles. Though, sometimes I felt frustrated while diving into unfamiliar territories, I am proud of the knowledge I acquired, particularly in the shaping and workings of the energy system. I hope the findings of this research contribute meaningfully to my peers, the academic community, and the company APPM.

Abstract

The research conducts an analysis of the Dutch day-ahead electricity market prices spanning from 2015 to 2022, examining the relationship between increasing RE penetration and day-ahead electricity price fluctuations. The electricity price fluctuations over this time period are reviewed for patterns and recalculated for inflation corrections that contribute to a surge in electricity prices post-August 2021.

This price volatility is further researched by three energy market phenomena. A part of these price fluctuations can be explained by the presence of the Duck Curve phenomenon in the Dutch market, highlighting challenges associated with limited RE production time and energy demand. The Duck Curve, which illustrates the net load over a 24-hour period, reveals a decrease in fossil energy production during daylight hours and a peak in production during the night. When compared to California, this Dutch Duck Curve is more stable with the incorporation of wind energy, signifying a more reliable and consistent energy supply throughout the day.

Moreover, the study delves into another energy market phenomenon called the merit order effect, where the increased penetration of RE with low marginal cost leads to declining day-ahead electricity prices. The phenomenon is researched through the implementation of an OLS regression analysis. By plotting the results in individual months and years the merit order effect is visualized. The results are showcasing increased volatility, particularly in the latter part of the analyzed period (2020-2022). Fluctuations resembling a Duck Curve are observed, emphasizing the impact of RE implementation on price decline during periods of abundant RE supply.

Additionally, the cannibalization effect phenomenon is addressed where the growing penetration of RE undermines their own economic value. The Unit Revenue and Value Factor are calculated to aid the analysis. Followed up by the Prais-Winsten method to quantify this cannibalization effect. The results are revealing negative correlations between solar and wind shares and Unit Revenue and electricity prices. Thus, as RE penetration increases, electricity prices decrease, underscoring the cannibalization effect's influence on price fluctuations.

In conclusion, this study offers insights into the dynamic transformation of the Dutch electricity market. The identification of key phenomena such as the Duck Curve, the merit order effect, and the cannibalization effect provides empirical evidence of the market's evolution. These findings underscore the critical need for strategic management, targeted interventions, and innovative solutions. It is imperative to navigate these changes effectively to facilitate the ongoing expansion of renewable energy technologies while upholding the stability and competitiveness of the electricity market.

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List of Abbreviations

RE - Renewable Energy

CBS - Central Bureau for Statistics

OTC - Over The Counter

ISO - Independent System Operator

RTO - Regional Transmission Organization

TRO - Transmission System Operator

CAISO - California Independent System Operator

MOE - Merit Order Effect

EU - European Union

ENTSO-E - European Network of Transmission System Operators for Electricity

EPEX - European Power Exchange

EEX - European Energy Exchange

CPI - Consumer Price Index

GDP - Gross Domestic Product

DA - Day-Ahead

UR - Unit Revenue

VF - Value Factor

p.p. - percent point

DMS - Demand Side Management

CHAPTER 1

Introduction

Europe is undergoing a transition from fossil fuel energy to renewable energy (RE), aiming to achieve goals set by the Paris Agreement and creating a more sustainable energy system. However, this transition is not without costs and challenges. The intermittency and variability of renewable energy production create problems with the stability and reliability of the energy supply. Balancing the fluctuating energy production with the inelastic demand is therefore key to making the energy transition succeed. [Prol and Schill, 2021] The fluctuating electricity price can be analyzed using various variables such as electricity production, energy demand, energy supply, and net load, which represent the total energy production minus renewable energy production. These variables can be examined on different time scales, including yearly, monthly, weekly, or daily basis. [Prol and Schill, 2021] The time scales of these variables intricately interplay within a nation's electricity system, shaping the dynamics of its energy market. As the Netherlands, with the rest of Europe, advances toward a RE-driven future, the challenge remains: To what extent does the incorporation of renewable energy generation and the resulting energy phenomena impact the fluctuation of day-ahead electricity prices for the Dutch electricity market?

1.1 Research introduction

1.1.1 Case study: The Netherlands

In the Netherlands, there has been a consistent rise in RE production over the past decade. At present, renewable sources contribute to 15 percent of the total electricity demand on average. This renewable energy primarily comprises wind, solar, and biofuels, making up 4, 6, and 5 percent point, respectively, of the energy mix. It's worth noting that the utilization of biofuels is gradually decreasing each year. This reduction is a response to increasingly stringent regulations imposed by the EU. [CBS, 2023a] Biofuels are typically introduced into conventional power plants, where they are combusted to generate heat and, subsequently, electricity. As a result, biofuels are not a part of the intermittency and variability associated with renewable energy production. This leaves us with solar and wind production, which are inherently tied to the intermittency of renewable energy generation. In the literature, these two renewable energy sources are extensively discussed, and various phenomena have been identified that could explain fluctuations in electricity prices attributed to these renewable energy generators. The research focuses on three of these identified phenomena namely, the Duck Curve, the merit order effect, and the cannibalization effect. Each of these phenomena plays a significant role in understanding the dynamics of renewable energy integration and its impact on electricity prices. The three phenomena will be explained in short in the following paragraph and further elaborated in the literature review.

1.1.2 Electricity market phenomenons

First, the Duck Curve is a graphical representation of the daily net electricity load. It plots the net load on the y-axis, which represents the total production for electricity minus the renewable energy production, and 24 hours of a day on the x-axis. Typically, the curve is based on the deduction of solar energy as a renewable energy source. The plotted points form a curve resembling a duck due to its distinctive shape. The belly of the Duck Curve represents excess energy supply during the day, when solar power is abundant, leading to a drop in demand from conventional sources. The neck of the Duck Curve signifies the rapid increase in demand in the evening as solar power diminishes and people return home, requiring more electricity from conventional sources to meet the total rising demand.[Roberts, 2018]

Second, the merit order effect refers to an effect from the economic principle applied in energy markets. This economic principle sets the electricity prices by prioritizing energy sources with the lowest marginal costs, such as renewable energy, ahead of higher-cost sources. During periods of abundant renewable energy generation, these sources are dispatched first, driving down electricity prices due to their low marginal costs. This effect underscores the influence of RE generation on price fluctuation in the energy market. [Figueiredo and Da Silva, 2019]

Third, the cannibalization effect occurs when the increase in renewable energy production leads to an overproduction of energy supply during peak production periods. This abundant supply pushes down electricity prices due to the merit order effect, resulting in an impact on the unit revenues of renewable energy generators. As the share of renewable energy in the market rises, the prices can decrease significantly, affecting the economic viability of these generators. [Prol and Schill, 2021]

Finally, it is noteworthy that these three phenomena are interconnected, influencing and reinforcing each other within the intricate framework of the energy market. The Duck Curve highlights the daily fluctuations in demand and supply, the merit order effect dictates pricing based on variable costs, and the cannibalization effect showcases the economic consequences of surplus energy supply on renewable energy generators. Combined, they reflect the volatile environment of renewable energy integration and its impact on fluctuating day-ahead electricity prices.

1.2 Context

1.2.1 Electricity market system

To understand the mechanism of an electricity system, it is essential to begin with a general overview. The electricity system comprises various components, including an energy trading market, which can be further subdivided into an intraday market, day-ahead market and Over-The-Counter (OTC) market. Additionally, there is a balancing market and an auction for import capacity. Together, these interconnected marketplaces form the comprehensive "electricity market". [Van Der Veen et al., 2007]

The production of electricity is traded on electricity trading markets or wholesale market or just electricity market, which operate on a global scale. These markets are not restricted to specific continents but overlap across different regions. For instance, multiple countries can participate in the same trading market, facilitating cross-border electricity transactions. Take, for example, the electricity exchange market EPEX, which is operational in Austria, Belgium, France, Germany, Luxembourg, The Netherlands, Switzerland, and the United Kingdom. Moreover, individual countries may have access to multiple electricity trading markets, allowing for greater flexibility and diversity in trading options. For instance, Germany can also participate in markets such as Nasdaq OMX, EXAA, Nordpool, and OMIP next to the EPEX. Each energy market has its own unique characteristics and trading mechanisms. They may involve various types of auctions, such as Over-The-Counter (OTC), Day-Ahead Auctions, Intraday Auctions, or real-time auctions, depending on the specific market design. These auctions provide opportunities for electricity suppliers and consumers to submit bids and offers for electricity transactions within specified timeframes. [EEX-Group and EPEX, 2023]

Next to the electricity trading markets are balancing markets where the Transmission System Operators (TSO) or Independent System Operator (ISO) are key players. TSOs are independent entities that are responsible for managing and operating the transmission grid, ensuring the efficient and reliable transmission of electricity with the use of the merit order dispatch. This merit order dispatch determines the most cost-effective way to dispatch power plants by prioritizing low-cost generation sources, such as renewable energy, before higher-cost fossil fuel-based generation. [Hirth and Khanna, 2020] TSOs serve parallel to the electricity trading markets as intermediaries between electricity suppliers and consumers. One of the roles of TSOs is to facilitate the competitive wholesale electricity market. They administer the market rules, oversee the auction processes, and ensure fair competition among market participants. The TSOs provide a centralized platform for electricity trading, where market participants can submit bids and offers for buying and selling electricity like EPEX. [EEX-Group and EPEX, 2023] [TenneT, 2023]

Additionally, the provision of a centralized platform allows the TSO to ensure grid reliability through a market-based mechanisms. They employ various market mechanisms, such as Day-Ahead Markets and Real-Time Markets, to manage the supply-demand balance in real-time. In the Day-Ahead Market, participants submit their bids and offer a day in advance, allowing the TSO to plan for the next day's electricity needs. In the Real-Time Market, participants can adjust their reserved amount of electricity and buy or sell in response to real-time changes in supply and demand conditions. TSOs also support the integration of intermittent renewable resources by implementing advanced forecasting and scheduling tools to manage their variability.[TenneT, 2023]

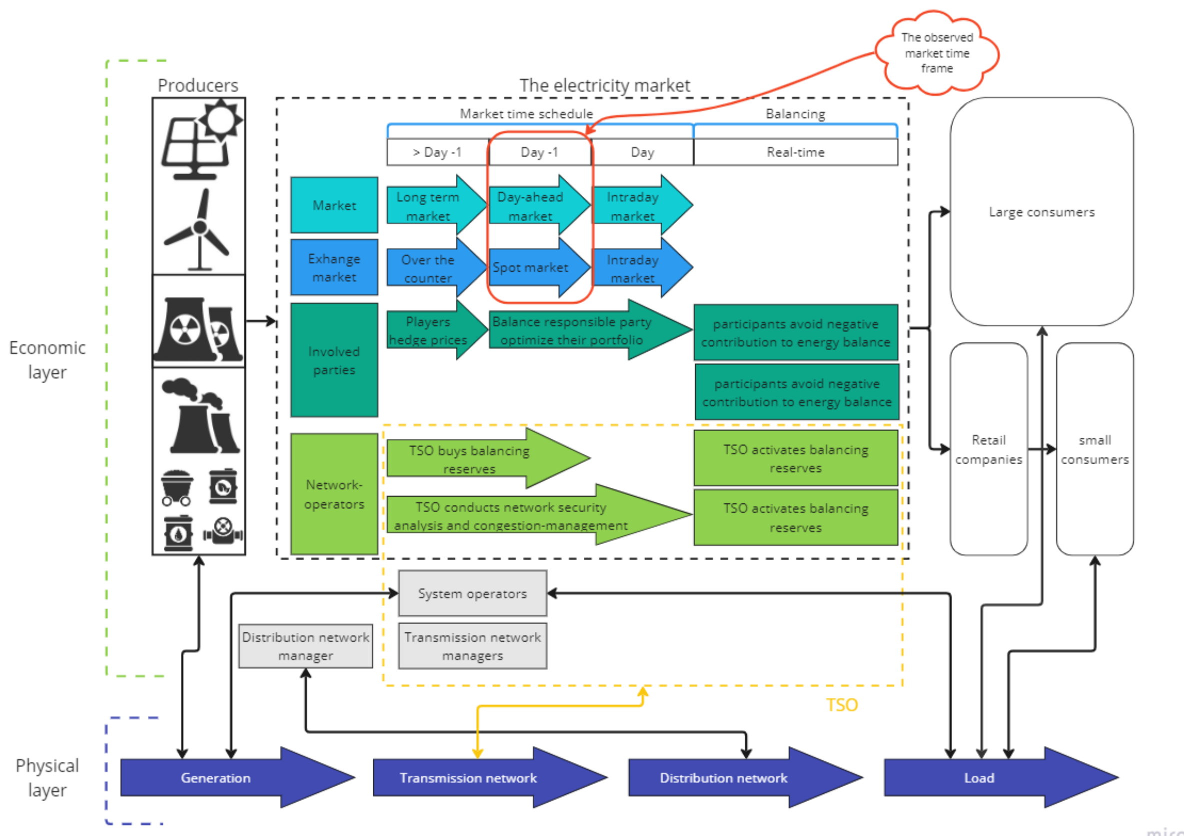

Figure 1.1: An overview of the electricity market [TenneT, 2023][Van Der Veen et al., 2007]

Figure 1.1 provides a simplified overview of the Dutch electricity system, incorporating the aforementioned topics. Starting with electricity generation, it illustrates how electricity is produced and subsequently traded on electricity markets. However, after reaching consumers, the actual electricity usage is measured and consumers receive individualized bills, which may differ from market prices due to factors like taxes, distribution costs, and subsidies. The figure also mentions the balancing market, which plays a crucial role in grid stability but will not be explored in detail in this context. Overall, this visual representation offers a clear understanding of the electricity system's flow, showcasing the interplay between electricity generation, trading, and consumption in the Netherlands. The red box delineates the research scope.

1.3 Social and Economic challenges

In the aforementioned sections, the impact of integrating RE and the phenomena due to this integration is briefly explained, followed by the fluctuations in day-ahead energy prices and their potential implications for the electricity market in the Netherlands. The societal issue of price fluctuations has been acknowledged by the European Central Bank as detrimental to consumers. Owing to the inelasticity and the high prices observed during peak demand hours, consumers find themselves compelled to either curtail consumption of non-energy goods and services, dip into their savings, or seek avenues to increase their income. Businesses, similarly affected by these fluctuating energy costs, experience significant pressure due to electricity costs constituting a substantial portion of their operational expenses. [Battistini, 2022] Consequently, the accelerated adoption of renewable energy sources has introduced several societal challenges, primarily associated with their intermittency. This intermittency results in unpredictable shifts in the energy supply, thereby leading to volatile day-ahead electricity prices. These fluctuations bear considerable implications for both consumers and businesses, thereby shaping the landscape of the electricity market in the Netherlands.

1.4 Research problem and objective

As explained in the previous paragraph fluctuating electricity prices due to RE generation phenomena could create social and economic challenges. However, when it comes to understanding how RE generation phenomena relate to electricity price fluctuations in the context of the Dutch electricity market, a notable gap in research pertains. To address this research problem, it is crucial to investigate whether the Netherlands experiences phenomena such as the Duck Curve, the merit order effect, and the cannibalization effect, which have been associated with renewable energy integration in other regions. These phenomena can shed light on the dynamics between RE generation and day-ahead energy prices, offering valuable insights into the Dutch electricity market's resilience and adaptability in the face of increasing renewable energy capacity. By comprehensively examining these interrelated factors through data analysis and regression modelling, this research aims to provide a deeper understanding of how the integration of renewable energy accounts for the fluctuations in the Dutch electricity market. The findings could aid in a renewable energy-driven future.

1.5 Masters relevance

The subject of the energy transition with the influences on energy market pricing is highly related to the Management of Technology master as the core of the master prescribes problems of a technological nature combined with sociotechnical and corporate influences. The master equips students with the essential skills to analyze and respond to complex technological challenges. Understanding the dynamics of renewable energy technologies and their influence on energy markets aligns seamlessly with the program's objectives. The fluctuations in energy prices due to renewable energy sources necessitate a nuanced understanding of market dynamics, providing insightful analyses and strategic solutions. Moreover, understanding and analyzing energy market pricing requires a multidimensional approach that incorporates both technological and financial knowledge. It provides the opportunity to combine financial and corporate influences with a technical approach. Finally, a better understanding of energy market pricing from a theoretical perspective creates the institutional and economic support needed to succeed in the energy transition. Thus, any findings from the research would result in valuable information for both theoretical and practical purposes.

1.6 Research overview

To achieve the research objective, this study is organized into several chapters, each serving as a step-by-step guide that helps readers navigate from the initial problem definition to the eventual presentation and interpretation of results. The following research structure provides an overview:

Chapter 1: Introduction

In this chapter, the subject is introduced with the research problem and objective. Furthermore, initial knowledge about the subject is provided including contextual information.

Chapter 2: Literature Review

The literature review provides information about existing research in the subject area and elaborates on the Duck Curve, merit order effect, and cannibalization effect. Finally reaching the identified knowledge gap.

Chapter 3: Method

The research question is addressed through distinct methodologies tailored to each of the aforementioned phenomena and day-ahead price analysis. Each of these subjects is thus approached uniquely, and these varied methods are thoroughly explored and detailed in this chapter.

Chapter 4: Data

The data chapter illuminates the types of data collected, its sources, the modifications made to align it with the desired dataset, and the validation processes undertaken to ensure its accuracy and reliability.

Chapter 5: Data Analysis

The data analysis chapter uses the data that was gathered in Chapter 4 including the knowledge from the literature review on the energy market phenomena. In turn, it provides the initial analysis of the discussed energy market phenomena.

Chapter 6: Regression Analysis

The regression analysis chapter discusses two out of the three energy market phenomena. As the chapter's title suggests, these phenomena are analyzed using regression methods. The specific techniques employed and their interpretations are explored and discussed in detail.

Chapter 7: Discussion

In the discussion, the findings are discussed including some of the shortcomings of the research. This elaborates on the effect of the scope and the constraining factors.

Chapter 8: Conclusion

The research ends with a recap of the objective and the research question. This chapter then provides answers to these research questions and describes any future research subjects.

CHAPTER 2

Literature Review

To explore existing scientific knowledge, gain general knowledge, and discover a potential knowledge gap, a literature review is carried out. The previously introduced subject of the influence of RE generation on electricity prices has a variety of angles that need to be studied in order to create a clear idea of this potential knowledge gap.

2.1 Search Methodology

A literature review can be conducted with the use of three different methodologies according to [Snyder, 2019]. The most fitting literature review, in this case, is a semi-systematic review which is suitable for "topics that have been conceptualized differently and studied by various groups of researchers" [Snyder, 2019]. The literature review is conducted using three different databases: scopus, Google Scholar, and the TU Delft repository. Google Scholar was used to find common themes and their synonyms. Starting off with "influence of renewables on energy prices" and "the merit order", "Duck Curve" or "the cannibalization effect". From forward snowballing, the terms "spot prices" and "EEX" (which is the european energy market) were found. Other keywords used to narrow down the search results are displayed in Table 2.1.

Keywords	Similar keywords
Duck Curve	-
Merit order	Merit order effect, MOE
Cannibalization effect	-
Influence	Impact, effect
Renewable energy	Sustainable energy
Energy prices	Electricity prices, Energy market, Electricity market
Day-ahead	Spot prices, EEX, EPEX
EU	Europe, Netherlands, Dutch

Table 2.1: Keywords

2.2 Literature Findings

The evaluated papers are discussed according to their research content and divided into overarching themes. The papers vary in types of data used, method of data analysis, types of energy sources, dates of publishing, and geographical location that is researched. Each article has been reviewed and the summary of what the article contains is visible in Table 2.2. The headers after Table 2.2 will discuss what the literature studies have concluded and mention the boundary conditions of these literature studies in relation to the problem statement.

Reference	Data		Energy sources			Date	Location
	Simulation	Historical	Wind	solar	others		
[Prokhorov and Dreisbach, 2022]		X	X	X	X	2022	Germany
[Schöniger and Morawetz, 2022]	X		X	X		2022	Europe
[Prol and Schill, 2021]	X	X	X	X	X	2021	Global
[Prol et al., 2020]			X	X		2020	Global
[Kolb et al., 2020]	X	X	X	X		2020	Germany
[Figueiredo and Da Silva, 2019]	X	X	X	X		2019	Germany
[Bublitz et al., 2017]	X	X	X	X		2017	Europe
[Dillig et al., 2016]		X	X	X	X	2016	Germany
[Paraschiv et al., 2014]	X	X	X	X	X	2014	Germany
[Edenhofer et al., 2013]	X	X	X	X		2013	Global
[Mulder and Scholtens, 2013]	X	X	X	X		2013	Netherlands
[Hirth, 2013]		X	X	X	X	2013	Global

Table 2.2: Relevant sources

2.2.1 Development in the energy markets

The notion that RE generation impacts energy markets has been a topic of interest even before 2013. However, the assessment of this impact has varied across different studies. [Hirth, 2013], for instance, adopts a unique approach to constructing their models. They consider a minimal RE penetration of only 3 percent in electricity markets and investigate the influence of variations in intensity, particularly different wind speeds. This approach differs from examining a straightforward increase in the RE generation market share, as it introduces complexities associated with comparing varying wind speeds. In another significant contribution, Hirth collaborates with [Edenhofer et al., 2013]. In this paper, the authors explicitly highlight that the impact of the variability of wind and solar power has not yet been adequately computed in the models. This observation emphasizes the importance of considering the intermittent nature of renewable energy sources when analyzing their impact on energy markets. Nevertheless, the other sources mentioned in Table 2.2 approach the analysis from a different perspective. They focus more on the general amount of energy generated by renewable sources and incorporate these figures into their analysis. This approach provides valuable insights into the overall contribution of RE to the energy mix without delving into the intricacies of variability and intensity. If the generation quantity eventually exceeds the maximum demand at any time there is no need for the variability examination of RE generation [Figueiredo and Da Silva, 2019].

As depicted in Table 2.2, 40 percent of the literature reviewed in this research was published more than three years ago. It is noteworthy that within the last three years, the RE generation in the Netherlands has doubled [CBS, 2020] [CBS, 2023a]. This substantial increase in RE generation highlights the importance of examining more recent data to capture the current dynamics of the energy market accurately. Interestingly, the two most recent papers in the review, [Schöniger and Morawetz, 2022], and [Prokhorov and Dreisbach, 2022], focus on analyzing their research question using data from either 2019 or 2020, respectively. Notably, the analysis conducted by [Schöniger and Morawetz, 2022] investigates the effects of different RE generation shares in the energy production mix, ranging from 0 to 100 percent. Surprisingly, the study finds that the start of the maximum fluctuations in energy prices occur when the share of RE generation reaches approximately 40 percent. Intriguingly, this percentage closely aligns with the current amount of RE generation in use, making their findings particularly relevant to the current energy landscape. Similarly, the research by [Prokhorov and Dreisbach, 2022] bases its analysis on a 40 percent market share of EU-wide RE generation.

Next to the changes in the electricity generation landscape has there been a change in electricity prices over these last three years. The trend of electricity prices has shifted from a decline to a sudden spike and a subsequent overall increase. These price fluctuations are influenced by various external factors that occur over the years, including taxes, inflation, and trade tensions.[CBS and Rijksoverheid, 2022] These changes in prices are visualized in Figure 2.1 which was provided by the Dutch CBS.

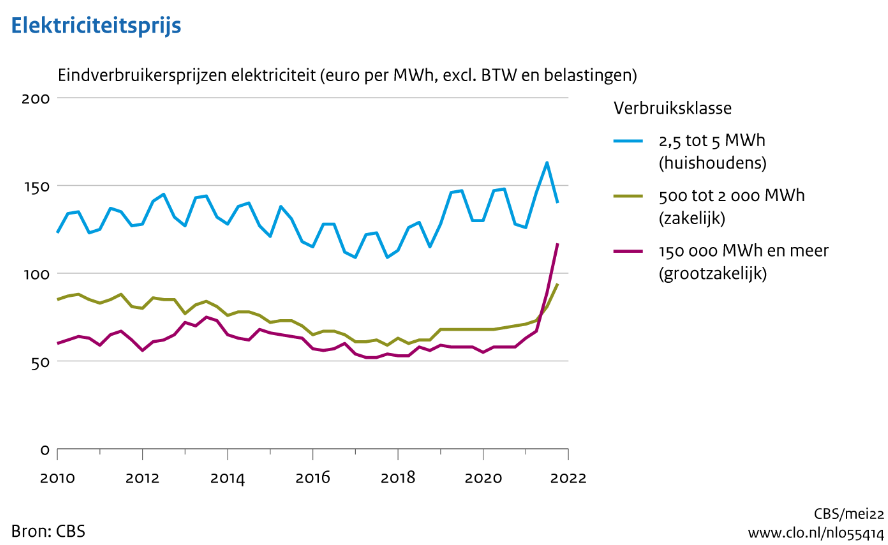

Figure 2.1: The energy prices at the consumer. [CBS and Rijksoverheid, 2022]

However, differing perspectives from studies such as those conducted by [Bublitz et al., 2017] and [Mulder and Scholtens, 20 challenge the prevailing notion that the changes in energy prices is primarily attributable to RE generation. According to these studies, the decrease in prices is more significantly influenced by fluctuations in natural gas prices, carbon prices, and coal prices. This perspective is supported by the results from their regression analyses, which reveal that the impact of RE was comparatively less significant over the observed period than the effects of fossil fuel prices and carbon prices. It is crucial to note that both studies conducted their research during a period marked by varying carbon pricing policies. Despite identifying an impact of the increasing RE share on electricity prices, both [Bublitz et al., 2017] and [Mulder and Scholtens, 2013] conclude that this influence is not substantial enough to emerge as the dominant driver of price dynamics during the examined timeframe.

On another note are researchers discussing whether weather conditions affect energy prices. The German and Dutch weather conditions were monitored and wind speeds, sunny hours, and water temperatures were reviewed. The effect that these variations had on electricity prices was barely significant for wind speeds, sunny hours, and water temperatures. [Mulder and Scholtens, 2013] It is even mentioned by others that the energy markets are likely to be re-visioned due to the increase of renewable energy sources. [Edenhofer et al., 2013]

2.2.2 Regression analysis

The reviewed literature discusses a range of regression analysis methods applied to different types of data. The choice of analysis method is contingent upon the nature of the data at hand. Specifically, when dealing with analyses over a period of time, a distinct regression analysis approach becomes imperative due to potential interference caused by autocorrelation. In the studies [Schöniger and Morawetz, 2022], [Paraschiv et al., 2014], [Figueiredo and Da Silva, 2019], and [Mulder and Scholtens, 2013], a specialized method called Autoregressive Conditional Heteroskedasticity (ARCH) was employed for time series analysis. This method, originally proposed by Engle (1982), is tailored to account for the intricate dynamics of time-dependent data. However, it's crucial to note that other studies listed in the table opted for the Ordinary Least Square (OLS) method, which does not incorporate considerations for autocorrelation in time series analysis. This fundamental principle holds significant weight when analyzing time series data spanning from 2015 to 2022. Failure to account for this could result in erroneous beta values derived from the regression analysis. Moreover, taking autocorrelation into consideration also addresses the assumption of independent observations. The degree of autocorrelation was quantified using the Durbin-Watson test, where the values can range from 0 to 4 [Kenton et al., 2023]. The value of 2 means that there is no autocorrelation anything below 2 is a positive autocorrelation and above 2 a negative autocorrelation according to [Kenton et al., 2023]. [Schöniger and Morawetz, 2022] highlighted a significant autocorrelation, [Paraschiv et al., 2014] reported a positive autocorrelation with an exact value of 1,689, and [Mulder and Scholtens, 2013] mentioned a significant autocorrelation without specifying the exact figure. Intriguingly, other studies that performed a regression analysis did not acknowledge the time series effect in their analyses thus, potentially introducing biases into their findings.

2.2.3 The Duck Curve

As briefly touched upon in the introduction, there is a phenomenon called the Duck Curve. In the following subsection, this phenomenon is explained in more detail. In 2008, researchers from the National Renewable Energy Laboratory (NREL) discovered the electricity phenomenon called the Duck Curve. By reviewing the daily net load in the electricity market they found that the fluctuating electricity production, due to the implementation of RE like solar and wind, led to the emergence of this Duck Curve. [Denholm et al., 2008] The name Duck Curve was given due to the shape of the curve. It showcases a distinctive shape resembling a duck, with a deep belly representing the drop in net demand during the day due to abundant renewable power production, and a steep neck depicting the rapid increase in demand as renewable energy generation declines and energy consumption rises in the evening. Integrating high levels of RE in the market is challenging. Excess daytime generation can exceed demand, while the evening peak strains the grid's capacity. [Roberts, 2018] To aid the description, Figure 2.2 is provided with the data from the California Independent System Operators.

The sudden increase in energy demand in the neck of the Duck Curve has significant financial and physical implications. From a financial perspective, meeting the surge in demand requires additional energy generation capacity to be activated, resulting in higher fuel costs, increased maintenance expenses, and elevated electricity prices due to the merit order (which will be covered in more detail below). On the physical aspect, the sudden increase strains the power plants, requiring investments in maintenance to ensure reliability, fuel storage to provide the needed fuel, and ramp-up rate to meet the required energy supply in time. [Kumar et al., 2012] Additionally, the significant drop in net load during the day, when RE generation is at its peak, can result in excess electricity supply in the market. This surplus RE generation, coupled with the economic principle of supply and demand, can lead to a decrease in energy prices during those hours. [Hirth, 2013] Moreover, for this Duck Curve, the geographical location plays a significant role in shaping it. Weather conditions, including sunlight availability and wind patterns, exhibit regional variations. These variations impact the generation patterns of RE sources and determine the limitations on where the energy can be distributed. [Hirth and Ueckerdt, 2013] Additionally, energy policies implemented differently in countries, such as Germany, also contribute to the variation in the extent and impact of the Duck Curve phenomenon. [Paraschiv et al., 2014]

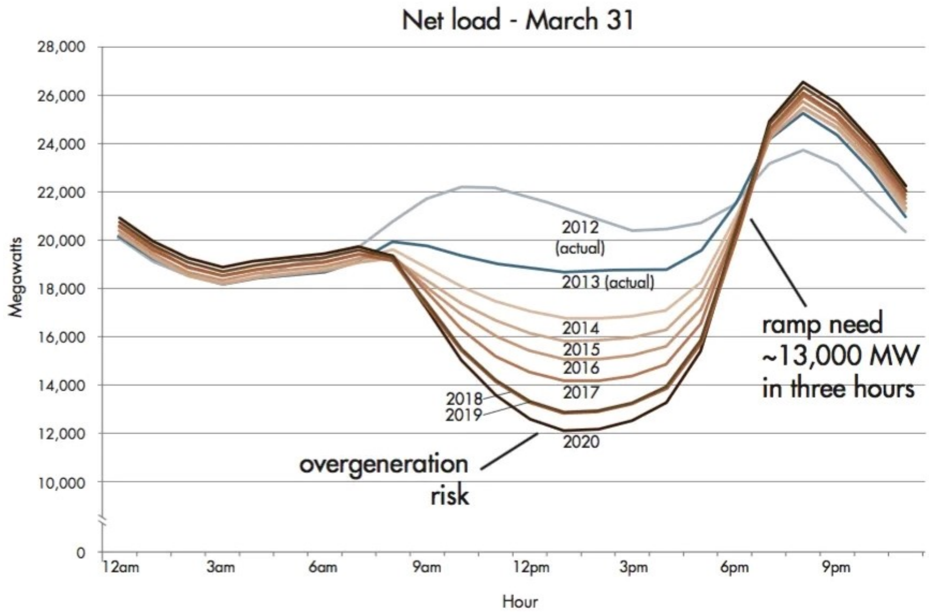

Figure 2.2: The Duck Curve due to solar energy penetration. [Roberts, 2018]

Additionally, the Duck Curve phenomenon could vary across continents and countries based on the quantity and type of renewable energy production. The initial discovery of the Duck Curve originated from NREL in California, as mentioned before, due to the anticipation of an increased share in PV installations. The models developed at that time utilized the parameter of 1 to 10 percent PV penetration. This represents the annual electrical energy supplied by the PV installations in the entire Western Interconnect. [Denholm et al., 2008] To put this in perspective, in 2020, the yearly energy production in California was 280 million MWh. [Commission and Nyberg, 2021] In the Netherlands, the energy production was 119 million MWh. [CBS, 2021] This is more than twice as much but the amount of solar that the Netherlands has installed produces 8,144 million MWh, [Van Middelkoop et al., 2021] which is within the percentage (6.8%) of the model's parameters creating an opportunity to compare the two.

2.2.4 Merit order effect

Next to the potential influence of the Duck Curve on electricity price fluctuation is the merit order effect. The merit order effect is a result of the merit order itself. The merit order sets energy prices depending on the demand and variable costs. It uses these variable costs of all the available energy sources which results in an order from low to high variable costs. The fixed costs are not taken into account in this order. The demand for energy during certain hours results in a specific price. Due to the low or zero variable or marginal costs of RE generation, these are dispatched first, pushing down the prices due to their competitive advantage over conventional fossil fuel-based generation. The effect of this merit order is thus the decrease in prices during RE generation hours. [Hirth and Khanna, 2020] A theoretical visualization of the merit order effect has been provided in Figure 2.3.

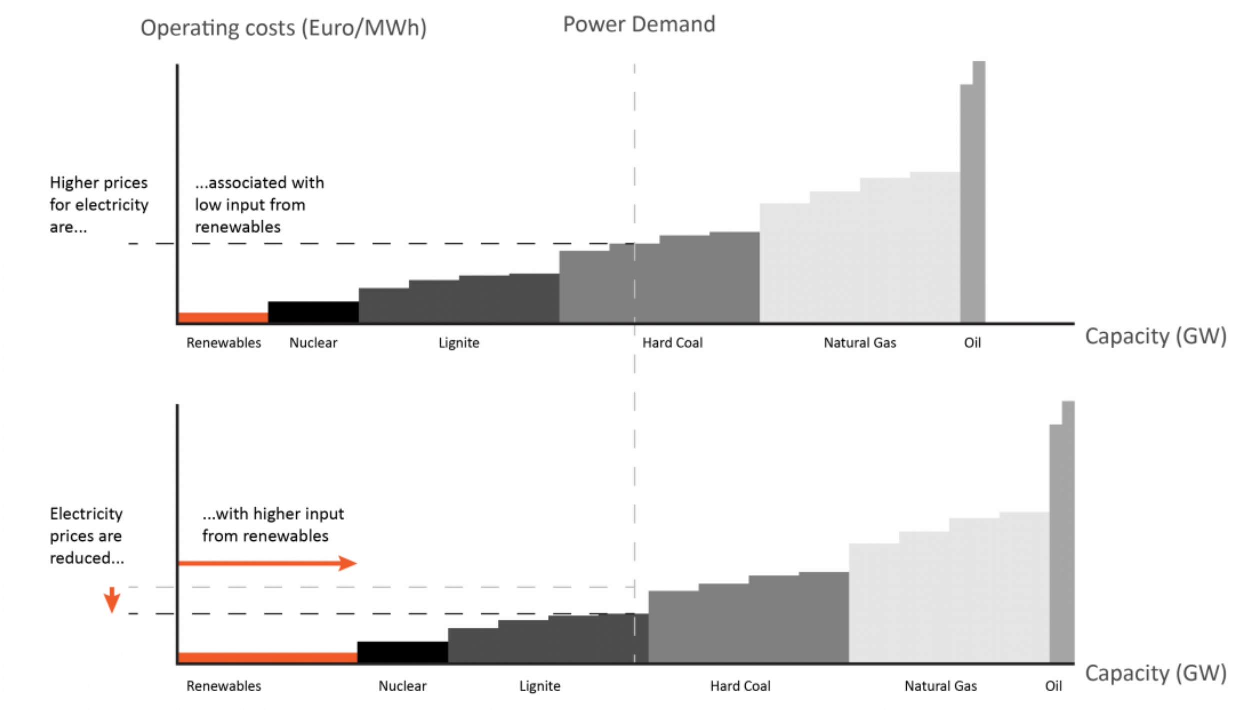

Figure 2.3: The merit order due to renewable energy sources. [Appunn, 2021]

In the pursuit of quantifying the merit order effect, researchers have employed diverse methodologies. [Hirth, 2013] and [Prol et al., 2020] utilized a value factor approach. This technique involves calculating value factors for day-ahead prices by dividing these prices by the hours within a day, thereby establishing a time-weighted average day-ahead price as a reference point. Specifically, for wind and solar, the value factors are defined as the ratios of average wind and solar revenues to this base price. Analyzing changes in these value factors over time provides insights into the merit order effect. However, it's important to note that these changes offer only percentage-based perspectives on the value of solar and wind, lacking an absolute context.

In contrast, [Figueiredo and Da Silva, 2019] took a different approach. They estimated the merit order effect by calculating a new market equilibrium considering wind and solar generation. This equilibrium, when integrated into an OLS regression analysis, allowed for a deeper understanding of the impact. It's worth mentioning that [Prol et al., 2020] accounted for autocorrelation in their analysis, employing the Prais-Winsten method within the regression framework. Both these methods, while differing in their approach, provide quantitative insights into the economic competitiveness and influence of renewable energy sources, utilizing day-ahead prices as a fundamental metric for their assessments.

2.2.5 Cannibalization effect

The merit order effect and the cannibalization effect are closely related phenomena within the realm of renewable energy integration, both impacting electricity markets according to [Prokhorov and Dreisbach, 2022]. The difference between the two phenomena can be best explained by first explaining the cannibalization effect itself. The cannibalization effect occurs as a consequence of the rapid integration of RE share into the grid. With the RE share expansion, particularly during peak production periods when renewable sources like wind and solar are at their most productive, the market experiences an influx of abundant energy. This exceeding demand drives down electricity prices due to the economic principle of supply and demand. Consequently, this price reduction diminishes the revenues for renewable energy generators, creating a situation where their own success paradoxically contributes to a decline in their economic viability. [Prol and Schill, 2021] Although this seems similar to the merit order effect are there some differences. The merit order effect focuses on the price setting due to marginal costs which with the influence of RE causes a decrease in prices whereas the cannibalization effect focuses on the Unit Revenue (UR) of RE sources. Next, the merit order is visualized by the differences in the day-ahead pricing on peak hours of RE generation and the cannibalization effect can be quantified by examining the decrease of Unit Revenue (UR) or Value Factor (VF). This observes the decreasing prices between the hours creating the absolute cannibalization effect. To create a better understanding, Figure 2.4 has been added with the difference between the merit order effect and the cannibalization effect.

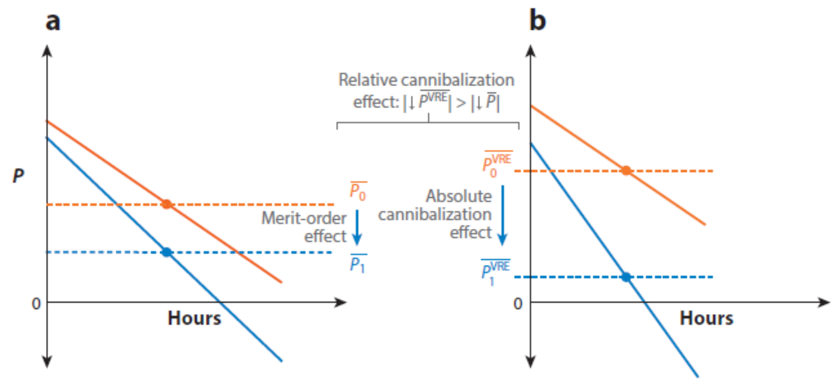

Figure 2.4: The (a) merit order effect and (b) cannibalization effect, both due to RE generation. Note the different values of the y-axis, (a) representing the electricity price and (b) representing Unit Revenue (UR) of electricity [Prol and Schill, 2021]

Figure 2.4 shows that next to the absolute cannibalization effect, the decline could also be expressed in a relative cannibalization effect, which entails comparing the value factors to average day-ahead electricity prices. Both these approaches provide different insights into the cannibalization effect. Besides the effects and calculation method, the cannibalization effect has only been mentioned in more recent literature. Surprisingly, discussions explicitly naming the cannibalization effect are relatively recent. [Prol et al., 2020] stand out as pioneers, delving into this concept within the context of the energy transition. It's noteworthy that [Hirth and Ueckerdt, 2013] and [Hirth, 2015] does discuss the effect itself, although not under the specific term "cannibalization", making previous research harder to identify. Additionally, recent studies like those by [Peña et al., 2022], [Prokhorov and Dreisbach, 2022], and [Prol and Schill, 2021] have explicitly referenced the cannibalization effect, although with data from diverse geographical locations. Moreover, even the most recent papers are using data up till 2020 and are missing essential insights due to the dynamic changes in the electricity market landscape during the years that followed.

2.3 Research Gap

The research on the impact of renewable energy on electricity markets requires a comprehensive examination of RE capacity, electricity demand, prices, and other factors to understand their true influence on the fluctuation of electricity prices. The recent increase in RE generation in the Netherlands underscores the need for up-to-date data and analysis to accurately assess the current market dynamics. The general data analyzed by the literature is not up-to-date as the latest data generated between 2020 and 2022 has not yet been reviewed. Moreover, many of the articles describe the potential changes and create simulations to prove their changes, none have empirically proven these changes using the data from the last 3 years. Furthermore, specific phenomena like the Duck Curve, the merit order effect, and the cannibalization effect have not been thoroughly investigated. Especially for the Netherlands are these phenomena not investigated, it remains uncertain whether these phenomena are indeed at play and, if they are, to what extent are they at play. Continuing with if they are at play to what extent are they responsible for the impact of fluctuations in electricity prices within the Dutch market.

2.4 Research Question

From the literature review a knowledge gap has been identified, to fill this research gap the following question must be answered. Thus the main research question that must be answered is:
To what extent does the incorporation of renewable energy generation and the resulting energy phenomena impact the fluctuation of day-ahead electricity prices for the Dutch electricity market?

2.4.1 Sub-question 1

Before the main research question can be answered, the prices and RE production over the last years must be examined and reviewed in search of any variations or patterns. This results in the following sub-question:
What are the changes in fluctuation in the day ahead electricity prices and RE production from 2015 to 2022?

2.4.2 Sub-question 2:

In addition to an in-depth study on the variations and patterns in day-ahead prices and RE production, the energy phenomenon must be researched using specific methods and historical data. For the Duck Curve, this results in the following sub-question:
Does the Netherlands exhibit a Duck Curve phenomenon in its daily electricity market demand, and if so, to what extent does it impact the day-ahead price fluctuations?

2.4.3 Sub-question 3:

Next to the research on the existence of the Duck Curve is another phenomenon called the merit order effect. To research this merit order effect, the following sub-question must be answered:
To what extent is the merit order effect in the Netherlands and what is the impact on the day-ahead electricity price fluctuation?

2.4.4 Sub-question 4:

The final energy market phenomenon to be explored for the Netherlands is the cannibalization effect. To research this final phenomenon, the following sub-question must be answered:
To what degree is the cannibalization effect in the Netherlands and does it affect electricity price fluctuations in the Dutch electricity market?

CHAPTER 3

Method

In this section, the goal is to explain methods that can be used to answer the main research question mentioned above. To comprehensively address this question, the formulated sub-questions are used to delve into specific aspects related to the influence of renewable energy on day-ahead prices. By employing diverse research methods for each sub-question, insights are gained into the complex dynamics of the Dutch energy market and the role of renewable energy sources in shaping price formations.

3.1 Type of research

Analyzing the fluctuations of prices within the Dutch electricity system, while specifically focusing on the phenomena of the Duck Curve, merit order effect, and cannibalization effect, presents a multifaceted research challenge. Given the complex interplay of these phenomena and their implications, the research must adopt a meticulous and targeted approach. While the complexities of these phenomena are interconnected, it is essential to delineate specific parameters and constraints to gain meaningful insights. [Bubaker, 2016] Therefore, the research employs an exploratory type of case study research. This type allows for in-depth empirical exploration of complex issues within their actual contexts, providing a nuanced understanding of the interactions between renewable energy fluctuations and electricity pricing mechanisms. By focusing solely on the Dutch electricity market, and examining the interrelated dynamics of the Duck Curve, merit order effect, and cannibalization effect, the case study methodology aligns with the research's need for detailed, context-specific analysis. Moreover, this approach enables a deep dive into the nuances of these phenomena, offering a comprehensive perspective that can inform effective decarbonization strategies and contribute valuable insights to the energy sector's stakeholders. Through this targeted research strategy, the study aims to unravel the intricate relationships between renewable energy variability, market dynamics, and their impact on energy pricing, providing valuable knowledge for future energy transition initiatives.

3.2 Approach

Sub-question 1, this sub-question focuses on understanding the changes and patterns in day-ahead prices in relation to the market share of renewable energy generation. To investigate this, a quantitative analysis will be conducted, comparing historical day-ahead prices with the corresponding market share of renewable energy. The historical data on the day-ahead electricity prices must therefore be gathered. This data can be found on public websites where open data about the prices are shared ([ENTSO-E, 2023] and

[EEX-Group and EPEX, 2023]). The available data from these websites for day-ahead prices are limited to the year 2015 and onward. To verify the gathered data, alternative sources or databases will be explored. in addition to this data, gas prices, wind energy production, solar energy production, and gas energy production data be gathered (This data is available through [CBS, 2023b] and [ENTSO-E, 2023]). This approach creates the possibility of analyzing the time series data of electricity prices and RE market share over a specific period, allowing for the identification of patterns, trends, and possible seasonality effects within the data.

Sub-questions 2, 3, and 4, though similar in phrasing, demand unique methods for their exploration.

Sub-question 2 delves into the intricate patterns of the Duck Curve, a phenomenon intricately linked to the net load plotted on a daily basis. To dissect this, bivariate data analysis is employed due to the multitude of variables contributing to the formation of the curve. The essential data, as outlined in the literature, includes the hourly records of total demand, solar energy production, and wind energy production. Ensuring these datasets are available on an hourly basis is crucial for a correct analysis and projection of the curve. By scrutinizing these variables in relation to one another, the Duck Curve can be unraveled, shedding light on its impact on the fluctuation of the energy market.

Sub-question 3, merit order effect, from the papers, has the merit order effect been identified using a variety of methods. The research from these papers will be applied in a similar way to achieve the quantification of the merit order effect. The selected method is an OLS regression analysis. This method allows for the examination of the relationships between multiple independent variables (such as hourly dummies) and the dependent variable (which in this case is the day-ahead energy price). Applying the method of OLS regression analysis enables quantifying the impact of these variables on the day-ahead energy prices and determining the significance of their relationships. It enables the identification of the merit order effect and their respective contributions to price variations. The formula for the regression analysis can be expressed as:

$$\text{Day-ahead price} = \beta 0 + \beta 1 \cdot \text{D2} + \beta 2 \cdot \text{D3} + \beta 3 \cdot \text{D4} + ... + \beta 23 \cdot \text{D24} + \epsilon$$

Where:

Day-ahead prices: The dependent variable represents the day-ahead price per hour.

D2, D3, D4, ... D23: The dummy variables to quantify the merit order effect.

$\beta 0$, $\beta 1$, $\beta 2$, $\beta 3$ etc.: The regression coefficients, indicating the strength and direction of the relationship between the independent dummy variables and day-ahead prices.

ϵ: The error term representing the unexplained variation in day-ahead prices.

The day-ahead price is filtered and used with a specific method. The filter selects only the specific month and year e.g. January 2015, then uses the dummies for hours to calculate each hourly average for that specific month and year. This can be mathematically expressed as:

$$\left(\begin{array}{c} HourlyDA \\ \left\{ \begin{array}{c} P_{1,1} \\ P_{2,2} \\ P_{3,3} \\ ... \\ P_{d,h} \end{array} \right\} \end{array} = \begin{array}{c} \begin{array}{ccccc} D1 & D2 & D3 & ... & D24 \end{array} \\ \left\{ \begin{array}{ccccc} 1 & 0 & 0 & ... & 0 \\ 0 & 1 & 0 & ... & 0 \\ 0 & 0 & 1 & ... & 0 \\ ... & ... & ... & \ddots & 0 \\ 0 & 0 & 0 & 0 & 1 \\ D_{d,h} & D_{d,h} & D_{d,h} & D_{d,h} & D_{d,h} \end{array} \right\} \end{array} \right)^t \quad \text{With} \quad \begin{array}{c} \text{d} \in 1, ..., 28 \vee 29 \vee 30 \vee 31 \\ \text{h} \in 1, ..., 24 \\ \text{t} \in 1, ..., 96 \end{array} \tag{3.1}$$

Sub-question 4, the cannibalization effect is mentioned with its possible impact on the price fluctuation. Nevertheless are these phenomena never explored in the Netherlands. The specifics on the quantification of the phenomenon are also researched with literature and compared to the results from the literature in this chapter. The selected method is a Prais-Winsten regression analysis. This method allows for the examination of the relationships between multiple independent variables (such as solar share, wind share, gas share, consumption, gas prices, and a variety of dummies) and the dependent variable (which again is the day-ahead energy price). Applying the method of Prais-Winsten regression analysis enables quantifying the impact of these variables on the day-ahead energy prices and determining the significance of their relationships while accounting for any autocorrelation. It enables the identification of the cannibalization effect and their respective contributions to price variations. The formulas for the regression analysis can be expressed as:

$$\text{Unit Revenue} = \beta 0 + \beta 1 \cdot \text{Solar share} + \beta 2 \cdot \text{Wind share} + \beta 4 \cdot \text{Consumption} + \beta 5 \cdot \text{Gas Price} + \beta 6 \cdot \text{D} + \epsilon \tag{3.2}$$

$$\text{Value Factor} = \beta 0 + \beta 1 \cdot \text{Solar share} + \beta 2 \cdot \text{Wind share} + \beta 4 \cdot \text{Consumption} + \beta 5 \cdot \text{Gas Price} + \beta 6 \cdot \text{D} + \epsilon \tag{3.3}$$

$$\text{Day-ahead price} = \beta 0 + \beta 1 \cdot \text{Solar share} + \beta 2 \cdot \text{Wind share} + \beta 4 \cdot \text{Consumption} + \beta 5 \cdot \text{Gas Price} + \beta 6 \cdot \text{D} + \epsilon \tag{3.4}$$

Where:

Unit revenue: The dependent variable represents the Unit Revenue of each day for 8 years.

Value Factor: The dependent variable represents the Value Factor of each day for 8 years.

Day-ahead price: The dependent variable represents the day-ahead prices per hour of each day for 8 years.

Solar share: Solar electricity production divided by total load.

Wind share: Wind electricity production divided by total load.

Consumption: Total demand at a specific day.

Gas Price: Price of gas at a specific day.

Dummies: dummies for 24 hours, weekdays, months, and years.

$\beta 0$, $\beta 1$, $\beta 2$, $\beta 3$, $\beta 4$, $\beta 5$, $\beta 6$: The regression coefficients, indicating the strength and direction of the relationship between the independent variables and day-ahead prices.

ϵ: The error term representing the unexplained variation in day-ahead prices.

These steps form a structured approach to researching the fluctuations in electricity prices and assessing the impact of renewable energy in the Netherlands. Each step contributes to a comprehensive understanding of the dynamics within the Dutch electricity market.

3.3 Research overview

In addition to the approach outlined above, a flow diagram has been created to visually represent the research framework in Figure 3.1. This diagram delineates the main research question along with its corresponding sub-questions and outlines the specific objectives associated with each sub-question. This visual aid provides a clear roadmap for the research process, guiding the exploration of the intricate dynamics surrounding the main topic.

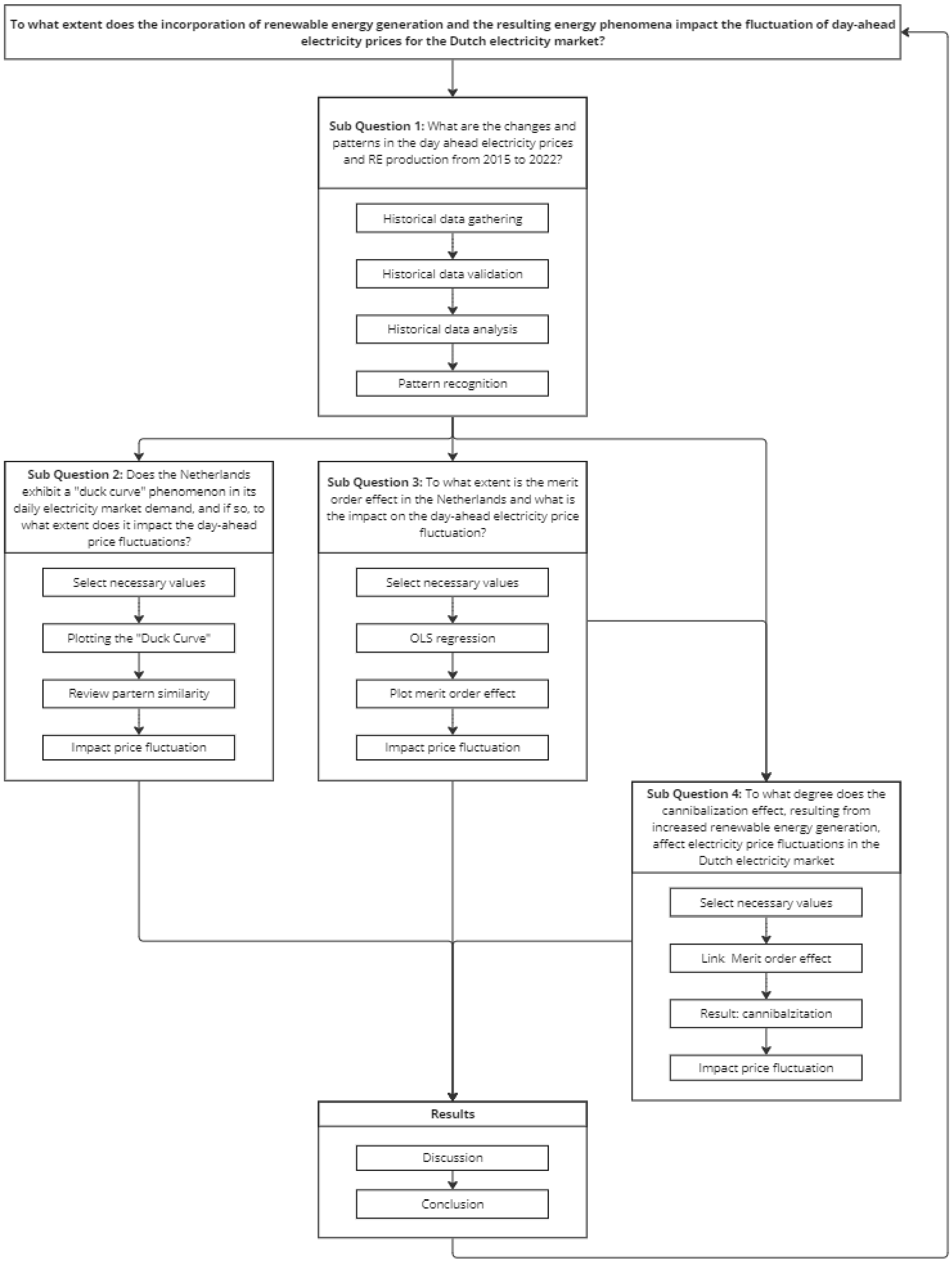

Figure 3.1: The research roadmap

CHAPTER 4

Data

The data-gathering phase of this research aims to collect relevant information on the factors influencing day-ahead energy prices in the Dutch electricity market, with a specific focus on the impact of renewable energy generation. Various data sources are explored, including historical electricity prices, renewable energy market share data, solar production, wind production, and other variables that might influence electricity prices. These data will be collected from reputable sources, such as energy market organizations, the Central Bureau for Statistics (CBS), and other research institutions. By compiling and organizing this data, build a comprehensive dataset that will serve as the foundation for the subsequent analysis of the effects of renewable energy on day-ahead prices.

4.1 Day-ahead electricity prices

The initial dataset for this research was sourced from the EPEX group, an institution operating under the EEX group, specializing in spot market trading. This dataset furnishes day-ahead electricity clearing prices on an hourly basis and covers the period from 2016 to September 2022. To ensure data accuracy and reliability, cross-verification was conducted using data available on the ENTSO-E website, which also provides day-ahead prices. The validation process revealed no percent difference between the EPEX and ENTSO-E datasets, affirming the quality of the EPEX data.

Consequently, the EPEX dataset was supplemented with additional data from ENTSO-E. The ENTSO-E website offers data dating back to 2015 and continuously updates with new day-ahead prices as they are cleared in the day-ahead market. These newly derived hourly prices were then integrated into the EPEX dataset, resulting in a comprehensive set of hourly electricity prices spanning from 2015 to 2022.

Furthermore, it's important to note that the dataset required adjustments for daylight saving time (DST) to ensure consistency. Between March 26th and March 31st each year, one hour of data was missing, resulting in 23 lines of data for those days. Conversely, between October 25th and October 31st, an extra hour of data was present, resulting in 25 lines of data for that day. To address this issue, the missing hour was filled by averaging the data from the hour before and after it, and the extra hour was removed. This adjustment was necessary to create a uniform dataset where each day consistently consisted of exactly 24 hours and therefore 24 lines of data.

4.2 Total load and RE production

The next dataset required for the analyses was the total electricity consumption, also provided by ENTSO-E. It's worth noting that ENTSO-E offers this data on a quarterly-hour basis. To align this data with the price dataset, hourly prices were derived by averaging the four quarterly-hour prices for each hour. Similar to the price data, the consumption data had to be adjusted to account for daylight saving time (DST), employing the same method to ensure a consistent dataset with 24 data points for each day. It's important to note that the total load provided by ENTSO-E is equal to the electricity consumption. The numbers presented on the platform have already factored in various elements. ENTSO-E's total load accounts for losses incurred during auxiliary consumption, including resistance in cables, self-consumption in power plants, and voltage conversion. Additionally, it considers electricity imports and exports, subtracting these from the data on gross generation to derive the total load data. To further clarify this process, an illustration (Figure 4.1) and a detailed calculation are included below.

$$\textit{Total load} = \textit{Gross generation - Auxilary + Imports - Exports - Consumption by storages}$$

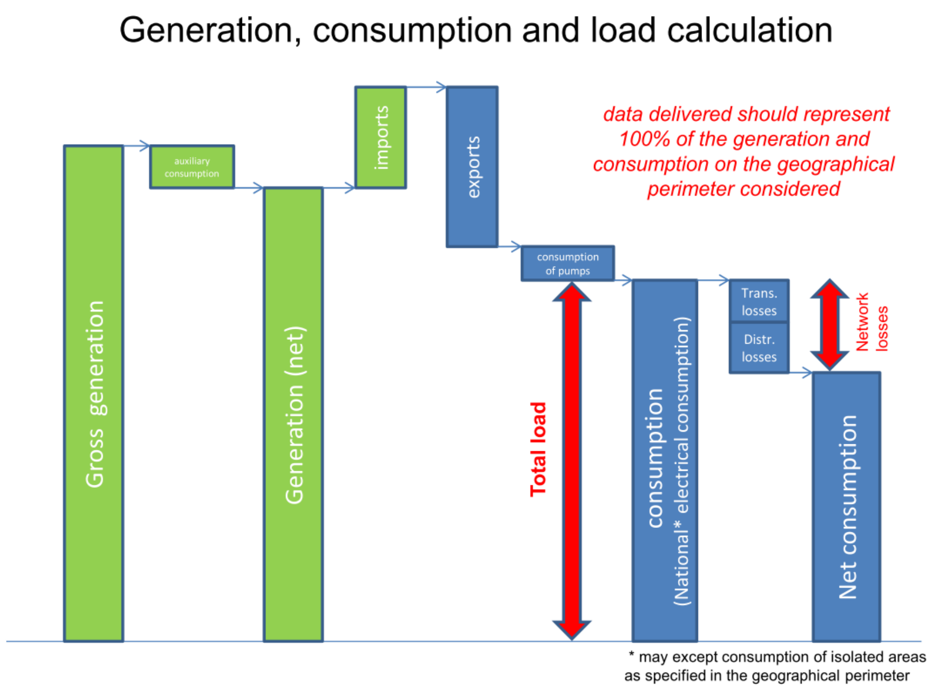

Figure 4.1: Insights of the data from ENTSO-E. [ENTSO-E, 2016]

Furthermore, RE production data was incorporated into the dataset for future computations. This dataset was also sourced from ENTSO-E. The RE production figures were available by each energy source and the Wind and Solar production was combined and included to create the total RE production.

Notably, dataset needed alignment with the price dataset. The same method used for the Total load where hourly prices were derived by averaging the four quarterly-hour prices for each hour was applied. As well as for the other two data sets, total load and price, the consumption data had to be adjusted to account for daylight saving time (DST), employing the same method to ensure a consistent dataset with 24 data points for each day.

4.3 Fossil fuels

To comprehensively research the impact of renewable energy, it's crucial to include data on fossil fuels, which used to be the primary drivers of electricity prices before the introduction of renewable energy sources. In the Netherlands, 70 percent of the electricity production from fossil fuels is created using natural gas [CBS, 2022]. Making the natural gas production a significant player in the electricity production. Fortunately, the ENTSO-E transparency platform offers data concerning fossil fuels, including electricity production from gas burning. The data on electricity generated from gas is also provided at a quarter-hourly interval. To align it with the same time intervals as the prices, total load, and renewable energy production, the four quarters were averaged per hour. Additionally, adjustments were necessary to accommodate DST with the same method as the other datasets, ensuring consistency in the combined dataset.

The final addition of data to the dataset is the gas prices which contribute to the prediction of the impact of RE. Unfortunately are gas prices not available through ENTSO-E and therefore not measured on the same interval scale as the other factors. The gas price data is obtained from the CBS database. The dataset, while originally available on a quarterly basis, was utilized for this analysis, even though the electricity price data is calculated on an hourly basis. To align the quarterly gas price data with the hourly intervals, a harmonization process is employed. This involved duplicating the gas prices corresponding to each specific quarter and populating them for each hour within that quarter. This method ensured that the gas price data could be effectively integrated into the hourly analysis.

4.4 ENTSO-E validation

In some instances, cross-referencing the collected data with other available sources was feasible. However, when it comes to validating the data from the ENTSO-E source, our primary reference was the comprehensive review conducted by [Hirth et al., 2018]. This review encompassed data from various countries, including the Netherlands, and assessed both its completeness and consistency. In terms of total load, the Netherlands received a favorable evaluation, boasting no missing data and maintaining consistency within a three percent deviation when compared to Eurostat data. Similarly, for generation per production type, specifically solar and wind, the Netherlands demonstrated impressive levels of data completeness, with minimal missing data (3.8% for solar and 1% for wind), and an even higher degree of consistency, with a deviation within 2 percent. Consequently, based on this assessment, can confidently be concluded that the ENTSO-E data accurately represents the factual data for the Netherlands [Hirth et al., 2018].

4.5 Software

In the process described, various datasets were amalgamated and refined. Microsoft Excel v2309 was the tool of choice for opening and modifying these datasets as both the company APPM and the Technical University of Delft provided access to a license. Excel, a versatile software, empowers users to create, arrange, and analyze data using rows and columns. Its capabilities span tasks such as calculations, data analysis, chart creation, graph design, and financial management. With a user-friendly interface and an extensive array of functions and formulas, Excel facilitates intricate mathematical, statistical, and logical operations. Its widespread usage in businesses, educational institutions, and personal finance management is owed to its efficacy in handling numerical data. [CFI-Team, 2023] For the regression analysis, IBM SPSS Statistics v29.0 was employed, a specialized program tailored for advanced statistical analysis, efficient data management, and comprehensive data documentation. [SPSS, 2023] While there are alternative options like Statistical Analysis System (SAS), Stata, R, and Minitab, the choice to use IBM SPSS Statistics was influenced by the accessibility of a license provided through the Technical University of Delft. This availability made IBM SPSS Statistics the practical choice to execute the analysis, ensuring both the necessary tools and time considerations were met effectively.

CHAPTER 5

Data analysis

In the following chapter, we delve into electricity prices, RE share, and the descriptive statistics. Descriptive statistics provide a concise summary of the main characteristics of a dataset. In the analysis of electricity prices, these statistics will be utilized to gain insights into central tendencies, variability, and patterns within the data. Key measures like the mean, median, standard deviation, and percentiles will help to grasp the overall distribution and behavior of electricity prices over the years 2015 to 2022. Figure 5.1 shows a graph with the descriptive statistics of the electricity prices and RE share for each year. Notably is the increase in RE share and the minimum and maximum prices. The absolute values used for the graph are also added in Table 5.1 below Figure 5.1.

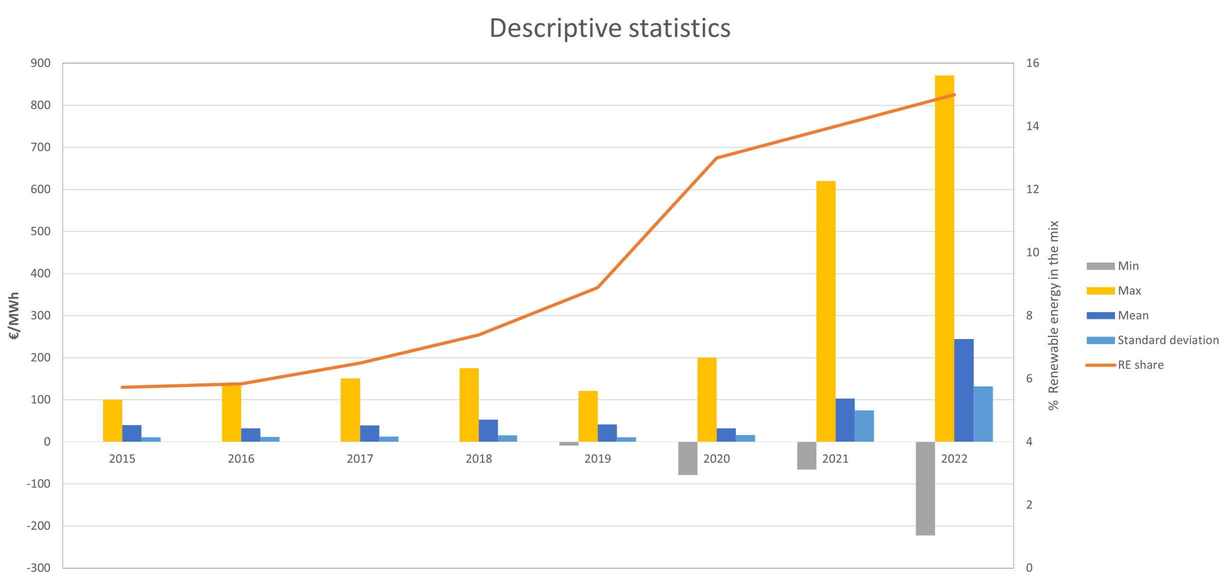

Figure 5.1: The descriptive statistics of the prices and RE share per year

Table 5.1: Table of descriptive statistics of the prices and RE share

Descriptive Statistics

Year	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
Std deviation	10,83012	11,31679	12,76522	15,17866	11,27492	16,11563	74,70981	131,5357
Min	0	0	0	0	-9,02	-79,19	-66,18	-222,36
Max	99,77	135	151,07	175	121,46	200,04	620	871
Mean	40,06292	32,103	39,32839	52,48128	41,25432	32,02264	102,8698	244,0314
Median	39,94	30,685	36,835	50,935	39,7	32,86	78,305	217
RE Share	5,73	5,84	6,5	7,39	8,89	13	14	15

5.1 Price pattern

In order to gain a more comprehensive understanding of electricity price behavior, the data undergoes a yearly review. Before plotting this data, it's essential to account for the influence of inflation. Given that the dataset spans from 2015 to 2022, the prices from different years are not inherently comparable due to the effects of inflation. To rectify this, the Consumer Price Index (CPI) is employed as a means to standardize these values. The CPI tracks changes over time in the prices of a specific basket of goods and services, making it a well-balanced measure for assessing inflation's impact on electricity prices.

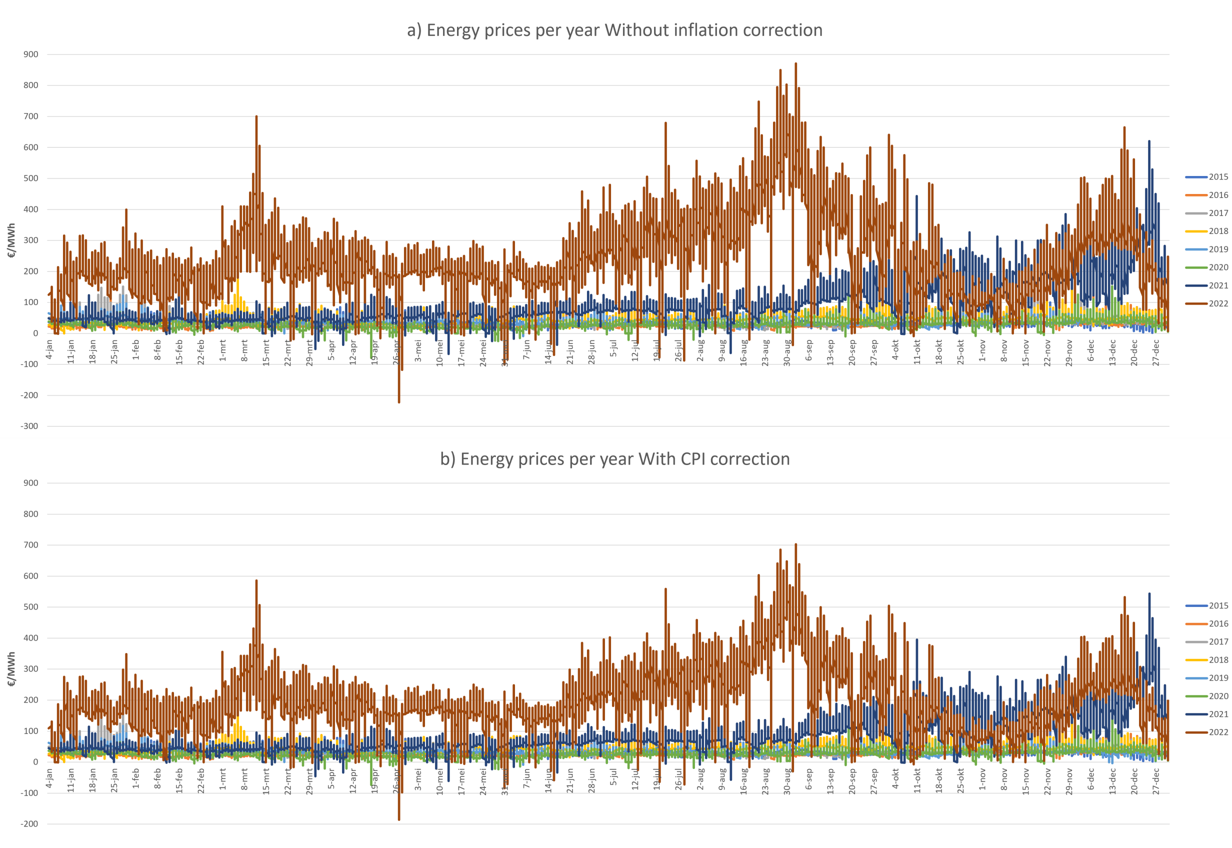

Figure 5.2: The hourly electricity prices plotted per year a) without and b) with CPI inflation correction

While another option could have been to use the GDP index, it's important to note that the GDP index primarily serves as a measure of the prices of all goods and services, while the CPI focuses exclusively on a specific basket of goods and services. This basket includes the energy prices making it better suitable for inflation correction. [CBS, 2007] Additionally, GDP includes a much broader spectrum of economic activities, encompassing not only consumption but also investments, government spending, and net exports. Therefore, using GDP as an inflation factor might introduce unnecessary complexity and less relevance when assessing the impact of inflation on electricity prices. [Faust and Wright, 2013] This selection of the CPI as the inflation factor ensures a more accurate reflection of how inflation influences electricity prices. The result of the inflation correction on the electricity prices can be shown in Figure 5.2. The figures are based on hourly price data, plotted for 8 years.

The presented figures (Figure 5.2) offer insights into patterns in electricity prices. First and foremost, both graphs in Figure 5.2 undeniably depict a substantial price surge that was initiated around August 2021, subsequently leading to heightened price volatility. It is noteworthy that this surge in electricity prices in 2022 may be attributed, at least in part, to the geopolitical tensions between Russia and Ukraine. Although this started in 2022, it is possible that the months preceding this tension already had an impact on the electricity market. [Europese-Raad, 2023]. Secondly, the role of inflation in contributing to this pronounced price surge appears to be rather limited. Although there was a modest reduction in the magnitude after the inflation correction during 2021 and 2022, prices have consistently maintained a significantly elevated position compared to previous years. This sustained increase in prices underscores the influence of factors beyond inflation on the observed price dynamics. Lastly, the heightened volatility aligns with the occurrence of negative prices. While negative prices began in 2019 (visible in the descriptive statistics in Figure 5.1), their magnitude substantially increased in tandem with rising volatility.

5.2 Renewable Energy share

Upon analyzing electricity price patterns and considering inflation, the next step involves investigating the patterns in RE share and load. As briefly mentioned in the descriptive statistics, this chapter commences by addressing the average RE generation, accounting for approximately 15 percent of the demand. This average RE production has nearly doubled since 2015, rising 7 percent points over the observed eight-year period. However, it is essential to note that this percentage is an average, and the portion of electricity demand covered by RE is significantly higher during the daily cycle. This RE generation share is illustrated in Figure 5.3, particularly in recent years where peak energy shares have frequently soared to 40 and 50 percent of the total energy demand.

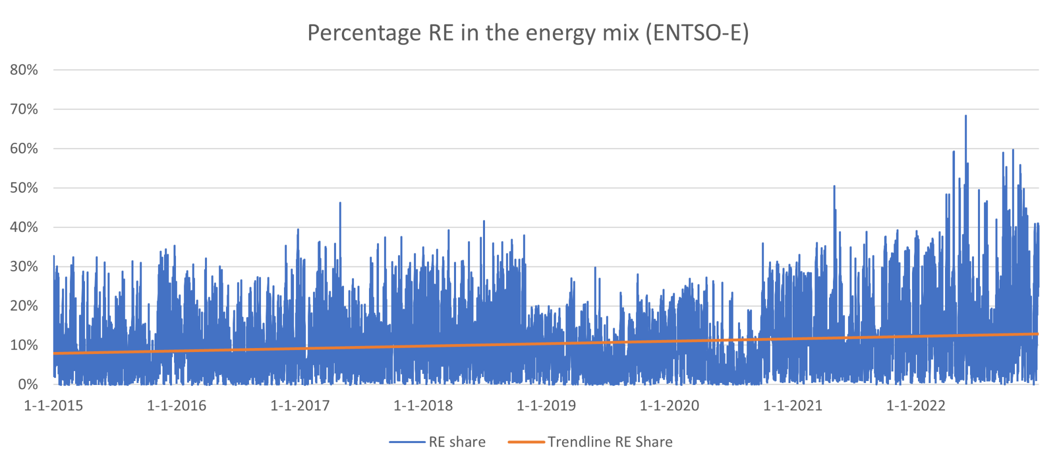

Figure 5.3: Share of RE provided by ENTSO-E

Despite the upward trajectory of RE production, the starting point on the graph still hovers above zero, signifying instances with no RE generation. However, there has been a noticeable shift over the years. In particular, the last three years have seen significant changes. The average RE production in the lowest quartile of each year has increased from 1 percent to 3 percent, suggesting a more consistent energy supply through RE sources. Similarly, the upper quartile has risen from 19 percent to 31 percent, indicating a more stable RE generation throughout the days. These numbers reflect an encouraging trend towards a more reliable and constant supply of energy from renewable sources. In the following sub-chapter is the daily demand covered and shown on a smaller scale.

5.3 The Dutch Duck Curve

While the yearly electricity price graphs provide valuable information about price levels, they do not inherently reveal the distinctive shape of a Duck Curve. To unveil this shape, two different scales are essential: the net load, which reflects the hour-by-hour electricity demand, and a 24-hour daily cycle. To introduce the concept of the Duck Curve, it is initially visualized within the context of the California electricity market, as demonstrated in the introduction in Figure 2.2. This iconic curve was originally constructed by the California Independent System Operator, representing a day in March. Notably, such a curve as visible in Figure 5.4 has never been produced for the Netherlands. To facilitate a more direct comparison, the Dutch Duck Curve is plotted on the same day as the California Independent System Operator (CAISO) curve, thereby providing an intriguing perspective on the evolving dynamics of the Dutch electricity landscape.

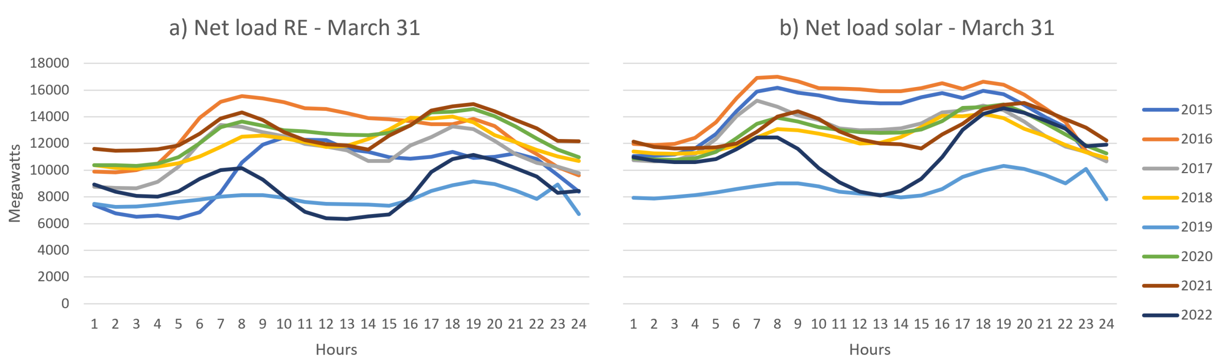

Figure 5.4: The Dutch Duck Curve with a) total RE and b) solar

The analysis of the Dutch Duck Curve shows patterns in the electricity demand. Similar to the CAISO for solar energy, the starting points of the Dutch Duck Curve reflect the absence of sunlight. This similarity implies that both regions share common challenges concerning solar energy production during periods of limited daylight. The curve prominently exhibits a distinctive "belly" resulting from robust solar electricity generation, followed by a steep ascent, wherein alternative energy sources must compensate for the lack of solar power. A noteworthy observation pertains to the energy consumption in 2019, which was notably lower than in other years. However, with the integration of wind energy (see Figure 5.4a), a significant divergence emerges. While the Dutch Duck Curve does indeed experience the inclusion of wind energy, the net load remains lower even during daylight hours. This addition of wind power contributes to a "flatter" Duck Curve, characterized by the reduction in the deep belly and steep neck. In conclusion, the incorporation of wind energy into the Dutch energy mix results in a less pronounced impact on the net load curve compared to solar energy. The Netherlands boasts a more substantial wind energy capacity than solar, thus elucidating the reduced prominence of the Duck Curve. Consequently, it can be inferred that the Dutch electricity market may be less susceptible to extreme price fluctuations driven by renewable energy sources in comparison to markets heavily reliant on solar power like California.

CHAPTER 6

Regression analysis

After preparing and formatting the dataset to be compatible with statistical analysis programs, a new series of analyses was undertaken. The program used is SPSS (Statistical Package for the Social Sciences), a versatile software program extensively employed for statistical analysis and data management. Its capabilities encompass a broad spectrum of statistical analyses, encompassing descriptive statistics, hypothesis testing, and regression analysis, among others. The regression analysis capability will be primarily used.

6.1 Quantifying the merit order effect

To address the third sub-question, a similar approach as employed by [Prol et al., 2020] was adopted to quantify and then visualize the merit order effect. This effect is quantified by the calculation of average hourly prices for 24 hours of a specific month for each year in the data set. To create these daily averages an OLS regression analysis was used. The results of the regression provided data that could be used to plot and visualize the merit order effect. Notably, did [Prol et al., 2020] initially visualize the merit order by plotting the hourly electricity prices for an average day for each month of the year. To emphasize the merit order effect specific to Dutch electricity prices, some modifications were introduced compared to Prol et al.'s visualization. Subsequently, a regression analysis was executed to quantitatively visualize the impact of this cannibalization effect. The regression formula that is used for this purpose is detailed below. The variables are also explained to add to the understanding of the calculation. The specifics of how this regression analysis operated will be elaborated upon in the subsequent paragraph.

$$\text{Day-ahead prices} = \beta 0 + \beta 1 \cdot \text{D2} + \beta 2 \cdot \text{D3} + \beta 3 \cdot \text{D4} + ... + \beta 23 \cdot \text{D24} + \epsilon \tag{6.1}$$

Where:

Day-ahead prices: The dependent variable represents the day-ahead prices per hour of each day for 8 years defined in Euro's per mega Watt hour.

D2, D3, D4, ... , D24: The dummy variables to quantify the merit order effect.

$\beta 0$, $\beta 1$, $\beta 2$, $\beta 3$ etc.: The regression coefficients, indicating the magnitude and direction of the relationship between the independent dummy variables and day-ahead prices.

ϵ: The error term representing the unexplained variation in day-ahead prices.

To delve deeper into the process, the analysis began with a dataset containing hourly price data spanning from 2015 to 2022. To extract the desired figures, two filters were applied: one to select specific months and another to isolate individual years within the dataset. Combining these filters created distinct month-year combinations, serving as input for the OLS regression analysis. The regression formula incorporated 24 dummies, representing the 24 hours in a day, allowing for a granular examination of price fluctuations throughout the day as explained above. With 96 separate regressions executed, corresponding to the 96 unique month-year combinations, detailed insights were gained. From these regressions, 12 figures were generated, each illustrating the variations in the average hourly price fluctuation for specific months across eight different years. These figures provide an empirical view of the market dynamics, capturing the interplay of time, price, annual fluctuations, and the merit order effect. Furthermore, to enhance the evolution of the merit order effect, these 12 figures were combined into a single figure, denoted as Figure 6.1.

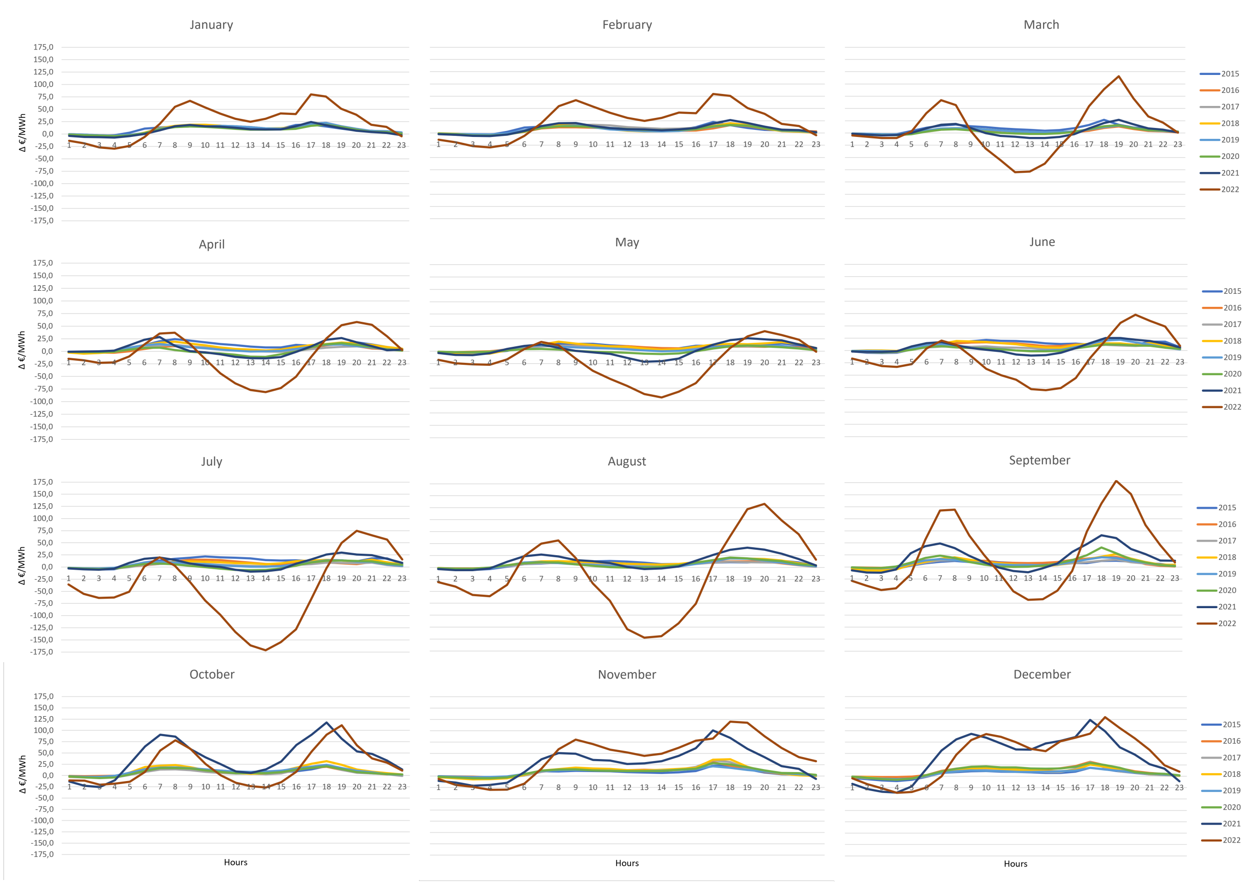

Figure 6.1: The effects of the merit order visualized on 24 hours. Each figure displays the average price change for a specific hour, month, and year. Subsequently, this data is plotted on a daily basis (24 hours), with the specific month and year shown above and to the right of the figure.

To clarify the figures presented (Figure 6.1), it is important to note what the values in each of the figures represent. The regression analysis calculates beta coefficients for each dummy. Each unstandardized beta is associated with a specific hour's dummy variable indicates the change in the electricity price relative to the chosen reference hour of 00:00 of a new day, this serves as the baseline. A positive beta suggests that, on average, electricity prices during that hour are higher compared to the reference hour, while a negative beta implies lower prices. The magnitude of the beta indicates the extent of this price change. These beta coefficients corresponding to specific hours are plotted, each representing a particular time of day, and these plots are generated for a selected year. This approach emphasises the fluctuations of the prices and provides a comparison over the years as the absolute value of the price of this year is left out.

When comparing Figure 6.1 with Figure 5.2, which displays annual price data, a similar conclusion arises, a noticeable increase in price volatility around August 2021. This is particularly evident as the blue line for 2021 starts to exhibit greater curvature, aligning more closely with the brown line for 2022. The figures also seem to portray a slight Duck Curve shape in certain months, although this is not the Duck Curve phenomenon. This shape could also formed by the introduction of RE generation when looking at the Duck Curve.

Furthermore, the merit order effect becomes clearly visible, consider the graph from August (Figure 6.1), a month characterized by sunny weather. Over the course of 24 hours, distinct price fluctuations reveal the impact of RE production on the market. In the initial four hours, prices steadily decline due to low energy demand during the early morning hours. However, at the fifth hour, a sharp price increase occurs, persisting until the seventh hour, triggered by a surge in demand coinciding with a reduction in RE production. The following hours, from 8 to 14 o'clock, witnessed a significant drop in prices. This drastic decrease is attributed to the abundant supply of RE generation flooding the grid, thereby driving down market prices. However, as the day progresses, around the fifteenth hour, prices begin to rise again. This uptick is fueled by increasing demand and a gradual reduction in RE production. The price surge continues until the nineteenth hour, at which point the escalation halts. From this point onward, prices start to decline steadily, reaching the lowest point at the twenty-fourth hour, mirroring the diminishing energy demand as the day comes to a close. These price fluctuations illustrate the merit order effect, showcasing the interplay between energy supply, demand, and RE production in shaping electricity prices.

6.2 Quantifying the cannibalization effect

From the quantification and visualization of the merit order is shown that there is a decrease in electricity prices when RE production enters the electricity market. However, to determine how much these price changes are directly influenced by the increasing renewable energy generation, a distinct analysis is required, which will also answer the fourth and final sub-question. To address this fourth sub-question, inspiration from the quantification method by [Prol et al., 2020] was used to quantify the cannibalization effect. In the paper, they use the unit revenue (UR) and Value factor (VF) as variables in their regression analysis for wind and solar integration. Nevertheless, a notable adjustment was made to incorporate the total RE production rather than focusing solely on wind and solar sources. This modification accounts for the days with zero solar production, which posed a challenge in the calculations. To mitigate errors caused by dividing by zero in such instances, the formulas use the total RE production rather than calculating solely wind and solar factors. The resulting formula for the calculation of the UR and VF is the following:

$$UR_t^{RE} = \frac{\sum_{h=1}^{24} p_h q_h^{RE}}{\sum_{h=1}^{24} q_h^{RE}} \quad with \quad t \in 1, ..., 2920 \tag{6.2}$$

$$VF_t^{RE} = \frac{UR_t^{RE}}{\bar{p}_t} = \frac{\sum_{h=1}^{24} p_h q_h^{RE} / \sum_{h=1}^{24} q_h^{RE}}{\sum_{h=1}^{24} p_h / 24} \quad with \quad t \in 1, ..., 2920 \tag{6.3}$$

To elaborate on these formulas, the UR^{RE} is determined as the RE generation-weighted electricity prices, providing a measure of the revenues or market value generated per unit of energy produced. To put it more simply, the UR calculates the revenue of RE in euros for one day of electricity. The VF^{RE}, on the other hand, represents the ratio between unit revenues and the average electricity prices. Furthermore, these two equations incorporate hourly day-ahead electricity prices, denoted as p_h, and the hourly quantity of generation of RE technologies denoted as q_h^{RE}. It's worth noting that next to [Prol et al., 2020] the approach also aligns with the study by [Hirth, 2015]. With the calculation of the UR and VF two graphs are created and visible in Figure 6.2. Notably, the data on the graphs for both y-axis is presented on a daily interval due to the calculation method utilized in the formulas. This method involves considering the 24-hour period, thereby providing daily values for analysis.

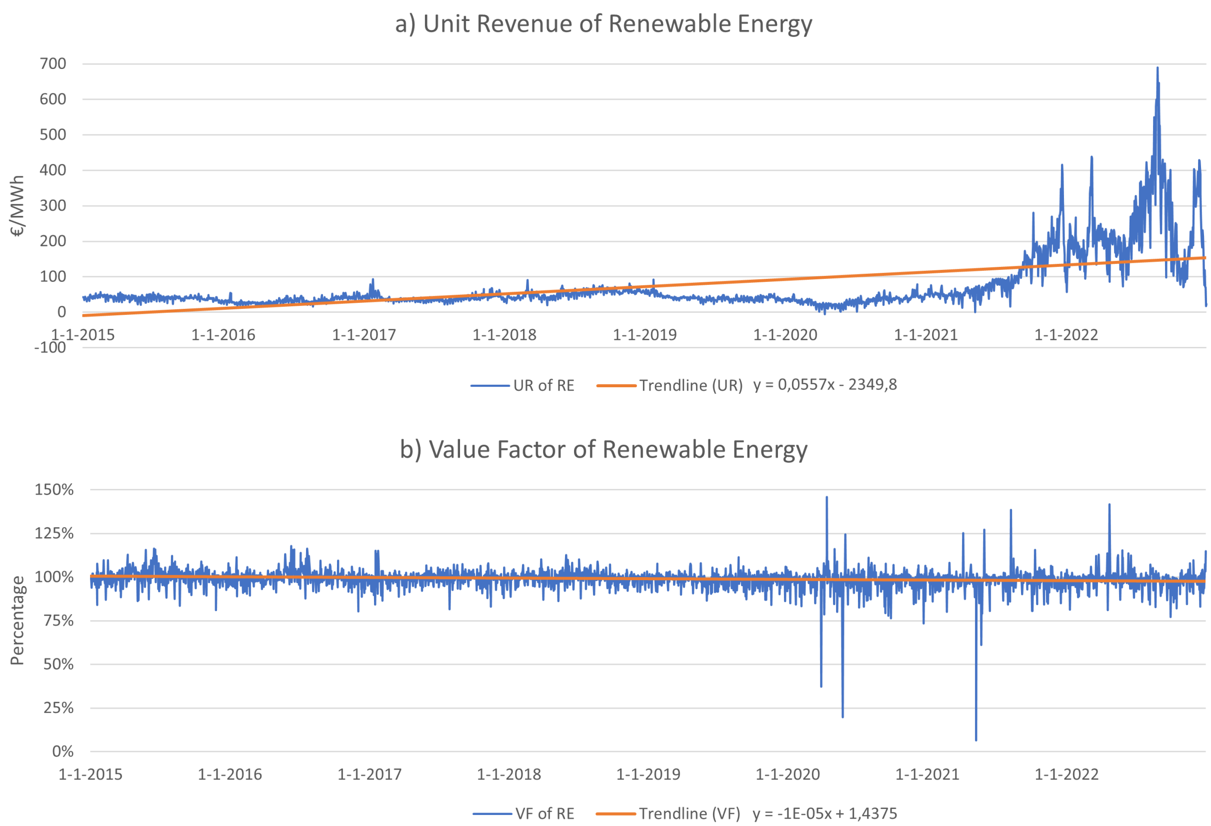

Figure 6.2: a) UR and b) VF

These graphs (Figure 6.2) exhibit notable changes in yearly patterns similar to the Duck Curve and the merit order effect, reflecting increased fluctuations in UR (for the last two years) and VF (for the last three years). The added trendlines offer quantitative insights into UR and VF patterns. The UR trendline shows a slope increase of €0.0557 per MWh over time, seemingly suggesting a rise in electricity revenue. However, this increase is a response to the overall escalation in electricity prices, as seen in Figure 5.2. The cannibalization effect becomes apparent in daily UR fluctuations due to RE generation. This observation will be checked by the interpretation of the results of the Prais-Winsten analysis.

Additionally, the VF trendline displays a nearly negligible negative slope of 0.0001 percent point, showing a subtle decline in the value of electricity. Notably, VF fluctuations intensified after 2020, indicating distinct periods during the day when electricity value peaks compared to other moments. In the middle of 2022, for instance, the VF reached its peak at 140 percent, signifying that renewable electricity was valued 40 percent higher than an average unit of electricity. Comparing this to the lowest peak in mid-2021 at 6 percent, there was a substantial difference of 134 percentage points. While this is an extreme illustration, the line shows more highs and lows than before 2020. Additionally, amidst these increased fluctuations, the average VF of RE stood at 99 percent, indicating that, on average, a unit of electricity generated from renewables was only 1 percent less valuable than conventionally generated electricity, suggesting a slight decline in the value of RE generation. This observation also hints at the presence of the cannibalization effect, which will be explored in the subsequent section.

The calculation of UR and VF comes with a single drawback: the loss of hourly comparison. This limitation arises from the method employed in the formulas, leading to the calculation of daily UR and VF values. As mentioned earlier, this daily aggregation results in the loss of some granularity.

To compare if the loss in data creates a difference in results, a variation on the regression formula, distinct from the one used by [Prol et al., 2020], is employed to provide a more comprehensive perspective. This formula utilizes different variables as the Prais-Winsten analysis for UR and VF. In their formula, they incorporate the gas share variable, aiming to enhance the R-squared value by introducing more independent variables to explain the dependent variable. However, a critical consideration arises regarding the potential consequence of prioritizing a higher R-squared by including numerous independent variables, as it may lead to the development of illogical models. An example of an illogical model is overcontrolling, where certain variables are integrated into the regression analysis when they shouldn't be there. This happens when the included variables are being fixed, despite their inherent need to fluctuate with changes in the dependent variable. [Wooldridge, 2019] In the analysis conducted by [Prol et al., 2020], the gas share is considered among the independent variables. However, as the share of RE increases, it becomes illogical to keep the gas share fixed. Since more energy is generated by RE, the gas share should logically decrease, as the same amount of energy would be needed. To address this, the analysis is run twice: first, without the gas share to observe the results without overcontrolling, and then again with the gas share to assess the influence on the R-squared and other variables in the analysis. In addition to the analysis conducted by [Prol et al., 2020] is another regression analysis with the electricity price as the dependent variable added for comparison. This inclusion, using hourly interval data, allows for a more detailed examination. The resulting regression formulas with their variables are as follows:

$$\text{UR}^{RE} = \beta 0 + \beta 1 \cdot \text{Solar share} + \beta 2 \cdot \text{Wind share} + \beta 4 \cdot \text{Consumption} + \beta 5 \cdot \text{Gas Price} + \beta 6 \cdot \text{D} + \epsilon \tag{6.4}$$

$$\text{VF}^{RE} = \beta 0 + \beta 1 \cdot \text{Solar share} + \beta 2 \cdot \text{Wind share} + \beta 4 \cdot \text{Consumption} + \beta 5 \cdot \text{Gas Price} + \beta 6 \cdot \text{D} + \epsilon \tag{6.5}$$

$$\text{Day-ahead price} = \beta 0 + \beta 1 \cdot \text{Solar share} + \beta 2 \cdot \text{Wind share} + \beta 4 \cdot \text{Consumption} + \beta 5 \cdot \text{Gas Price} + \beta 6 \cdot \text{D} + \epsilon \tag{6.6}$$

Where:

UR^{RE}: The dependent variable represents the Unit Revenue of each day for 8 years.

VF^{RE}: The dependent variable represents the day-ahead prices per hour of each day for 8 years.

DA prices: The dependent variable represents the day-ahead prices per hour of each day for 8 years.

Solar share: Solar electricity production divided by total supply.

Wind share: Wind electricity production divided by total supply.

Consumption: Total demand at a specific day.

Gas Price: Price of gas at a specific day.

Dummies: dummies for 24 hours (is only used if IV is the Day-ahead prices), weekdays, months, and years.

$\beta 0$, $\beta 1$, $\beta 2$, $\beta 3$, $\beta 4$, $\beta 5$, $\beta 6$: The regression coefficients, indicating the strength and direction of the relationship between the independent variables and day-ahead prices.

ϵ: The error term representing the unexplained variation in day-ahead prices.

The analysis results are presented in Table 6.1, where various key variables are displayed, including Consumption, Solar Share, Wind Share, and Gas Price, denoted in units of MWh, percent, percent, and Euros respectively.

Table 6.1: The Prais-Winsten regression analysis results

Dependent variable	$\mathbf{UR}^{RE}$	$\mathbf{VF}^{RE}$	**Electricity Price**
Regression Coefficients	Unstandardized B	Unstandardized B	Unstandardized B
Consumption	-0,005***	-1,679E-6	0,003***
Solar Share	-139,986*	0,336*	-58,982***
Wind Share	-113,391***	0,073***	-36,695***
Gas Price	-0,615	-0,001***	0,664*
Rho (AR1)	0,895	0,090	0,958
R Square	0,280	0,060	0,162
Adjusted R Square	0,273	0,051	0,161
Durbin-Watson	2,066	1,999	1,570

The Prais-Winsten estimation method
*p<0,1
**p<0,05
***p<0,01

By going step by step through the output, several key relationships are interpreted and highlighted. Firstly, in analyzing the UR column, an increase of one MWh in consumption results in a 0,005 decrease in UR. Furthermore, a one percent point increase in solar share and wind share correlates with a 139,986 euro per MWh RE decrease in UR and a 113,391 euro per MWh RE decrease in UR. This implies that as RE production rises (solar and wind share increase), the revenue per unit of electricity of RE decreases. It's important to note that the Solar share's Unstandardized B was not significant, indicated by a P-value of 0,101, but the wind share exhibited strong significance. The combination of these two variables provides the quantified cannibalization effect for the Netherlands proven by UR. Among the control variables, however, the gas price variable does not show a significant P-value (p=0,136) making it not relevant for the interpretation. Nevertheless, an interesting observation with the dummy variables was the higher, non-significant P-values from September to December compared to the months before September.

Secondly, the column of the VF. In the case of consumption, a one MWh increase in consumption results in a negligible decrease of 1,679E-6 p.p. in VF, indicating that the increase in consumption has little influence on the value of one MWh of electricity supplied. Thus, showing little elasticity in energy demand. Surprisingly, both solar and wind shares positively influence VF, seemingly contradicting the trendline from Figure 6.2b which is showing a small VF decrease due to RE penetration. This discrepancy might be due to the moderate significance of solar share. Gas share and gas prices exhibit strong correlations with VF, indicating their influence. The dummies demonstrated non-significant results in winter compared to summer months.

Thirdly, analyzing the electricity prices column, what can be observed is that a one MWh increase in consumption corresponds to a mere 0,004 euro rise in electricity price, indicating again a minimal impact. This positive correlation presents a logical relationship, as the increase of consumption (thus demand) the electricity prices rise. Nevertheless, the results are of a negligible magnitude. Moreover, the solar and wind shares affirm the cannibalization effect for the Netherlands, mirroring the patterns seen in UR, with both indicating a negative correlation with electricity price increments. Essentially, as solar and wind energy shares rise, the electricity price decreases. This destruction of market revenue is the literal description of the cannibalization effect. Conversely, gas share and price exhibit a logical and opposite relationship to renewable energy, suggesting that higher gas share and prices lead to increased electricity prices. A noteworthy observation regarding dummy variables is their lack of significance when prices transition from positive to negative or vice versa. This finding implies nuanced dynamics in response to shifting market trends.

Next to the specific column interpretation, several general insights emerged from the data analysis. Firstly, the daily interval showed a generally lower P-value, indicating its significance. In this interval, two out of the five UR^{RE} variables were not significant, while three variables from VF^{RE} had p-values above 0,01, 0,05, and 0,1. In the hourly interval, only one variable had a p-value above 0,05, highlighting its higher significance. Additionally, considering autocorrelation (Durbin-Watson values), the hourly interval analysis scored higher (all staying within a relatively normal range between 1,5 and 2,5) which could be due to the larger number of observations. The daily interval comprised 2922 lines of observations, while the hourly interval had 70127 lines. Moreover, the analysis revealed that overall consumption was not significantly influenced by UR, VF, or Electricity price, confirming an inelastic demand for electricity. Lastly, the UR^{RE} analysis proved to be the best predicting model of the three, explaining nearly 30 percent of the variable UR^{RE}. It's important to note that while the research was not aimed at creating a predictive model but rather an evidential one, the current values of R Square suggest the potential for adding more variables to enhance predictability. Although a value of 60 percent is preferable for predictive models are values of almost 30 and 20 percent acceptable in this case, as the price fluctuations are not only dictated by the included variables. The VF^{RE} exhibits a remarkably low R Square, indicating that there are likely other variables that provide a better explanation for VF^{RE}.

The regression analysis of the UR^{RE} and electricity price clearly reveals the cannibalization effect for the Netherlands. The UR^{RE} shows a strong negative correlation with solar share and wind share of -139,986 euro per MWh RE and -113,391 euro per MWh RE respectively. Similarly, the correlation with electricity prices and solar and wind share is negative, -58,982 and -36,695. These negative correlations provide evidence and quantify the cannibalization effect in the Netherlands. Consequently, this effect influences electricity prices, indicating that a higher RE share leads to more substantial price decreases during production hours.

CHAPTER 7

Discussion

The discussion on the analysis of day-ahead electricity price fluctuations and RE production in the Netherlands highlights several crucial points. These are discussed and evaluated on what the results of the chapters entail and how relate to more practical circumstances.

7.1 Findings

7.1.1 Results discussion

In the analysis of the duck curve, the outcome was unmistakable. However, it's important to note that the results are only compared to one specific day, and this day could be an exception compared to others throughout the year. To provide a more comprehensive assessment of the existence of the duck curve, the evaluation could benefit from additional comparisons with other days. This approach would contribute to a more thorough review, although it is likely to yield similar results, given the low probability of this particular day being the best comparison to the chosen day provided by CAISO.

The visualized merit order effect, derived from the analysis, supports its existence but involves certain assumptions. The assumption is that the decreasing prices during the investigated period are solely explained by the oversupply of solar and wind, based on the Dutch duck curve results showing a dip in fossil fuel energy production during RE production hours. While this connection seems evident, some argue that comparing two figures without an individual regression to assess whether both phenomena correlate and influence the price fluctuations might lead to a different outcome.

Additionally, the cannibalization effect found on UR and electricity price yielded a concrete quantified result, but the VF provided a more controversial answer, contrary to the previously found results. The reason for this unexpected outcome remains unclear after reviewing the calculations from the data, especially as the other two factors provide an answer in line with the previously found results. The UR is also calculated from the same data, and the VF calculation also uses the data from UR, suggesting that the outcome of VF would be similar.

Moreover, outliers were included in the regression analysis from the cannibalization effect. While outliers are often considered as data points that deviate significantly from the overall trend, the use of historical data showed that they could provide valuable insights. Although regression analysis typically assumes the absence of outliers, retaining these exceptional data points added to the comprehensiveness of the data. As the assumption is made that there are no outliers but only extreme fluctuation, no reduction of the data was made and all anomalies were included that have a significant impact on the observed relationships. This assumption could be wrong and result in reduced model robustness.

7.1.2 Practical implementation

In the literature review are discoveries made on the solution of these price fluctuations. This is on a more practical level also where this thesis tries to work towards, by providing an answer to the problems of unstable electricity markets. However, the desirability of such stability remains uncertain. It's noteworthy that certain enterprises thrive on the inherent volatility of electricity prices. Intriguingly, a hypothetical scenario arises: in a world powered entirely by RE generation, in accordance with the expected trend would this universal shift lead to consistently low prices. Paradoxically, this situation might create razor-thin profit margins for companies, challenging their very existence. In the literature, it is also mentioned that the advent of an entirely RE-based energy system could prompt a fundamental redesign of electricity markets. [Edenhofer et al., 2013]

Furthermore, in the solution of stable electricity market prices are mitigation strategies a must. To address these challenges posed by fluctuating renewable energy production and as a result their impact on prices, implementing mitigation measures becomes imperative. Solutions like energy storage systems, both at grid-scale and distributed levels, can help balance the supply-demand equation during intermittent RE periods. Interestingly, the Duck Curve would still be a crucial phenomenon with mitigation strategies. Due to the the remaining variability of RE is this phenomenon crucial in maintaining the required amount of storage during low RE production hours.

Additionally, demand-side management strategies (DMS), such as smart grids and demand response programs, enable more efficient utilization of available energy, reducing price volatility. These strategies allow consumers to utilize energy in a manner that aligns with the fluctuations in its availability, thereby suppressing price volatility. To improve the DSM effectiveness is the merit order effect an essential instrument. This principle ensures that electricity from the most cost-effective sources, often renewable energy like solar and wind, is utilized first. Consequently, during periods when these renewable sources are abundant, the merit order effect drives down prices, creating an incentive for increased consumption. This incentive-driven mechanism is already at play in various scenarios, such as electric vehicle charging during working hours when the sun is shining brightly. Lower electricity prices during these periods encourage consumers to charge their vehicles, effectively aligning their energy usage with the availability of renewable resources. By doing so, consumers not only benefit from reduced costs but also contribute to a more balanced demand-supply equation within the energy market. Including the reduction of price fluctuations as less energy is necessary during the hours at home.

7.2 Limitations

In the course of this research, a variety of research activities were undertaken to unravel the complexities of integrating renewable energy into the Dutch electricity market, specifically focusing on the limitations posed by the Dutch case study. The research methodology employed an empirical historical data analysis approach, coupled with a literature review. However, the Dutch case study had limitations that influenced the research findings.

First and foremost, the Dutch case study presented constraints by restricting the volume of renewable energy produced and excluding certain renewable energy sources with their variability, such as bio-fuels, hydro power or geothermal. This limitation inherently influenced the scope and depth of the analysis, which could provide insights into a subset of renewable energy dynamics.

Furthermore, the dataset encountered limitations, particularly the absence of solar power data for specific months in 2019. This data gap posed challenges, hindering parts of the analysis of solar energy's impact on electricity prices during those periods. Consequently, the absence of this critical data could potentially lead to skewed conclusions, highlighting the need for comprehensive and complete datasets in future studies.

Importantly, the study did not incorporate import and export prices of energy, factors that can impact domestic electricity prices, especially in interconnected energy markets like Germany and France. In these markets could the RE generation provide clean energy during a lack of electricity in the Netherlands, creating a lower price overall. Ignoring these aspects potentially created gaps in the interpretation of the electricity market prices. Cross-border transactions play a substantial role in influencing price fluctuations, and the lack of this data inclusion may have resulted in an incomplete depiction of the pricing dynamics.

Next to the import and export does the research simplify the nature of electricity prices. These prices are not only influenced by supply and demand dynamics but are also intricately connected with geopolitical events, government policies, global market trends, and weather conditions. Regrettably, these complex factors could not taken into account in the study as they were not measurable or would make the study incomprehensible. Neglecting these variables might have simplified the analysis excessively, possibly missing elements that contribute to price variations.

CHAPTER 8

Conclusion

In conclusion, this study provides a comprehensive analysis of the research objectives. It systematically addresses the main research question and its sub-questions. Each sub-question is stated first, followed by their answers. Subsequently, the main research question is tackled, resulting in a detailed and conclusive response.

8.1 Answering the research Questions

Stated after the literature review are the sub-questions and the main research question, these will repeated and answered below.

8.1.1 Sub-question 1

What are the changes in fluctuation in the day ahead electricity prices and RE production from 2015 to 2022?

The analysis of electricity prices and RE production from 2015 to 2022 reveals significant shifts in the energy landscape. Descriptive statistics highlight a rising RE share and notable price fluctuations. To ensure accurate comparisons, inflation correction using the CPI was applied. The corrected data shows a substantial price surge from August 2021, indicating heightened electricity prices and increasing volatility. Geopolitical tensions, particularly the Russia-Ukraine conflict in 2022, likely influenced this trend. The increased volatility aligns with intensified negative prices, emphasizing the intricate relationship between electricity prices and RE production.

8.1.2 Sub-question 2

Does the Netherlands exhibit a Duck Curve phenomenon in its daily electricity market demand, and if so, to what extent does it impact the day-ahead price fluctuations?

The analysis of the Dutch electricity market reveals the Dutch Duck Curve phenomenon. Similar to the CAISO curve, the Dutch Duck Curve showcases challenges related to limited RE production time, particularly in the absence of sunlight. The Dutch Duck Curve displays a distinct belly in the curve, representing the net load, which indicates solar electricity generation, followed by a steep ascent where alternative energy sources compensate for the lack of solar power. Intriguingly, the introduction of wind energy flattens the curve, reducing the deep belly and steep neck. This indicates that the Netherlands, with a substantial wind energy capacity, experiences a less pronounced impact on the net load curve compared to solar-reliant markets like California. Consequently, the Dutch electricity market appears to be less susceptible to extreme price fluctuations when looking at the Duck Curve driven by RE sources due to the inclusion of high shares of wind energy. Nevertheless, the Duck curve is still very much present in the Netherlands and contributes partially to price fluctuations throughout the day.

8.1.3 Sub-question 3

To what extent is the merit order effect in the Netherlands and what is the impact on the day-ahead electricity price fluctuation?

The analysis of the merit order effect in the Netherlands reveals more quantified insights into electricity price fluctuations. The comparison between hourly price data and annual trends shows a notable increase in volatility around August 2021. Additionally, certain months display fluctuations resembling a Duck Curve which is a price decline due to the implementation of RE. For instance, in August, prices drop due to abundant renewable energy supply, spike during increased demand, and gradually decline as energy demand decreases. The shapes are different over the years and months but are best observed during the last two years and summer months. These shapes are the quantified merit order effect proving that this phenomenon exists in the Netherlands and contributes to the price fluctuation.

8.1.4 Sub-question 4

To what degree is the cannibalization effect in the Netherlands and does it affect electricity price fluctuations in the Dutch electricity market?

In this question, research on the cannibalization effect in the Dutch electricity market was conducted. With the calculation of key variables such as UR and VF patterns similar to the previous sub-questions were discovered like the increase in fluctuation of electricity prices from 2021. The Prais-Winsten regression analysis is performed with UR, VF, and electricity prices as dependent variables which uncovered relationships in the Dutch electricity market. This resulted, for UR, in a negative correlation, with a one p.p. increase in solar share and wind share corresponding to a 139,986 euro decrease in UR and a 113,391 decrease in UR, indicating declining revenue per unit of electricity as RE production rises. Additionally, a one p.p. increase in solar share and wind share resulted in a decrease of 58,982 euros and a decrease of 36,965 in electricity price, respectively. The results from the analysis confirm the cannibalization effect, with solar and wind shares displaying negative correlations with electricity price increments, leading to reduced prices as RE penetration increases.

8.1.5 Main research question

To what extent does the incorporation of renewable energy generation and the resulting energy phenomena impact the fluctuation of day-ahead electricity prices for the Dutch electricity market?

In exploring the impact of RE generation on day-ahead electricity price fluctuations in the Dutch market, several key phenomena including price patterns have been identified and analyzed. From 2015 to 2022, a significant shift in the RE landscape was observed, marked by a 7 p.p. rise in RE share and notable price fluctuations, particularly after August 2021. The study identified the Dutch Duck Curve, depicting challenges in RE production time and the impact of wind energy in flattening the curve and reducing extreme fluctuations. The merit order effect analysis highlighted increased volatility, especially in the last two years, demonstrating the phenomenon's existence in the Netherlands and its contribution to price fluctuations. Additionally, the investigation into the cannibalization effect through Prais-Winsten regression analysis validated negative correlations, indicating declining revenue per unit of electricity as RE production rises. Solar and wind shares exhibited negative correlations with UR and electricity prices, leading to reduced prices as RE penetration increased, underscoring the cannibalization effect's influence on price fluctuations.

Thus, the incorporation of renewable energy generation in the Dutch electricity market has substantial consequences for fluctuations in day-ahead electricity prices. However, quantifying the individual influence of each phenomenon on these price fluctuations is hardly doable due to the different units, scales, and visualizations. nevertheless, it is evidently clear that there is a correlation between the researched energy market phenomena and price fluctuations.

8.2 Future research

Future research in the realm of energy markets should explore emerging phenomena that may arise due to higher shares of RE. As the energy landscape continues to evolve, understanding new market dynamics aids the effectiveness of policymaking and industry adaptation. Additionally, integrating data beyond 2022 could be explored. Newer datasets can offer fresh perspectives, enabling researchers to observe trends, changes, and potential shifts in phenomena. This updated information would provide a more accurate and current understanding of the market, aiding in better decision-making processes. Another direction for exploration involves determining the individual influence of each identified phenomenon. Research efforts could focus on quantifying the impact of the Duck Curve, merit order effect, and cannibalization effect. Establishing comparable metrics for these phenomena would facilitate a deeper comprehension of their respective roles, aiding in devising targeted strategies to manage their effects. The rise of energy storage technologies presents an intriguing area for future investigation. Researchers could delve into how storage solutions mitigate price fluctuations caused by low marginal costs of RE production. Understanding the interplay between storage systems and market dynamics could pave the way for innovative market designs that capitalize on the benefits of RE while ensuring stability and reliability. Furthermore, expanding the scope to include other renewable energy sources is essential. Investigating the impact of various RE sources on price fluctuations would provide a holistic view of the market. By analyzing the unique characteristics of different renewables, researchers can assess their contributions and challenges, informing comprehensive strategies for a diverse and sustainable energy future.

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APPENDIX A

Appendix

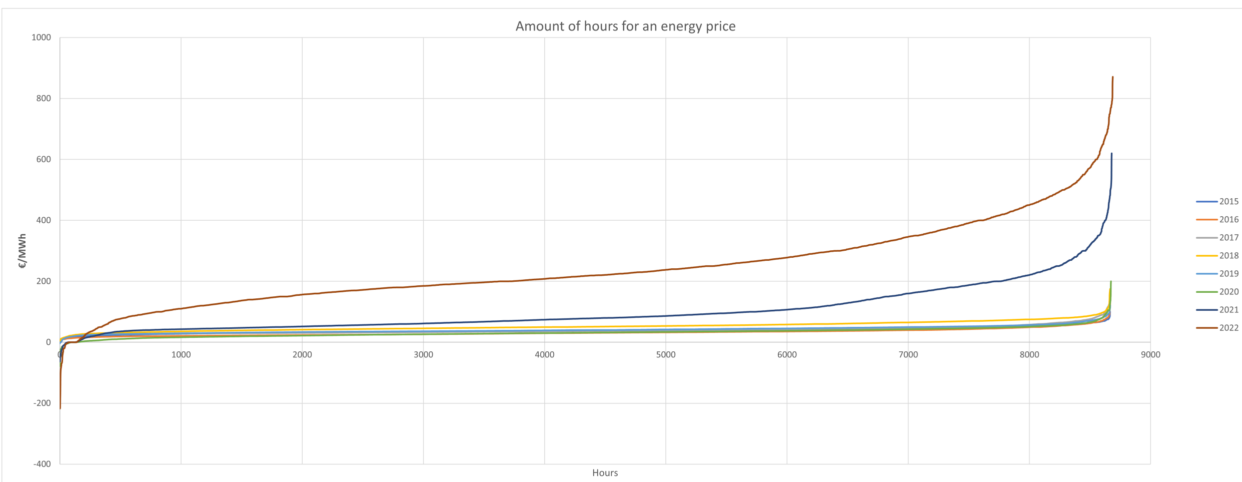

Figure A.1: Hours of specific electricity prices

Table A.1: The merit order effect phenomena plotted on euro per MWh basis instead of Delta price resulting in a similar shape as the Dutch duck curve.

Model Description

Model Name		MOD_1
Dependent Series		Electricity Price
Independent Series	1	Consumption
	2	Solar Share
	3	Wind Share
	4	Gas Price
	5	D1 Hour 00:00
	6	D2 Hour 01:00
	7	D3 Hour 02:00
	8	D4 Hour 03:00
	9	D5 Hour 04:00
	10	D6 Hour 05:00
	11	D7 Hour 06:00
	12	D8 Hour 07:00
	13	D9 Hour 08:00
	14	D10 Hour 09:00
	15	D11 Hour 10:00
	16	D12 Hour 11:00
	17	D13 Hour 12:00
	18	D14 Hour 13:00
	19	D15 Hour 14:00
	20	D16 Hour 15:00
	21	D17 Hour 16:00
	22	D18 Hour 17:00
	23	D19 Hour 18:00
	24	D20 Hour 19:00
	25	D21 Hour 20:00
	26	D22 Hour 21:00
	27	D23 Hour 22:00
	28	D24 Hour 23:00
	29	D1 Monday
	30	D2 Tuesday
	31	D3 Wednesday
	32	D4 Thursday
	33	D5 Friday
	34	D6 Saturday
	35	D7 Sunday
	36	D1 Januari
	37	D2 Februari
	38	D3 March
	39	D4 April
	40	D5 May
	41	D6 June
	42	D7 July

Figure A.2: Electricity price regression output page 1

Model Description

	43	D8 August
	44	D9 September
	45	D10 October
	46	D11 November
	47	D12 December
	48	D1 2015
	49	D2 2016
	50	D3 2017
	51	D4 2018
	52	D5 2019
	53	D6 2020
	54	D7 2021
	55	D8 2022
Constant		Included
AR		1

Applying the model specifications from MOD_1

Iteration Termination Criteria

Maximum Parameter Change Less Than	,001
Number of Iterations Equal to	10

Case Processing Summary

Series Length		70127
Number of Cases Skipped Due to Missing Values	At the Beginning of the Series	0
	At the End of the Series	4999
Number of Cases with Missing Values within the Series		0
Number of Forecasted Cases		4999
Number of New Cases Added to the Current Working File		0

Figure A.3: Electricity price regression output page 2

Requested Initial Configuration

Rho (AR1)		AUTO
Regression Coefficients	Consumption	AUTO[a]
	Solar Share	AUTO[a]
	Wind Share	AUTO[a]
	Gas Price	AUTO[a]
	D1 Hour 00:00	AUTO[a]
	D2 Hour 01:00	AUTO[a]
	D3 Hour 02:00	AUTO[a]
	D4 Hour 03:00	AUTO[a]
	D5 Hour 04:00	AUTO[a]
	D6 Hour 05:00	AUTO[a]
	D7 Hour 06:00	AUTO[a]
	D8 Hour 07:00	AUTO[a]
	D9 Hour 08:00	AUTO[a]
	D10 Hour 09:00	AUTO[a]
	D11 Hour 10:00	AUTO[a]
	D12 Hour 11:00	AUTO[a]
	D13 Hour 12:00	AUTO[a]
	D14 Hour 13:00	AUTO[a]
	D15 Hour 14:00	AUTO[a]
	D16 Hour 15:00	AUTO[a]
	D17 Hour 16:00	AUTO[a]
	D18 Hour 17:00	AUTO[a]
	D19 Hour 18:00	AUTO[a]
	D20 Hour 19:00	AUTO[a]
	D21 Hour 20:00	AUTO[a]
	D22 Hour 21:00	AUTO[a]
	D23 Hour 22:00	AUTO[a]
	D24 Hour 23:00	AUTO[a]
	D1 Monday	AUTO[a]
	D2 Tuesday	AUTO[a]
	D3 Wednesday	AUTO[a]
	D4 Thursday	AUTO[a]
	D5 Friday	AUTO[a]
	D6 Saturday	AUTO[a]
	D7 Sunday	AUTO[a]
	D1 Januari	AUTO[a]
	D2 Februari	AUTO[a]
	D3 March	AUTO[a]
	D4 April	AUTO[a]

Figure A.4: Electricity price regression output page 3

Requested Initial Configuration

	D5 May	AUTO[a]
	D6 June	AUTO[a]
	D7 July	AUTO[a]
	D8 August	AUTO[a]
	D9 September	AUTO[a]
	D10 October	AUTO[a]
	D11 November	AUTO[a]
	D12 December	AUTO[a]
	D1 2015	AUTO[a]
	D2 2016	AUTO[a]
	D3 2017	AUTO[a]
	D4 2018	AUTO[a]
	D5 2019	AUTO[a]
	D6 2020	AUTO[a]
	D7 2021	AUTO[a]
	D8 2022	AUTO[a]
Constant		AUTO[a]

a. The prior parameter value is invalid and is reset to 0.1.

Iteration 0

Autocorrelation Coefficient

Rho (AR1)	Std. Error
0	49,091

The Prais-Winsten estimation method is used.

Model Fit Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
,825	,680	,680	49,091	,092

The Prais-Winsten estimation method is used.

Figure A.5: Electricity price regression output page 4

ANOVA

	Sum of Squares	df	Mean Square
Regression	359335198,83	51	7045788,212
Residual	168872873,66	70075	2409,888

The Prais-Winsten estimation method is used.

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
Consumption	,002	,000	,069	18,900	,000
Solar Share	-62,127	11,538	-,015	-5,384	,000
Wind Share	-178,289	2,497	-,169	-71,387	,000
Gas Price	,190	,059	,022	3,226	,001
D1 Hour 00:00	-10,168	1,338	-,023	-7,600	,000
D2 Hour 01:00	-13,226	1,346	-,030	-9,826	,000
D3 Hour 02:00	-15,423	1,349	-,036	-11,430	,000
D4 Hour 03:00	-17,629	1,347	-,041	-13,092	,000
D5 Hour 04:00	-18,857	1,333	-,043	-14,141	,000
D6 Hour 05:00	-16,167	1,311	-,037	-12,329	,000
D7 Hour 06:00	-9,346	1,294	-,022	-7,223	,000
D8 Hour 07:00	-2,702	1,286	-,006	-2,101	,036
D10 Hour 09:00	-2,235	1,286	-,005	-1,737	,082
D11 Hour 10:00	-6,225	1,290	-,014	-4,824	,000
D12 Hour 11:00	-10,063	1,293	-,023	-7,780	,000
D13 Hour 12:00	-14,552	1,294	-,034	-11,247	,000
D14 Hour 13:00	-17,879	1,291	-,041	-13,853	,000
D15 Hour 14:00	-19,482	1,286	-,045	-15,150	,000
D16 Hour 15:00	-18,325	1,285	-,042	-14,261	,000
D17 Hour 16:00	-13,011	1,290	-,030	-10,089	,000
D18 Hour 17:00	-1,879	1,294	-,004	-1,452	,146
D19 Hour 18:00	5,230	1,297	,012	4,031	,000
D20 Hour 19:00	6,002	1,298	,014	4,625	,000
D21 Hour 20:00	2,029	1,298	,005	1,564	,118
D22 Hour 21:00	-1,332	1,302	-,003	-1,024	,306
D23 Hour 22:00	-3,854	1,312	-,009	-2,938	,003
D24 Hour 23:00	-8,506	1,326	-,020	-6,416	,000
D1 Monday	4,744	,718	,019	6,607	,000
D2 Tuesday	5,864	,726	,024	8,073	,000
D3 Wednesday	5,530	,726	,022	7,613	,000
D4 Thursday	6,064	,726	,024	8,358	,000
D5 Friday	4,380	,720	,018	6,085	,000

Figure A.6: Electricity price regression output page 5

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
D7 Sunday	-3,129	,698	-,013	-4,486	,000
D1 Januari	-13,184	,936	-,042	-14,083	,000
D2 Februari	-17,394	,957	-,054	-18,170	,000
D3 March	-8,616	,923	-,028	-9,336	,000
D4 April	-18,470	,929	-,058	-19,879	,000
D5 May	-20,627	,932	-,066	-22,126	,000
D6 June	-16,036	,939	-,051	-17,076	,000
D7 July	-3,953	1,209	-,013	-3,271	,001
D8 August	15,227	1,207	,049	12,616	,000
D9 September	11,193	1,208	,035	9,264	,000
D11 November	6,886	,913	,022	7,540	,000
D12 December	21,555	,919	,069	23,465	,000
D1 2015	12,906	,780	,049	16,548	,000
D3 2017	7,938	,756	,030	10,502	,000
D4 2018	20,707	,774	,079	26,758	,000
D5 2019	10,710	,874	,041	12,257	,000
D6 2020	2,267	,882	,009	2,569	,010
D7 2021	77,437	,894	,295	86,590	,000
D8 2022	221,913	1,599	,845	138,746	,000
(Constant)	18,911	2,546		7,426	,000

The Prais-Winsten estimation method is used.

Iteration History

	Rho (AR1)			
	Value	Std. Error	Durbin-Watson	Mean Squared Errors
0	,954	,001	1,564	211,478
1	,958	,001	1,570	211,436
2	,958	,001	1,570	211,436
3	,958	,001	1,570	211,436
4	,958	,001	1,570	211,436
5[a]	,958	,001	1,570	211,436

The Prais-Winsten estimation method is used.

a. The estimation terminated at this iteration, because all the parameter estimates changed by less than ,001.

Final Iteration 5

Figure A.7: Electricity price regression output page 6

Autocorrelation Coefficient

Rho (AR1)	Std. Error
,958	,001

The Prais-Winsten estimation method is used.

Model Fit Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
,402	,162	,161	14,541	1,570

The Prais-Winsten estimation method is used.

ANOVA

	Sum of Squares	df	Mean Square
Regression	2858385,259	51	56046,770
Residual	14816136,797	70074	211,436

The Prais-Winsten estimation method is used.

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
Consumption	,003	,000	,121	24,537	,000
Solar Share	-58,982	10,230	-,023	-5,765	,000
Wind Share	-36,695	4,139	-,033	-8,867	,000
Gas Price	,664	,361	,020	1,838	,066
D1 Hour 00:00	-9,902	,731	-,176	-13,551	,000
D2 Hour 01:00	-12,987	,766	-,231	-16,947	,000
D3 Hour 02:00	-15,122	,786	-,269	-19,229	,000
D4 Hour 03:00	-17,137	,791	-,305	-21,672	,000
D5 Hour 04:00	-17,953	,770	-,320	-23,312	,000
D6 Hour 05:00	-14,681	,727	-,261	-20,205	,000
D7 Hour 06:00	-7,296	,687	-,130	-10,622	,000
D8 Hour 07:00	-,404	,667	-,007	-,605	,545
D9 Hour 08:00	2,254	,661	,040	3,409	,001
D10 Hour 09:00	-,211	,660	-,004	-,319	,750
D11 Hour 10:00	-4,504	,656	-,080	-6,860	,000
D12 Hour 11:00	-8,608	,641	-,153	-13,419	,000
D13 Hour 12:00	-13,259	,612	-,236	-21,676	,000
D14 Hour 13:00	-16,604	,560	-,296	-29,634	,000

Figure A.8: Electricity price regression output page 7

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
D15 Hour 14:00	-18,042	,486	-,321	-37,159	,000
D16 Hour 15:00	-16,650	,388	-,296	-42,866	,000
D17 Hour 16:00	-11,194	,272	-,199	-41,090	,000
D19 Hour 18:00	7,031	,271	,125	25,978	,000
D20 Hour 19:00	7,572	,377	,135	20,101	,000
D21 Hour 20:00	3,362	,459	,060	7,326	,000
D22 Hour 21:00	-,259	,536	-,005	-,484	,628
D23 Hour 22:00	-3,084	,612	-,055	-5,040	,000
D24 Hour 23:00	-8,040	,679	-,143	-11,844	,000
D1 Monday	-2,342	,929	-,016	-2,521	,012
D2 Tuesday	-1,826	,929	-,012	-1,965	,049
D3 Wednesday	-1,860	,851	-,013	-2,186	,029
D4 Thursday	-,954	,664	-,006	-1,438	,150
D6 Saturday	,813	,664	,006	1,225	,221
D7 Sunday	-,430	,851	-,003	-,505	,614
D1 Januari	1,847	4,952	,002	,373	,709
D2 Februari	1,028	4,953	,001	,207	,836
D3 March	5,986	4,764	,007	1,257	,209
D4 April	-1,453	3,704	-,002	-,392	,695
D6 June	5,587	3,704	,007	1,509	,131
D7 July	9,701	5,801	,012	1,672	,094
D8 August	20,230	5,927	,024	3,413	,001
D9 September	16,345	5,980	,019	2,733	,006
D10 October	18,017	4,598	,021	3,918	,000
D11 November	20,860	4,627	,025	4,509	,000
D12 December	24,320	4,647	,028	5,233	,000
D1 2015	7,152	5,053	,006	1,415	,157
D2 2016	-5,076	4,816	-,005	-1,054	,292
D4 2018	10,933	4,819	,010	2,269	,023
D5 2019	5,105	5,313	,005	,961	,337
D6 2020	-2,248	5,482	-,002	-,410	,682
D7 2021	65,398	5,629	,061	11,618	,000
D8 2022	191,293	9,511	,174	20,114	,000
(Constant)	-18,174	10,317		-1,762	,078

The Prais-Winsten estimation method is used.

Autoregression

Figure A.9: Electricity price regression output page 8

Model Description

Model Name		MOD_7
Dependent Series		VF RE
Independent Series	1	Consumption
	2	Solar Share
	3	Wind Share
	4	Gas Price
	5	D1 Monday
	6	D2 Tuesday
	7	D3 Wednesday
	8	D4 Thursday
	9	D5 Friday
	10	D6 Saturday
	11	D7 Sunday
	12	D1 Januari
	13	D2 Februari
	14	D3 March
	15	D4 April
	16	D5 May
	17	D6 June
	18	D7 July
	19	D8 August
	20	D9 September
	21	D10 October
	22	D11 November
	23	D12 December
	24	D1 2015
	25	D2 2016
	26	D3 2017
	27	D4 2018
	28	D5 2019
	29	D6 2020
	30	D7 2021
	31	D8 2022
Constant		Included
AR		1

Applying the model specifications from MOD_7

Iteration Termination Criteria

Maximum Parameter Change Less Than	,001
Number of Iterations Equal to	10

Figure A.10: VF regression output page 1

Case Processing Summary

Series Length		2922
Number of Cases Skipped Due to Missing Values	At the Beginning of the Series	0
	At the End of the Series	0
Number of Cases with Missing Values within the Series		0
Number of Forecasted Cases		0
Number of New Cases Added to the Current Working File		0

Requested Initial Configuration

Rho (AR1)		AUTO
Regression Coefficients	Consumption	AUTO[a]
	Solar Share	AUTO[a]

Figure A.11: VF regression output page 2

Requested Initial Configuration

	Wind Share	AUTO[a]
	Gas Price	AUTO[a]
	D1 Monday	AUTO[a]
	D2 Tuesday	AUTO[a]
	D3 Wednesday	AUTO[a]
	D4 Thursday	AUTO[a]
	D5 Friday	AUTO[a]
	D6 Saturday	AUTO[a]
	D7 Sunday	AUTO[a]
	D1 Januari	AUTO[a]
	D2 Februari	AUTO[a]
	D3 March	AUTO[a]
	D4 April	AUTO[a]
	D5 May	AUTO[a]
	D6 June	AUTO[a]
	D7 July	AUTO[a]
	D8 August	AUTO[a]
	D9 September	AUTO[a]
	D10 October	AUTO[a]
	D11 November	AUTO[a]
	D12 December	AUTO[a]
	D1 2015	AUTO[a]
	D2 2016	AUTO[a]
	D3 2017	AUTO[a]
	D4 2018	AUTO[a]
	D5 2019	AUTO[a]
	D6 2020	AUTO[a]
	D7 2021	AUTO[a]
	D8 2022	AUTO[a]
Constant		AUTO[a]

a. The prior parameter value is invalid and is reset to 0.1.

Iteration 0

Figure A.12: VF regression output page 3

Autocorrelation Coefficient

Rho (AR1)	Std. Error
0	,055

The Prais-Winsten estimation method is used.

Model Fit Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
,258	,067	,058	,055	1,821

The Prais-Winsten estimation method is used.

ANOVA

	Sum of Squares	df	Mean Square
Regression	,617	28	,022
Residual	8,633	2893	,003

The Prais-Winsten estimation method is used.

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
Consumption	-1,490E-6	,000	-,047	-1,156	,248
Solar Share	,359	,134	,079	2,678	,007
Wind Share	,061	,016	,077	3,826	,000
Gas Price	-,001	,000	-,164	-3,739	,000
D1 Monday	-,022	,005	-,138	-4,803	,000
D2 Tuesday	,000	,004	-,002	-,087	,931
D3 Wednesday	,001	,004	,004	,182	,856
D4 Thursday	,000	,004	,002	,079	,937
D5 Friday	,001	,004	,008	,351	,726
D7 Sunday	-,005	,004	-,034	-1,267	,205
D1 Januari	,002	,005	,012	,467	,640
D2 Februari	,002	,005	,008	,332	,740
D3 March	-4,126E-5	,005	,000	-,008	,993
D4 April	,016	,005	,080	3,111	,002
D5 May	,001	,005	,003	,105	,917
D6 June	,019	,005	,095	3,626	,000
D7 July	,018	,006	,088	3,015	,003
D8 August	,021	,006	,106	3,644	,000

Figure A.13: VF regression output page 4

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
D9 September	,011	,006	,054	1,903	,057
D11 November	,001	,005	,006	,253	,800
D12 December	,001	,005	,003	,099	,921
D1 2015	,000	,005	-,002	-,057	,955
D3 2017	-,008	,004	-,049	-1,987	,047
D4 2018	-,005	,004	-,029	-1,093	,274
D5 2019	-,008	,005	-,047	-1,574	,116
D6 2020	-,017	,005	-,101	-3,619	,000
D7 2021	-,011	,005	-,063	-2,032	,042
D8 2022	-,002	,007	-,010	-,247	,805
(Constant)	1,027	,019		53,160	,000

The Prais-Winsten estimation method is used.

Iteration History

	Rho (AR1)			
	Value	Std. Error	Durbin-Watson	Mean Squared Errors
0	,088	,019	1,994	,003
1	,090	,019	1,998	,003
2	,090	,019	1,999	,003
3	,090	,019	1,999	,003
4	,090	,019	1,999	,003
5	,090	,019	1,999	,003
6	,090	,019	1,999	,003
7[a]	,090	,019	1,999	,003

The Prais-Winsten estimation method is used.

a. The estimation terminated at this iteration, because all the parameter estimates changed by less than ,001.

Final Iteration 7

Autocorrelation Coefficient

Rho (AR1)	Std. Error
,090	,019

The Prais-Winsten estimation method is used.

Figure A.14: VF regression output page 5

Model Fit Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
,245	,060	,051	,054	1,999

The Prais-Winsten estimation method is used.

ANOVA

	Sum of Squares	df	Mean Square
Regression	,548	28	,020
Residual	8,565	2892	,003

The Prais-Winsten estimation method is used.

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
Consumption	-1,679E-6	,000	-,050	-1,217	,224
Solar Share	,336	,141	,069	2,387	,017
Wind Share	,073	,017	,088	4,353	,000
Gas Price	-,001	,000	-,151	-3,445	,001
D1 Monday	-,024	,005	-,154	-4,941	,000
D2 Tuesday	-,002	,004	-,011	-,446	,656
D3 Wednesday	-,001	,004	-,004	-,157	,875
D4 Thursday	-,001	,004	-,006	-,281	,779
D6 Saturday	-,001	,004	-,009	-,370	,711
D7 Sunday	-,007	,004	-,046	-1,621	,105
D1 Januari	,003	,006	,011	,440	,660
D2 Februari	,002	,006	,008	,331	,741
D3 March	3,327E-5	,005	,000	,006	,995
D4 April	,016	,006	,073	2,849	,004
D5 May	,001	,006	,005	,198	,843
D6 June	,020	,006	,088	3,363	,001
D7 July	,018	,006	,084	2,875	,004
D8 August	,022	,006	,100	3,402	,001
D9 September	,011	,006	,051	1,795	,073
D11 November	,001	,006	,005	,191	,849
D12 December	,000	,006	,002	,068	,946
D1 2015	,017	,005	,092	3,297	,001
D2 2016	,018	,005	,096	3,432	,001
D3 2017	,009	,006	,051	1,682	,093
D4 2018	,013	,006	,071	2,174	,030
D5 2019	,009	,005	,049	2,007	,045

Figure A.15: VF regression output page 6

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
D7 2021	,006	,005	,033	1,294	,196
D8 2022	,015	,006	,080	2,454	,014
(Constant)	1,013	,020		49,916	,000

The Prais-Winsten estimation method is used.

Figure A.16: VF regression output page 7

Model Description

Model Name		MOD_8
Dependent Series		UR RE
Independent Series	1	Consumption
	2	Solar Share
	3	Wind Share
	4	Gas Price
	5	D1 Monday
	6	D2 Tuesday
	7	D3 Wednesday
	8	D4 Thursday
	9	D5 Friday
	10	D6 Saturday
	11	D7 Sunday
	12	D1 Januari
	13	D2 Februari
	14	D3 March
	15	D4 April
	16	D5 May
	17	D6 June
	18	D7 July
	19	D8 August
	20	D9 September
	21	D10 October
	22	D11 November
	23	D12 December
	24	D1 2015
	25	D2 2016
	26	D3 2017
	27	D4 2018
	28	D5 2019
	29	D6 2020
	30	D7 2021
	31	D8 2022
Constant		Included
AR		1

Applying the model specifications from MOD_8

Iteration Termination Criteria

Maximum Parameter Change Less Than	,001
Number of Iterations Equal to	10

Figure A.17: UR regression output page 1

Case Processing Summary

Series Length		2922
Number of Cases Skipped Due to Missing Values	At the Beginning of the Series	0
	At the End of the Series	0
Number of Cases with Missing Values within the Series		0
Number of Forecasted Cases		0
Number of New Cases Added to the Current Working File		0

Requested Initial Configuration

Rho (AR1)		AUTO
Regression Coefficients	Consumption	AUTO[a]
	Solar Share	AUTO[a]

Figure A.18: UR regression output page 2

Requested Initial Configuration

	Wind Share	AUTO[a]
	Gas Price	AUTO[a]
	D1 Monday	AUTO[a]
	D2 Tuesday	AUTO[a]
	D3 Wednesday	AUTO[a]
	D4 Thursday	AUTO[a]
	D5 Friday	AUTO[a]
	D6 Saturday	AUTO[a]
	D7 Sunday	AUTO[a]
	D1 Januari	AUTO[a]
	D2 Februari	AUTO[a]
	D3 March	AUTO[a]
	D4 April	AUTO[a]
	D5 May	AUTO[a]
	D6 June	AUTO[a]
	D7 July	AUTO[a]
	D8 August	AUTO[a]
	D9 September	AUTO[a]
	D10 October	AUTO[a]
	D11 November	AUTO[a]
	D12 December	AUTO[a]
	D1 2015	AUTO[a]
	D2 2016	AUTO[a]
	D3 2017	AUTO[a]
	D4 2018	AUTO[a]
	D5 2019	AUTO[a]
	D6 2020	AUTO[a]
	D7 2021	AUTO[a]
	D8 2022	AUTO[a]
Constant		AUTO[a]

a. The prior parameter value is invalid and is reset to 0.1.

Iteration 0

Figure A.19: UR regression output page 3

Autocorrelation Coefficient

Rho (AR1)	Std. Error
0	42,176

The Prais-Winsten estimation method is used.

Model Fit Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
,855	,731	,728	42,176	,244

The Prais-Winsten estimation method is used.

ANOVA

	Sum of Squares	df	Mean Square
Regression	13983031,486	28	499393,982
Residual	5146188,665	2893	1778,842

The Prais-Winsten estimation method is used.

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
Consumption	-,003	,001	-,072	-3,293	,001
Solar Share	-37,904	103,419	-,006	-,367	,714
Wind Share	-198,208	12,374	-,174	-16,019	,000
Gas Price	-1,014	,170	-,140	-5,954	,000
D1 Monday	-19,622	3,575	-,085	-5,489	,000
D2 Tuesday	,155	2,920	,001	,053	,958
D3 Wednesday	2,129	2,925	,009	,728	,467
D4 Thursday	2,417	2,924	,010	,827	,409
D5 Friday	2,919	2,922	,013	,999	,318
D7 Sunday	-12,406	3,289	-,054	-3,772	,000
D1 Januari	-9,648	4,061	-,033	-2,375	,018
D2 Februari	-13,034	4,136	-,043	-3,151	,002
D3 March	-10,519	3,840	-,036	-2,739	,006
D4 April	-16,397	4,044	-,056	-4,055	,000
D5 May	-20,411	4,153	-,070	-4,914	,000
D6 June	-14,212	4,133	-,048	-3,438	,001
D7 July	8,655	4,563	,030	1,897	,058
D8 August	27,442	4,553	,095	6,028	,000

Figure A.20: UR regression output page 4

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
D9 September	24,047	4,504	,082	5,339	,000
D11 November	10,853	3,913	,037	2,773	,006
D12 December	28,195	4,057	,097	6,949	,000
D1 2015	2,056	3,630	,008	,566	,571
D3 2017	13,997	3,255	,057	4,301	,000
D4 2018	27,087	3,449	,111	7,853	,000
D5 2019	8,577	3,903	,035	2,198	,028
D6 2020	5,625	3,669	,023	1,533	,125
D7 2021	88,506	4,079	,362	21,697	,000
D8 2022	237,232	5,321	,969	44,588	,000
(Constant)	116,954	14,921		7,838	,000

The Prais-Winsten estimation method is used.

Iteration History

	Rho (AR1)		Durbin-Watson	Mean Squared Errors
	Value	Std. Error		
0	,875	,009	2,022	381,391
1	,892	,008	2,060	380,465
2	,894	,008	2,065	380,408
3	,895	,008	2,065	380,400
4	,895	,008	2,066	380,399
5	,895	,008	2,066	380,398
6	,895	,008	2,066	380,398
7	,895	,008	2,066	380,398
8	,895	,008	2,066	380,398
9[a]	,895	,008	2,066	380,398

The Prais-Winsten estimation method is used.

a. The estimation terminated at this iteration, because all the parameter estimates changed by less than ,001.

Final Iteration 9

Autocorrelation Coefficient

Rho (AR1)	Std. Error
,895	,008

The Prais-Winsten estimation method is used.

Figure A.21: UR regression output page 5

Model Fit Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
,529	,280	,273	19,504	2,066

The Prais-Winsten estimation method is used.

ANOVA

	Sum of Squares	df	Mean Square
Regression	428311,601	28	15296,843
Residual	1100111,609	2892	380,398

The Prais-Winsten estimation method is used.

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
Consumption	-,005	,001	-,246	-7,035	,000
Solar Share	-139,986	57,648	-,040	-2,428	,015
Wind Share	-113,391	6,483	-,282	-17,490	,000
Gas Price	-,615	,413	-,043	-1,490	,136
D1 Monday	-28,548	2,121	-,632	-13,462	,000
D2 Tuesday	-3,341	1,323	-,074	-2,526	,012
D3 Wednesday	-,562	1,201	-,012	-,468	,640
D4 Thursday	-,471	,932	-,010	-,506	,613
D6 Saturday	-3,092	,940	-,069	-3,291	,001
D7 Sunday	-19,666	1,742	-,436	-11,288	,000
D1 Januari	-29,507	11,042	-,096	-2,672	,008
D2 Februari	-29,802	11,064	-,098	-2,694	,007
D3 March	-27,634	10,895	-,092	-2,536	,011
D4 April	-29,975	9,382	-,099	-3,195	,001
D5 May	-31,398	8,965	-,104	-3,502	,000
D6 June	-27,331	8,292	-,090	-3,296	,001
D7 July	-12,085	6,130	-,040	-1,971	,049
D9 September	2,881	6,128	,010	,470	,638
D10 October	-11,154	9,395	-,037	-1,187	,235
D11 November	-8,324	10,010	-,028	-,832	,406
D12 December	-3,440	10,328	-,011	-,333	,739
D1 2015	-21,410	12,157	-,037	-1,761	,078
D2 2016	-17,422	10,785	-,033	-1,615	,106
D4 2018	2,188	10,779	,004	,203	,839
D5 2019	-11,537	11,914	-,022	-,968	,333
D6 2020	-4,307	12,196	-,008	-,353	,724

Figure A.22: UR regression output page 6

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
D7 2021	64,943	12,942	,121	5,018	,000
D8 2022	181,009	15,449	,311	11,716	,000
(Constant)	168,825	20,703		8,155	,000

The Prais-Winsten estimation method is used.

Figure A.23: UR regression output page 7

APPENDIX B

Appendix

The Prais-Winsten regression has also been run with the inclusion of gas share to check the differences in outcome. The results are displayed below.

$$\begin{aligned} \text{UR}^{RE} =& \beta 0 + \beta 1 \cdot \text{Solar share} + \beta 2 \cdot \text{Wind share} + \beta 3 \cdot \text{Gas share} + \beta 4 \cdot \text{Consumption} + \\ & \beta 5 \cdot \text{Gas Price} + \beta 6 \cdot \text{D} + \epsilon \qquad \text{(B.1)} \\ \text{VF}^{RE} =& \beta 0 + \beta 1 \cdot \text{Solar share} + \beta 2 \cdot \text{Wind share} + \beta 3 \cdot \text{Gas share} + \beta 4 \cdot \text{Consumption} + \\ & \beta 5 \cdot \text{Gas Price} + \beta 6 \cdot \text{D} + \epsilon \qquad \text{(B.2)} \\ \text{Day-ahead prices} =& \beta 0 + \beta 1 \cdot \text{Solar share} + \beta 2 \cdot \text{Wind share} + \beta 3 \cdot \text{Gas share} + \beta 4 \cdot \text{Consumption} + \\ & \beta 5 \cdot \text{Gas Price} + \beta 6 \cdot \text{D} + \epsilon \qquad \text{(B.3)} \end{aligned}$$

Where:

UR^{RE}: The dependent variable represents the Unit Revenue of each day for 8 years.

VF^{RE}: The dependent variable represents the day-ahead prices per hour of each day for 8 years.

DA prices: The dependent variable represents the day-ahead prices per hour of each day for 8 years.

Solar share: Solar electricity production divided by total supply.

Wind share: Wind electricity production divided by total supply.

Gas share: Gas electricity production divided by total supply.

Consumption: Total demand at a specific day.

Gas Price: Price of gas at a specific day.

Dummies: dummies for 24 hours (is only used if IV is the Day-ahead prices), weekdays, months, and years.

$\beta 0$, $\beta 1$, $\beta 2$, $\beta 3$, $\beta 4$, $\beta 5$, $\beta 6$: The regression coefficients, indicating the strength and direction of the relationship between the independent variables and day-ahead prices.

ϵ: The error term representing the unexplained variation in day-ahead prices.

Table B.1: The Prais-Winsten regression analysis results with gas share

Dependent variable	**UR**^{RE}	**VF**^{RE}	**Electricity Price**
Regression Coefficients	Unstandardized B	Unstandardized B	Unstandardized B
Consumption	-0,004***	-6,087E-7	0,004***
Solar Share	-93,916	0,386*	-35,752***
Wind Share	-79,049***	0,110***	-14,287***
Gas Share	38,334***	0,034**	100,847***
Gas Price	-0,599	-0,001***	0,799*
Rho (AR1)	0,897	0,094	0,958
R Square	0,293	0,063	0,198
Adjusted R Square	0,285	0,053	0,197
Durbin-Watson	2,083	1,999	1,638

The Prais-Winsten estimation method
*p<0,1
**p<0,05
***p<0,01

These results are similar to the observations from the regression analysis chapter. The magnitude has overall changed. Interestingly gas share had the expected positive effect on RE UR, indicating a reversed cannibalization effect when gas share increases. The impact is substantial, with a 38.334 euro per MWh increase for the UR of RE if gas share increases by one percent point. The R-squared which would be affected when removing a variable has shown a small decrease of 0,02 meaning that the exclusion of gas share results in a 2 percent less predictive model.

Autoregression

Model Description

Model Name		MOD_6
Dependent Series		UR RE
Independent Series	1	Consumption
	2	Solar Share
	3	Wind Share
	4	Gas Share
	5	Gas Price
	6	D1 Monday
	7	D2 Tuesday
	8	D3 Wednesday
	9	D4 Thursday
	10	D5 Friday
	11	D6 Saturday
	12	D7 Sunday
	13	D1 Januari
	14	D2 Februari
	15	D3 March
	16	D4 April
	17	D5 May
	18	D6 June
	19	D7 July
	20	D8 August
	21	D9 September
	22	D10 October
	23	D11 November
	24	D12 December
	25	D1 2015
	26	D2 2016
	27	D3 2017
	28	D4 2018
	29	D5 2019
	30	D6 2020
	31	D7 2021
	32	D8 2022
Constant		Included
AR		1

Applying the model specifications from MOD_6

Figure B.1: UR regression with gas share output page 1

Iteration Termination Criteria

Maximum Parameter Change Less Than	,001
Number of Iterations Equal to	10

Case Processing Summary

Series Length		2922
Number of Cases Skipped Due to Missing Values	At the Beginning of the Series	0
	At the End of the Series	0
Number of Cases with Missing Values within the Series		0
Number of Forecasted Cases		0
Number of New Cases Added to the Current Working File		0

Requested Initial Configuration

Rho (AR1)		AUTO
Regression Coefficients	Consumption	AUTO[a]
	Solar Share	AUTO[a]
	Wind Share	AUTO[a]
	Gas Share	AUTO[a]
	Gas Price	AUTO[a]
	D1 Monday	AUTO[a]
	D2 Tuesday	AUTO[a]
	D3 Wednesday	AUTO[a]
	D4 Thursday	AUTO[a]
	D5 Friday	AUTO[a]
	D6 Saturday	AUTO[a]
	D7 Sunday	AUTO[a]
	D1 Januari	AUTO[a]
	D2 Februari	AUTO[a]
	D3 March	AUTO[a]
	D4 April	AUTO[a]
	D5 May	AUTO[a]
	D6 June	AUTO[a]
	D7 July	AUTO[a]
	D8 August	AUTO[a]
	D9 September	AUTO[a]
	D10 October	AUTO[a]
	D11 November	AUTO[a]
	D12 December	AUTO[a]
	D1 2015	AUTO[a]

Figure B.2: UR regression with gas share output page 2

Requested Initial Configuration

	D2 2016	AUTO[a]
	D3 2017	AUTO[a]
	D4 2018	AUTO[a]
	D5 2019	AUTO[a]
	D6 2020	AUTO[a]
	D7 2021	AUTO[a]
	D8 2022	AUTO[a]
Constant		AUTO[a]

a. The prior parameter value is invalid and is reset to 0.1.

Iteration 0

Autocorrelation Coefficient

Rho (AR1)	Std. Error
0	42,102

The Prais-Winsten estimation method is used.

Model Fit Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
,856	,732	,729	42,102	,239

The Prais-Winsten estimation method is used.

ANOVA

	Sum of Squares	df	Mean Square
Regression	14002910,467	29	482858,982
Residual	5126309,684	2892	1772,583

The Prais-Winsten estimation method is used.

Figure B.3: UR regression with gas share output page 3

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
Consumption	-,002	,001	-,054	-2,379	,017
Solar Share	2,894	103,953	,000	,028	,978
Wind Share	-169,552	15,026	-,149	-11,284	,000
Gas Share	26,868	8,023	,056	3,349	,001
Gas Price	-1,069	,171	-,148	-6,260	,000
D1 Monday	-15,424	3,782	-,067	-4,078	,000
D2 Tuesday	,522	2,917	,002	,179	,858
D3 Wednesday	1,753	2,922	,008	,600	,548
D4 Thursday	2,085	2,921	,009	,714	,475
D5 Friday	2,583	2,919	,011	,885	,376
D7 Sunday	-9,488	3,397	-,041	-2,793	,005
D1 Januari	-11,144	4,079	-,038	-2,732	,006
D2 Februari	-13,563	4,131	-,045	-3,283	,001
D3 March	-9,843	3,839	-,034	-2,564	,010
D4 April	-13,312	4,140	-,045	-3,215	,001
D5 May	-17,360	4,245	-,060	-4,090	,000
D6 June	-12,008	4,178	-,041	-2,874	,004
D7 July	10,713	4,596	,037	2,331	,020
D8 August	29,627	4,591	,102	6,453	,000
D9 September	26,029	4,535	,088	5,740	,000
D11 November	9,725	3,921	,033	2,480	,013
D12 December	27,443	4,057	,095	6,765	,000
D1 2015	4,671	3,707	,019	1,260	,208
D3 2017	11,953	3,306	,049	3,616	,000
D4 2018	25,103	3,494	,103	7,185	,000
D5 2019	4,288	4,101	,018	1,045	,296
D6 2020	,194	4,006	,001	,048	,961
D7 2021	86,425	4,119	,353	20,981	,000
D8 2022	235,970	5,324	,964	44,318	,000
(Constant)	95,349	16,232		5,874	,000

The Prais-Winsten estimation method is used.

Figure B.4: UR regression with gas share output page 4

Iteration History

	Rho (AR1) Value	Rho (AR1) Std. Error	Durbin-Watson	Mean Squared Errors
0	,877	,009	2,039	373,355
1	,894	,008	2,076	372,457
2	,897	,008	2,082	372,397
3	,897	,008	2,083	372,388
4	,897	,008	2,083	372,387
5	,897	,008	2,083	372,386
6	,897	,008	2,083	372,386
7	,897	,008	2,083	372,386
8	,897	,008	2,083	372,386
9	,897	,008	2,083	372,386
10[a]	,897	,008	2,083	372,386

The Prais-Winsten estimation method is used.

a. The estimation terminated at this iteration, because the maximum number of iterations 10 was reached.

Final Iteration 10

Autocorrelation Coefficient

Rho (AR1)	Std. Error
,897	,008

The Prais-Winsten estimation method is used.

Model Fit Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
,541	,293	,285	19,297	2,083

The Prais-Winsten estimation method is used.

ANOVA

	Sum of Squares	df	Mean Square
Regression	445355,903	29	15357,100
Residual	1076568,191	2891	372,386

The Prais-Winsten estimation method is used.

Figure B.5: UR regression with gas share output page 5

Regression Coefficients

	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig
Consumption	-,004	,001	-,185	-5,192	,000
Solar Share	-93,916	57,281	-,027	-1,640	,101
Wind Share	-79,049	7,729	-,198	-10,228	,000
Gas Share	38,334	4,831	,173	7,935	,000
Gas Price	-,599	,411	-,042	-1,457	,145
D2 Tuesday	19,318	1,905	,429	10,140	,000
D3 Wednesday	20,981	2,210	,466	9,494	,000
D4 Thursday	21,160	2,272	,470	9,311	,000
D5 Friday	21,643	2,271	,481	9,531	,000
D6 Saturday	19,027	2,096	,424	9,080	,000
D7 Sunday	6,938	1,033	,154	6,716	,000
D1 Januari	-30,088	11,017	-,097	-2,731	,006
D2 Februari	-30,006	11,040	-,099	-2,718	,007
D3 March	-29,588	10,875	-,098	-2,721	,007
D4 April	-30,369	9,366	-,101	-3,242	,001
D5 May	-29,016	8,945	-,096	-3,244	,001
D6 June	-25,465	8,258	-,084	-3,084	,002
D7 July	-11,488	6,087	-,038	-1,887	,059
D9 September	2,701	6,085	,009	,444	,657
D10 October	-13,210	9,358	-,044	-1,412	,158
D11 November	-10,301	9,982	-,034	-1,032	,302
D12 December	-6,245	10,309	-,020	-,606	,545
D1 2015	-80,060	13,768	-,135	-5,815	,000
D2 2016	-78,483	13,152	-,145	-5,967	,000
D3 2017	-64,878	13,019	-,119	-4,984	,000
D4 2018	-62,402	12,778	-,115	-4,884	,000
D5 2019	-79,664	12,072	-,147	-6,599	,000
D6 2020	-73,164	11,036	-,135	-6,630	,000
D8 2022	114,319	11,879	,193	9,624	,000
(Constant)	175,788	23,762		7,398	,000

The Prais-Winsten estimation method is used.

Autoregression

Figure B.6: UR regression with gas share output page 6

Model Description

Model Name		MOD_9
Dependent Series		VF RE
Independent Series	1	Consumption
	2	Solar Share
	3	Wind Share
	4	Gas Share
	5	Gas Price
	6	D1 Monday
	7	D2 Tuesday
	8	D3 Wednesday
	9	D4 Thursday
	10	D5 Friday
	11	D6 Saturday
	12	D7 Sunday
	13	D1 Januari
	14	D2 Februari
	15	D3 March
	16	D4 April
	17	D5 May
	18	D6 June
	19	D7 July
	20	D8 August
	21	D9 September
	22	D10 October
	23	D11 November
	24	D12 December
	25	D1 2015
	26	D2 2016
	27	D3 2017
	28	D4 2018
	29	D5 2019
	30	D6 2020
	31	D7 2021
	32	D8 2022
Constant		Included
AR		1

Applying the model specifications from MOD_9

Iteration Termination Criteria

Maximum Parameter Change Less Than	,001
Number of Iterations Equal to	10

Figure B.7: UR regression with gas share output page 7

Case Processing Summary

Series Length		2922
Number of Cases Skipped Due to Missing Values	At the Beginning of the Series	0
	At the End of the Series	0
Number of Cases with Missing Values within the Series		0
Number of Forecasted Cases		0
Number of New Cases Added to the Current Working File		0

Requested Initial Configuration

Rho (AR1)		AUTO
Regression Coefficients	Consumption	AUTO[a]
	Solar Share	AUTO[a]
	Wind Share	AUTO[a]
	Gas Share	AUTO[a]
	Gas Price	AUTO[a]
	D1 Monday	AUTO[a]
	D2 Tuesday	AUTO[a]
	D3 Wednesday	AUTO[a]
	D4 Thursday	AUTO[a]
	D5 Friday	AUTO[a]
	D6 Saturday	AUTO[a]
	D7 Sunday	AUTO[a]
	D1 Januari	AUTO[a]
	D2 Februari	AUTO[a]
	D3 March	AUTO[a]
	D4 April	AUTO[a]
	D5 May	AUTO[a]
	D6 June	AUTO[a]
	D7 July	AUTO[a]
	D8 August	AUTO[a]
	D9 September	AUTO[a]
	D10 October	AUTO[a]
	D11 November	AUTO[a]
	D12 December	AUTO[a]
	D1 2015	AUTO[a]
	D2 2016	AUTO[a]
	D3 2017	AUTO[a]
	D4 2018	AUTO[a]
	D5 2019	AUTO[a]
	D6 2020	AUTO[a]

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Figure B.8: UR regression with gas share output page 8

Requested Initial Configuration

	D7 2021	AUTO[a]
	D8 2022	AUTO[a]
Constant		AUTO[a]

a. The prior parameter value is invalid and is reset to 0.1.

Iteration 0

Autocorrelation Coefficient

Rho (AR1)	Std. Error
0	,055

The Prais-Winsten estimation method is used.

Model Fit Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
,263	,069	,060	,055	1,815

The Prais-Winsten estimation method is used.

ANOVA

	Sum of Squares	df	Mean Square
Regression	,640	29	,022
Residual	8,610	2892	,003

The Prais-Winsten estimation method is used.

Figure B.9: VF regression with gas share output page 2

Regression Coefficients

	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig
Consumption	-5,824E-7	,000	-,018	-,439	,661
Solar Share	,403	,135	,089	2,990	,003
Wind Share	,092	,019	,116	4,739	,000
Gas Share	,029	,010	,086	2,792	,005
Gas Price	-,001	,000	-,176	-3,996	,000
D1 Monday	-,018	,005	-,110	-3,611	,000
D2 Tuesday	6,677E-5	,004	,000	,018	,986
D3 Wednesday	,000	,004	,002	,074	,941
D4 Thursday	-5,788E-5	,004	,000	-,015	,988
D5 Friday	,001	,004	,006	,255	,799
D7 Sunday	-,002	,004	-,014	-,509	,610
D1 Januari	,001	,005	,004	,159	,873
D2 Februari	,001	,005	,006	,225	,822
D3 March	,001	,005	,003	,138	,890
D4 April	,020	,005	,096	3,658	,000
D5 May	,004	,006	,019	,701	,483
D6 June	,022	,005	,106	4,025	,000
D7 July	,020	,006	,099	3,365	,001
D8 August	,024	,006	,118	4,009	,000
D9 September	,013	,006	,065	2,253	,024
D11 November	6,320E-5	,005	,000	,012	,990
D12 December	,000	,005	-,001	-,056	,955
D1 2015	,003	,005	,015	,533	,594
D3 2017	-,011	,004	-,062	-2,470	,014
D4 2018	-,007	,005	-,041	-1,552	,121
D5 2019	-,013	,005	-,074	-2,369	,018
D6 2020	-,023	,005	-,136	-4,443	,000
D7 2021	-,013	,005	-,076	-2,433	,015
D8 2022	-,003	,007	-,018	-,445	,657
(Constant)	1,004	,021		47,728	,000

The Prais-Winsten estimation method is used.

Figure B.10: VF regression with gas share output page 3

Iteration History

	Rho (AR1) Value	Rho (AR1) Std. Error	Durbin-Watson	Mean Squared Errors
0	,091	,019	1,993	,003
1	,094	,019	1,999	,003
2	,094	,019	1,999	,003
3[a]	,094	,019	1,999	,003

The Prais-Winsten estimation method is used.

a. The estimation terminated at this iteration, because all the parameter estimates changed by less than ,001.

Final Iteration 3

Autocorrelation Coefficient

Rho (AR1)	Std. Error
,094	,019

The Prais-Winsten estimation method is used.

Model Fit Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
,251	,063	,053	,054	1,999

The Prais-Winsten estimation method is used.

ANOVA

	Sum of Squares	df	Mean Square
Regression	,574	29	,020
Residual	8,537	2891	,003

The Prais-Winsten estimation method is used.

Figure B.11: VF regression with gas share output page 4

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
Consumption	-6,087E-7	,000	-,018	-,427	,669
Solar Share	,386	,142	,079	2,724	,006
Wind Share	,110	,020	,132	5,382	,000
Gas Share	,034	,011	,096	3,123	,002
Gas Price	-,001	,000	-,163	-3,711	,000
D2 Tuesday	,018	,005	,112	3,623	,000
D3 Wednesday	,018	,005	,113	3,379	,001
D4 Thursday	,017	,005	,110	3,305	,001
D5 Friday	,018	,005	,117	3,504	,000
D6 Saturday	,017	,005	,111	3,456	,001
D7 Sunday	,015	,004	,098	4,116	,000
D1 Januari	-,004	,007	-,020	-,631	,528
D2 Februari	-,004	,007	-,017	-,542	,588
D3 March	-,004	,006	-,019	-,676	,499
D4 April	,015	,005	,067	2,775	,006
D6 June	,017	,005	,077	3,188	,001
D7 July	,016	,006	,073	2,776	,006
D8 August	,020	,006	,089	3,408	,001
D9 September	,009	,006	,040	1,503	,133
D10 October	-,005	,006	-,023	-,851	,395
D11 November	-,005	,007	-,025	-,833	,405
D12 December	-,006	,007	-,026	-,823	,411
D1 2015	,027	,006	,146	4,452	,000
D2 2016	,025	,006	,133	4,382	,000
D3 2017	,014	,006	,074	2,388	,017
D4 2018	,018	,006	,094	2,831	,005
D5 2019	,011	,005	,057	2,306	,021
D7 2021	,010	,005	,056	2,098	,036
D8 2022	,020	,006	,108	3,201	,001
(Constant)	,965	,019		50,803	,000

The Prais-Winsten estimation method is used.

Figure B.12: VF regression with gas share output page 5

Autoregression

Model Description

Model Name		MOD_7
Dependent Series		Electricity Price
Independent Series	1	Consumption
	2	Solar Share
	3	Wind Share
	4	Gas Share
	5	Gas Price
	6	D1 Hour 00:00
	7	D2 Hour 01:00
	8	D3 Hour 02:00
	9	D4 Hour 03:00
	10	D5 Hour 04:00
	11	D6 Hour 05:00
	12	D7 Hour 06:00
	13	D8 Hour 07:00
	14	D9 Hour 08:00
	15	D10 Hour 09:00
	16	D11 Hour 10:00
	17	D12 Hour 11:00
	18	D13 Hour 12:00
	19	D14 Hour 13:00
	20	D15 Hour 14:00
	21	D16 Hour 15:00
	22	D17 Hour 16:00
	23	D18 Hour 17:00
	24	D19 Hour 18:00
	25	D20 Hour 19:00
	26	D21 Hour 20:00
	27	D22 Hour 21:00
	28	D23 Hour 22:00
	29	D24 Hour 23:00
	30	D1 Monday
	31	D2 Tuesday
	32	D3 Wednesday
	33	D4 Thursday
	34	D5 Friday
	35	D6 Saturday
	36	D7 Sunday
	37	D1 Januari
	38	D2 Februari
	39	D3 March
	40	D4 April

Figure B.13: Electricity price regression with gas share output page 1

Model Description

	41	D5 May
	42	D6 June
	43	D7 July
	44	D8 August
	45	D9 September
	46	D10 October
	47	D11 November
	48	D12 December
	49	D1 2015
	50	D2 2016
	51	D3 2017
	52	D4 2018
	53	D5 2019
	54	D6 2020
	55	D7 2021
	56	D8 2022
Constant		Included
AR		1

Applying the model specifications from MOD_7

Iteration Termination Criteria

Maximum Parameter Change Less Than	,001
Number of Iterations Equal to	10

Case Processing Summary

Series Length		70127
Number of Cases Skipped Due to Missing Values	At the Beginning of the Series	0
	At the End of the Series	4999
Number of Cases with Missing Values within the Series		0
Number of Forecasted Cases		4999
Number of New Cases Added to the Current Working File		0

Figure B.14: Electricity price regression with gas share output page 2

Requested Initial Configuration

Rho (AR1)		AUTO
Regression Coefficients	Consumption	AUTO[a]
	Solar Share	AUTO[a]
	Wind Share	AUTO[a]
	Gas Share	AUTO[a]
	Gas Price	AUTO[a]
	D1 Hour 00:00	AUTO[a]
	D2 Hour 01:00	AUTO[a]
	D3 Hour 02:00	AUTO[a]
	D4 Hour 03:00	AUTO[a]
	D5 Hour 04:00	AUTO[a]
	D6 Hour 05:00	AUTO[a]
	D7 Hour 06:00	AUTO[a]
	D8 Hour 07:00	AUTO[a]
	D9 Hour 08:00	AUTO[a]
	D10 Hour 09:00	AUTO[a]
	D11 Hour 10:00	AUTO[a]
	D12 Hour 11:00	AUTO[a]
	D13 Hour 12:00	AUTO[a]
	D14 Hour 13:00	AUTO[a]
	D15 Hour 14:00	AUTO[a]
	D16 Hour 15:00	AUTO[a]
	D17 Hour 16:00	AUTO[a]
	D18 Hour 17:00	AUTO[a]
	D19 Hour 18:00	AUTO[a]
	D20 Hour 19:00	AUTO[a]
	D21 Hour 20:00	AUTO[a]
	D22 Hour 21:00	AUTO[a]
	D23 Hour 22:00	AUTO[a]
	D24 Hour 23:00	AUTO[a]
	D1 Monday	AUTO[a]
	D2 Tuesday	AUTO[a]
	D3 Wednesday	AUTO[a]
	D4 Thursday	AUTO[a]
	D5 Friday	AUTO[a]
	D6 Saturday	AUTO[a]
	D7 Sunday	AUTO[a]
	D1 Januari	AUTO[a]
	D2 Februari	AUTO[a]
	D3 March	AUTO[a]

Figure B.15: Electricity price regression with gas share output page 3

Requested Initial Configuration

	D4 April	AUTO[a]
	D5 May	AUTO[a]
	D6 June	AUTO[a]
	D7 July	AUTO[a]
	D8 August	AUTO[a]
	D9 September	AUTO[a]
	D10 October	AUTO[a]
	D11 November	AUTO[a]
	D12 December	AUTO[a]
	D1 2015	AUTO[a]
	D2 2016	AUTO[a]
	D3 2017	AUTO[a]
	D4 2018	AUTO[a]
	D5 2019	AUTO[a]
	D6 2020	AUTO[a]
	D7 2021	AUTO[a]
	D8 2022	AUTO[a]
Constant		AUTO[a]

a. The prior parameter value is invalid and is reset to 0.1.

Iteration 0

Autocorrelation Coefficient

Rho (AR1)	Std. Error
0	48,711

The Prais-Winsten estimation method is used.

Model Fit Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
,828	,685	,685	48,711	,089

The Prais-Winsten estimation method is used.

Figure B.16: Electricity price regression with gas share output page 4

ANOVA

	Sum of Squares	df	Mean Square
Regression	361942178,00	52	6960426,500
Residual	166265894,49	70074	2372,719

The Prais-Winsten estimation method is used.

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
Consumption	,003	,000	,091	24,770	,000
Solar Share	-36,236	11,476	-,009	-3,158	,002
Wind Share	-131,101	2,858	-,124	-45,872	,000
Gas Share	51,161	1,543	,106	33,147	,000
Gas Price	,205	,058	,024	3,502	,000
D1 Hour 00:00	-8,892	1,328	-,020	-6,695	,000
D2 Hour 01:00	-10,424	1,338	-,024	-7,788	,000
D3 Hour 02:00	-11,847	1,343	-,027	-8,820	,000
D4 Hour 03:00	-13,526	1,342	-,031	-10,080	,000
D5 Hour 04:00	-14,280	1,330	-,033	-10,734	,000
D6 Hour 05:00	-11,642	1,308	-,027	-8,898	,000
D7 Hour 06:00	-6,085	1,288	-,014	-4,725	,000
D8 Hour 07:00	-1,192	1,277	-,003	-,933	,351
D10 Hour 09:00	-3,133	1,277	-,007	-2,454	,014
D11 Hour 10:00	-7,280	1,281	-,017	-5,684	,000
D12 Hour 11:00	-11,041	1,284	-,025	-8,600	,000
D13 Hour 12:00	-15,264	1,284	-,035	-11,887	,000
D14 Hour 13:00	-18,095	1,281	-,042	-14,130	,000
D15 Hour 14:00	-19,084	1,276	-,044	-14,956	,000
D16 Hour 15:00	-17,351	1,275	-,040	-13,605	,000
D17 Hour 16:00	-11,990	1,280	-,028	-9,367	,000
D18 Hour 17:00	-1,679	1,284	-,004	-1,308	,191
D19 Hour 18:00	4,553	1,288	,010	3,536	,000
D20 Hour 19:00	4,701	1,288	,011	3,649	,000
D21 Hour 20:00	,449	1,288	,001	,348	,728
D22 Hour 21:00	-2,830	1,292	-,007	-2,190	,029
D23 Hour 22:00	-5,113	1,302	-,012	-3,926	,000
D24 Hour 23:00	-8,919	1,315	-,021	-6,780	,000
D1 Monday	1,110	,721	,004	1,540	,124
D2 Tuesday	,814	,737	,003	1,105	,269
D3 Wednesday	,712	,735	,003	,968	,333
D4 Thursday	1,240	,735	,005	1,689	,091

Figure B.17: Electricity price regression with gas share output page 5

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
D5 Friday	-,034	,727	,000	-,046	,963
D7 Sunday	-,886	,695	-,004	-1,273	,203
D1 Januari	-14,037	,929	-,045	-15,105	,000
D2 Februari	-16,905	,950	-,052	-17,795	,000
D3 March	-6,595	,918	-,021	-7,186	,000
D4 April	-13,589	,934	-,043	-14,555	,000
D5 May	-15,973	,936	-,051	-17,071	,000
D6 June	-12,964	,936	-,041	-13,844	,000
D7 July	-2,014	1,201	-,006	-1,677	,093
D8 August	17,317	1,199	,056	14,439	,000
D9 September	13,056	1,200	,041	10,878	,000
D11 November	5,056	,908	,016	5,569	,000
D12 December	20,916	,912	,067	22,942	,000
D1 2015	15,584	,778	,059	20,028	,000
D3 2017	5,469	,754	,021	7,257	,000
D4 2018	18,534	,771	,071	24,049	,000
D5 2019	,309	,922	,001	,335	,738
D6 2020	-9,671	,947	-,037	-10,217	,000
D7 2021	71,700	,904	,273	79,306	,000
D8 2022	215,852	1,598	,822	135,116	,000
(Constant)	-9,858	2,672		-3,690	,000

The Prais-Winsten estimation method is used.

Iteration History

	Rho (AR1)		Durbin-Watson	Mean Squared Errors
	Value	Std. Error		
0	,955	,001	1,633	202,296
1	,958	,001	1,638	202,273
2	,958	,001	1,638	202,273
3	,958	,001	1,638	202,273
4	,958	,001	1,638	202,273
5	,958	,001	1,638	202,273
6	,958	,001	1,638	202,273
7	,958	,001	1,638	202,273
8	,958	,001	1,638	202,273
9	,958	,001	1,638	202,273
10[a]	,958	,001	1,638	202,273

The Prais-Winsten estimation method is used.

a. The estimation terminated at this iteration, because all the parameter estimates changed by less than ,001.

Figure B.18: Electricity price regression with gas share output page61

Final Iteration 10

Autocorrelation Coefficient

Rho (AR1)	Std. Error
,958	,001

The Prais-Winsten estimation method is used.

Model Fit Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
,445	,198	,197	14,222	1,638

The Prais-Winsten estimation method is used.

ANOVA

	Sum of Squares	df	Mean Square
Regression	3492890,917	52	67170,979
Residual	14173858,415	70073	202,273

The Prais-Winsten estimation method is used.

Figure B.19: Electricity price regression with gas share output page 7

Regression Coefficients

	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig
Consumption	,004	,000	,162	33,254	,000
Solar Share	-35,752	10,014	-,014	-3,570	,000
Wind Share	-14,287	4,068	-,013	-3,512	,000
Gas Share	100,847	1,790	,217	56,349	,000
Gas Price	,799	,355	,024	2,249	,024
D1 Hour 00:00	1,809	,445	,032	4,064	,000
D2 Hour 01:00	1,711	,365	,030	4,684	,000
D3 Hour 02:00	1,058	,263	,019	4,018	,000
D5 Hour 04:00	-,022	,268	,000	-,082	,934
D6 Hour 05:00	3,017	,392	,054	7,703	,000
D7 Hour 06:00	7,845	,507	,140	15,471	,000
D8 Hour 07:00	11,386	,604	,203	18,862	,000
D9 Hour 08:00	11,264	,668	,201	16,875	,000
D10 Hour 09:00	7,285	,711	,130	10,243	,000
D11 Hour 10:00	2,914	,737	,052	3,952	,000
D12 Hour 11:00	-,871	,754	-,016	-1,155	,248
D13 Hour 12:00	-4,924	,763	-,088	-6,454	,000
D14 Hour 13:00	-7,338	,763	-,131	-9,621	,000
D15 Hour 14:00	-7,733	,762	-,138	-10,144	,000
D16 Hour 15:00	-5,402	,774	-,096	-6,977	,000
D17 Hour 16:00	-,009	,788	,000	-,011	,991
D18 Hour 17:00	9,428	,785	,168	12,004	,000
D19 Hour 18:00	14,677	,776	,261	18,912	,000
D20 Hour 19:00	14,023	,748	,250	18,736	,000
D21 Hour 20:00	9,301	,703	,166	13,222	,000
D22 Hour 21:00	5,875	,645	,105	9,101	,000
D23 Hour 22:00	3,566	,584	,064	6,107	,000
D24 Hour 23:00	,340	,519	,006	,656	,512
D1 Monday	-4,397	,833	-,030	-5,276	,000
D2 Tuesday	-4,342	,910	-,029	-4,772	,000
D3 Wednesday	-4,317	,910	-,029	-4,746	,000
D4 Thursday	-3,556	,833	-,024	-4,268	,000
D5 Friday	-2,450	,650	-,017	-3,769	,000
D7 Sunday	-1,047	,650	-,007	-1,612	,107
D1 Januari	-16,392	4,518	-,019	-3,628	,000
D2 Februari	-14,635	4,606	-,017	-3,177	,001
D3 March	-9,475	4,584	-,011	-2,067	,039
D4 April	-15,947	4,533	-,019	-3,518	,000
D5 May	-13,673	4,517	-,016	-3,027	,002
D6 June	-9,776	4,514	-,012	-2,165	,030

Figure B.20: Electricity price regression with gas share output page 8

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
D7 July	-7,392	6,459	-,009	-1,144	,252
D8 August	1,797	6,344	,002	,283	,777
D9 September	-2,661	5,996	-,003	-,444	,657
D11 November	1,047	3,634	,001	,288	,773
D12 December	5,330	4,201	,006	1,269	,205
D1 2015	14,483	4,975	,013	2,911	,004
D2 2016	-2,426	4,738	-,002	-,512	,609
D4 2018	9,325	4,741	,009	1,967	,049
D5 2019	-13,733	5,239	-,013	-2,622	,009
D6 2020	-23,141	5,407	-,022	-4,279	,000
D7 2021	58,118	5,541	,054	10,488	,000
D8 2022	183,155	9,354	,165	19,580	,000
(Constant)	-61,263	9,351		-6,551	,000

The Prais-Winsten estimation method is used.

Figure B.21: Electricity price regression with gas share output page 9