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Renewable Energy Integration and Electricity Price Volatility in Nordic Countries: A case study of Wind and Solar Power

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Declaration

I, Amoah, Samuel Tettey, author of the thesis titled "Renewable Energy Integration and Electricity Price Volatility in Nordic Countries: A case study of Wind and Solar Power."

I hereby declare that this submission is my work toward the Master of Science (MSc.) Degree in Applied Economics and Sustainability. To the best of my knowledge, except where due acknowledgment has been entirely made, it contains no material previously published by another person or that has been accepted for the award of any degree by any other University.

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15th August 2023

Acknowledgment

I want to express my sincere gratitude and appreciation to God for His grace and mercies throughout my academic life and ultimately complete this thesis.

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Abstract

The research sought to look at how the integration of renewable energy, that is, wind and solar power, affect the volatility of electricity prices in Nordic countries. The study mainly assesses the relationship between wind and solar power integration and volatility of electricity prices and how hourly integration of solar and wind power affects electricity price volatility in Nordic Countries. The study employed a case study approach by purposively selecting the following trading areas: NO2, SE2, DK2, and F1, representing Norway, Sweden, Denmark, and Finland. The study used secondary data from 2018 to 2022 collected from the ENTSO-E database using Python queries and TTF day-ahead benchmark natural Gas prices in Europe from the Montel online database. The data underwent cleaning and preparation to ensure its usability. The volatility of electricity prices was estimated using a 24-hour rolling window as used in financial modeling. To ensure that the data is stationary, an Augmented Dicky-Fuller unit root test and KSPP test were undertaken. The research used the identified ARIMA pattern, best information criterion, and seasonal pattern to develop the SARIMA model. Based on the developed SARIMA model, an EGARCH model was used to estimate the conditional volatility of electricity prices. The conditional volatility of prices was used as the dependent variable for the multivariate OLS estimation.

The result showed that solar power integration had a statistically negative relationship with the volatility of electricity prices in Denmark, while there was no relationship in Sweden. In the case of wind power, it had a significant positive relationship with Denmark and Finland. In contrast, no significant relationship between wind power and the volatility of electricity prices was found for Sweden and Norway.

Table of Content

Contents **Page**

List of Tables

List of Figure

Chapter One

Introduction

1.1 Background

The pursuit of sustainable energy to mitigate climate change's impact has brought countries on board various forms of energy to help meet this goal. These sustainable energy sources, including hydro, solar, biogas, and wind, are forms of renewable energy. As such, various policies have been put in place by multiple institutions and governments to promote using renewable power in their energy mix. Renewable energy has accounted for a global increase in its contribution to electricity production. According to the Eurostat report, renewable energy contributed to 39 percent of gross electricity generation in 2020 as against 37 percent in 2019 in European Union Countries.

The Nordic countries have, over these years, also towed the path of renewable energy to provide sustainable power to their citizenry while contributing to the low carbon emission and overall helping to meet the global climate target. Countries, including Sweden, Finland, Denmark, and Norway, have invested heavily in renewable energy by reducing their reliance on carbon-emitting energy sources. Norway's energy mix is made 98 percent renewable, with solar and wind accounting for 126 GWh and 9911 GWh, respectively (IRENA report, 2022). Also, other Nordic countries like Denmark and Sweden have various levels of renewables, making up for their total energy mix. These Nordic countries have thus exceeded the EU target of 20 percent renewable in the entire energy mix as of 2020. Solar Pv and wind Power are renewable energies that have increased in the total energy mix of Nordic countries over the years. In Denmark, Solar and Wind account for 15 percent and 68 percent of the renewable energy capacity in the total energy mix. This has increased over time.

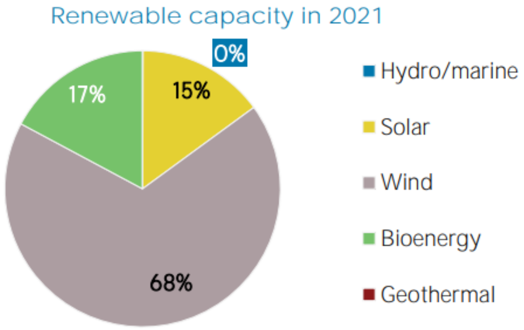


Figure 1.1: Renewable Energy Capacity for Denmark in 2021

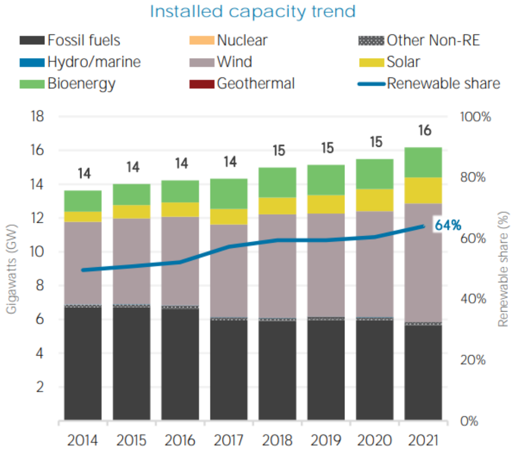


Figure 1.2: Renewable Installed Capacity Trend

Source: IRENA (2022)

From the above, wind and solar for Denmark increased from 2014 to 2021. This increase in wind and solar showed an increase in Denmark's share of renewable energy installed capacity. The increase in solar and wind shows a significant investment in renewable energy. Also, Statistics Norway (2022) indicates that power generation from wind power increased to 5.5 TWh in 2019, representing about a 43 percent increase. This increase in wind power in Norway implies that wind power production has also increased in Norway's total energy mix, which is predominantly hydro-powered.

Integrating solar and wind power into the total energy mix affects electricity pricing depending on production time, leading to price volatility. Season changes, especially in the world's temperate regions, may affect the power demand, especially during the winter. Due to this, there is a need for additional sources of power to augment the existing sources. With the increase in renewable energy as a source in the energy mix due to global policy on climate change, adding renewable energy to the energy mix is the option for most countries.

According to Gjerland and Gjerde (2020), an increase in the share of renewable energy in the total energy mix affects electricity prices, leading to a fall in price. The difference in the price of producing additional power to meet the demand leads to volatility in electricity pricing. This phenomenon, referred to as the Merit-order effect, occurs due to a rightward shift in the merit-order curve, hence a fall in price.

In a wholesale electricity market, just as in the Nordic region, prices are determined by the interaction of demand and supply. The market involves bidding from a pool of contracts that depends on spot markets and is primarily contingent on dispatching (Bahar and Sauvage, 2013). The market design ensures equal competition among participants involved in the market (Bahar and Sauvage, 2013). Therefore, there is an auction by a market operator who guarantees no bias. As stated by Energifaktanorge (2022), contingent on the existing grid capacity and the bids from individual participants in the market, the wholesale price is fixed hourly, at the back, for 24 hours. Here the lowest cost of generation infrastructure is first called into action. Hence, the Merit order dispatch.

Dispatching a low-cost power generation infrastructure will mean calling upon a renewable energy source in a typical energy mix. Dispatching wind power and solar power may lead to volatility in electricity prices.

Research conducted has looked chiefly at how dispatching will affect electricity price volatility. Most of this research looked at the day-ahead prices. Wiredemo (2017), Gjerland and Gjerde (2020), and Sa Cunha's (2021) looked at price volatility in the electricity market by considering the day ahead price of renewable energy prices. Research such as Pereira da Silva and Horta (2019) examined this relationship by considering the hourly price changes. Not much of the existing research has looked at the hourly relationship extensively.

Gjerland and Gjerde (2020) examine this relationship by focusing on Norway. The research findings indicated a positive relationship between wind power production and electricity price volatility. Also, the relationship between renewable energy and electricity price volatility was positive (Kyritsis et al., 2014; Ketterer, 2014). However, the research focused on Norway's NO2 bidding area, which comprises the southwestern part of Norway. Also, other Nordic countries have invested heavily in renewable energy; as such, the need to study how power production from renewable energy leads to electricity price volatility in the Nordic countries.

Thus, this research will explore the relationship of other Nordic countries with solar power and wind power as part of their total energy mix. Unlike earlier analyses that looked at this relationship based on the day-ahead effect; this study will look at this relationship by looking at how hourly changes in load integration because of the additional output affect electricity prices.

1.2 Objective

The research examines the impact of renewable power integration on electricity price volatility in Nordic countries. Specifically, the study will assess the relationship between wind and solar Integration and electricity price volatility and how hourly Integration of solar and wind power integration affects electricity price volatility in Nordic Countries.

Thus, this research will seek to answer the following questions:

- What is the relationship between Nordic countries' wind and solar integration and electricity price volatility?
- How does the hourly integration of solar and wind power affect electricity price volatility in Nordic Countries?

1.3 Hypothesis

The following hypothesis will help answer the research question.

Research Question 1

H_0: No relationship exists between wind power integration and electricity price volatility in Norway.

H_0: No relationship exists between wind power integration and electricity price volatility in Finland.

H_0: No relationship exists between wind and solar power integration and electricity price volatility in Sweden.

H_0: No relationship exists between wind and solar power integration and electricity price volatility in Sweden.

Research Question 2

H_0: Hourly Integration of solar and wind power does not affect electricity price volatility in Norway.

H_0: Hourly Integration of solar and wind power does not affect electricity price volatility in Finland.

H_0: Hourly Integration of solar and wind power does not affect electricity price volatility in Sweden.

H_0: Hourly Integration of solar and wind power does not affect electricity price volatility in Denmark.

1.4 Scope of Study

The study will focus on the Integration of Electricity in Nordic countries. The Nordic countries considered in the study are Norway, Sweden, Denmark, and Finland. These Nordic countries have increased their renewable capacity over the years. Also, the study will consider the period between 2015 till 2022.

1.5 Motivation

Nordic countries have, over the years, invested heavily in increasing renewable energy in their total energy mix. Increasing the renewable energy in the entire energy mix implies that the energy mix is diversified, leading to electricity price volatility. Thus, this thesis will provide policymakers with an overview of how hourly wholesale prices affect electricity price volatility in the Nordic region.

1.6 Outline of the Research

This research is divided into five main chapters. The first chapter introduces the study by providing a background to the study. It states the objectives, research questions, and scope of the study. The second chapter of this research looks at the background and conceptual framework related to the topic. It provides contextual knowledge, literature reviews, and reviews of plausible theories. The third chapter presents the methodology employed to answer the research questions. The fourth chapter also undertakes a data analysis of the study. In this chapter, the data is analyzed in relation to the research question using the methodology described in the third chapter. The chapter also describes the data and looks at the trends in the data. It looks at the test results, such as the unit root tests. It discusses the data analysis findings by comparing the outcome to the existing theoretical and empirical literature. The final chapter, chapter five, summarizes the entire research and makes conclusions and recommendations based on the findings and discussions in the fourth chapter.

Chapter Two

Background and Conceptual Framework

2.1 Introduction

This part has three main sections: contextual background, literature review, and theories. The contextual background discusses topics including European Union Renewable Energy Targets, policies to increase renewable Energy in Europe, Evolution of renewable energy in Nordic Countries. Other topics include renewable energy production and its effect on power production, Electricity production, and pricing with a focus on Nordic Countries, Drivers of Electricity Price volatility, Renewable Energy and Electricity Price Volatility, and Drivers of others. The second part reviews existing literature and published studies on the topic. The third part looks at theories related to the topic, like the Merit Order theory. Based on the review, an appropriate developed methodology to meet the objective

2.2 Contextual Background

2.2.1 European Union Renewable Targets

To increase the shares of renewable energy in the energy mix of European countries, the European Commission in 2009 agreed to use a policy called the Renewable Energy Directive (2009/28/EC (RED)) (Nordic Energy Research, 2021). This aimed to increase renewable energy gross final energy consumption from a low of 8.5 percent by 20 percent from 2004 to 2020 (Nordic Energy Research, 2021). Also, according to a policy paper authored by Amanatidis (2019), the RED aimed to reduce Green House gas by 20 percent below the level of 1990. Additionally, to decrease primary energy like oil and gas by 20 percent, the policy was to help to improve the efficient use of energy (Amanatidis, 2019). Based on this policy, various countries, including the Nordic countries, agreed to a specific national standard to increase their percentages of renewable energy consumption in their energy mix.

Within the period, the share of renewable energy increased in many European Countries. According to Eurostat (2022), the percentage of energy consumption considering the European Union level increased from 9.6 percent in 2004 to a level of 22.1 percent in 2020. This shows that the targeted level of the European Union was exceeded by 2.1 percent. This can be seen in the Figure below.

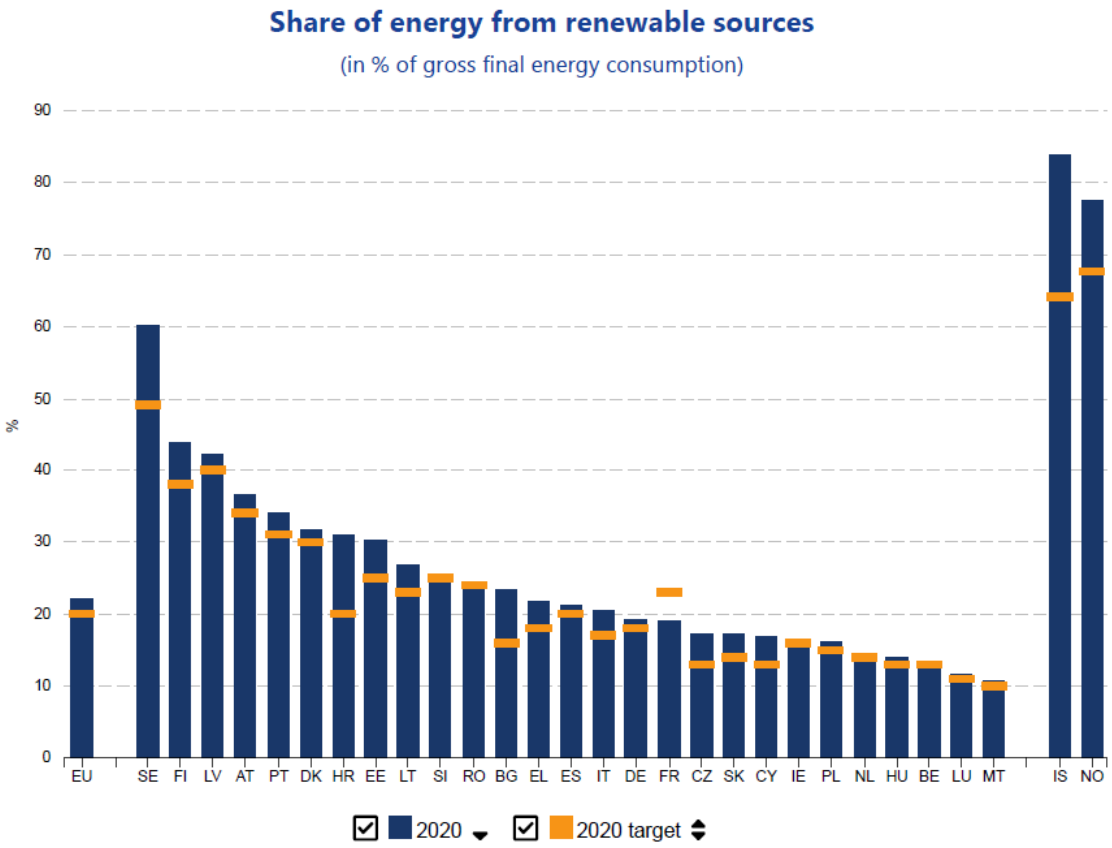


Figure 2.1: Share of Renewable Energy for European Countries

Source: Eurostats (2022)

In the future, the European Union seeks to further enhance these gains due to the worsening impact of climate change being experienced in the world today. Thus, the European Parliament in June 2022, agreed to increase the renewable energy targets of increasing renewable energy in the energy mix by 40 percent. Still, this target was revised by a vote on 14th September, 2022, to raise it upwards by 45 percent of EU members' total energy mix by 2030 (European Parliament, 2022).

2.2.2 Policies to Increase Renewable Energy in Europe

Various member countries have outlined and used several policies to reach the policy targets set by the European Union Commission and now the European Parliament. These policies include Feed-in-Tariffs, Feed-in-Premiums, Quota Obligations with tradeable green certificates, Investments, tendering schemes, and soft loans (Fruhmann and Tuerk, 2014). Countries have thus adopted a mixture of some of these policies to reach their set targets. Also, nations have collaborated on various levels to implement policies to meet this target. One such is the Green Certificate Market jointly established by Norway and Sweden.

In January 2012, Sweden and Norway established a green certificate market with the primary objective of increasing Renewable energy production by 28.4 TWh in 2020 in both countries (Swedish-Norwegian Electricity Certificate Market, 2) (Smelværvær, 2015). The market, created based on an existing Swedish electricity market, works to increase renewable energy in the total energy mix using cost-effective means.

Since its establishment, it has led to an increase in a new renewable capacity of 13.9TWh. Norway has benefited by 0.5 TWh, while Sweden helped by way of 3.1 TWh new capacity in 2015 (Swedish-Norwegian Electricity Certificate Market, 2020).

2.2.3 Renewable Energy Production and its Effect on Power Production

Renewable energy production has been thought to impact the intermittent supply of power supply, the economy, and the environment over the years as such various studies have examined these effects.

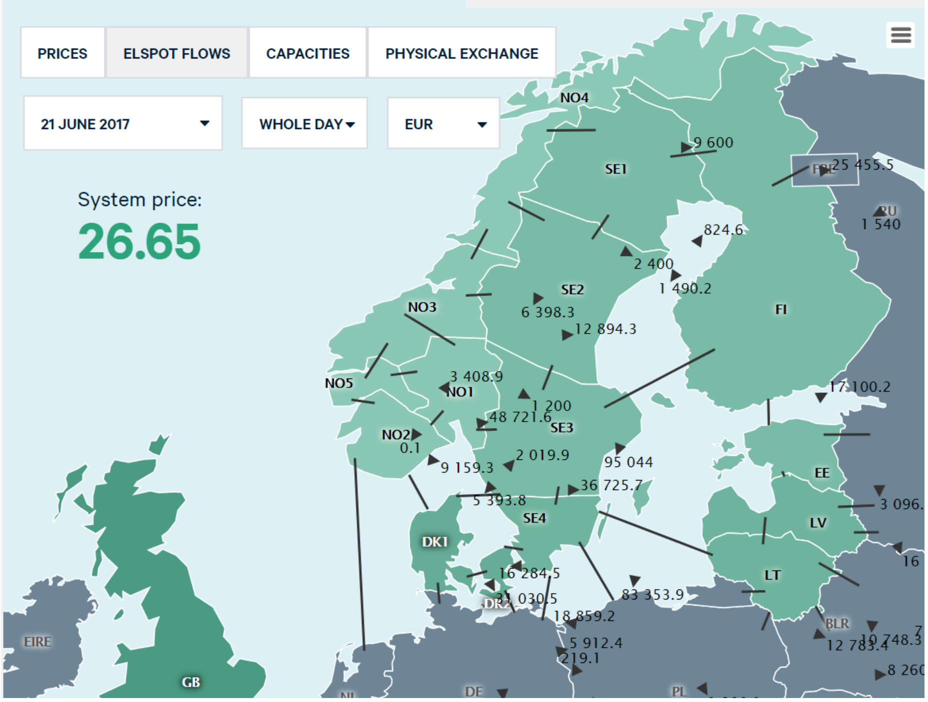
In their study, Maddaloni et al. (2009) measured the economic and environmental impact of mixing wind power into three different generational mixes. This study aimed to see if an alternative power source could reduce the effects of climate deterioration due to carbon-based fossil fuels on the environment.

2.2.4 Nordic Electricity Market

The Nordic market mainly consists of Norway, Sweden, Finland, and Denmark. This market is characterized by competition in generating and selling power. The Nordic market is integrated into other European markets. Countries interconnected in the Nordic Market include Germany, Netherlands, Poland, Russia, and the BALTIC states (energifaktanorge, 2023).

One feature of the Nordic market is the auctioning among various stakeholders. This involves a day ahead bidding and offers market participants, which happens hourly within 24 hours. This gives the right to electricity generators to generate electricity regardless of where they are in the market. The wholesale market determines prices through bidding in the day-ahead market, a continuous intraday market, and the balancing market. A common platform for trading for both the day-ahead market and the intraday market is the Nordpool Exchange. The Nordic day-ahead market is coupled with other markets across Europe.

As such, participants in the day-ahead market are allowed to bid between 8 am when the market opens till 12 pm when the market closes (energifaktanorge, 2023). This bidding allocates capacities and the corresponding prices to participants and hence helps determine the wholesale price the next day. A producer in the market typically bids based on his running cost of production, plant capacity, and the value it places on the production. The Nordic market consists of several interconnected bidding areas. This is shown in the Figure below.



21 JUNE 2017

WHOLE DAY

EUR

System price:

26.65

Figure 2.2: Nordpool Trading Area

Source: Nordpool (2023)

In the case of the study area, Norway has three main bidding areas. These are NO1, NO2 and NO3. Sweden also has four bidding areas NAMELY se1, SE2, SE3 and SE4. Denmark has two bidding areas which are dk1 and dk2, while Finland has only one. The electricity price varies in these bidding areas.

2.3 Empirical Review

2.3.1 Review of Previous Studies

Several researchers have conducted various studies on renewable energy and price volatility dynamics. Some of these studies are below.

Wiredemo (2017) study looked at price volatility in the Nordic Wholesale electricity exchange Nord Pool due to Sweden producing more power. The study used data including daily price and wind data ranging from 2015 to 2017. The study used a GARCH model to analyze the data. The study's findings indicated that increases in wind production induce electricity price volatility in the long run.

Pereira da Silva and Horta (2019) also investigated the effect of variable renewable energy sources on electricity price volatility in the Iberian market. Hourly (one-day ahead) prices, wind supply, solar PV for Spain, Portugal, and France, and other data, including natural gas data, were collected, and used to investigate the relationship between renewable energy supply and electricity price volatility. Thus, regression and EGARCH models were used to analyze these data sets. The study found that wind power intensifies the volatility in price. Also, when there is much more intraday variability due to renewable energy, it stimulates price volatility.

Garland and Gjerde (2020), in their thesis on Wind power production and electricity price volatility, aimed to assess how an intermittent renewable energy source will affect the price of electricity. The research used electricity price data from 2013 to 2019. Augmented Dicky-Fuller unit root test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) to test the stationarity of the various variables. The study used two different regression models for different time periods. The first one was used to assess intraday volatility while the second one focused on intra weekly volatility. The findings suggest a positive relationship exists between wind power production and intra-weekly volatility in electricity prices in Norway.

Sa Cunha's (2021) thesis aimed to ascertain the association between day-ahead electricity prices in the market and production in the Nordic area. The day-ahead production and consumption data sourced from ENTSO-E from 2015 to 2021. Unlike other research, this examined whether production follows day-ahead price signals differ within Nordic countries. It also ascertained how drivers of price vary. Among other things, the research looked at the relationship that has existed between prices and production differences since 2015. The study found that day-ahead prices are associated with the product type and the production area.

Oosthuizen et al. (2022) studied how increasing renewable electricity percentage affects retail prices in 34 countries. This depended on variations made for 23 European Union countries in the electricity market —the study data span from 1997 to 2015. The study tested for the presence of unit root and undertook a cointegration analysis. The paper's result revealed a positive impact on retail electricity prices as renewable energy share increases. This was found to be statistically significant.

Kyriaki Tselika (2022) also researched "The impact of variable renewables on the distribution of hourly electricity prices and their variability: A panel approach." The research aimed to find the impact of renewable energy generation on electricity prices and their variability in Denmark and Germany. The research used hourly data ranging from 2015 to 2020. It also used a panel quantile approach (Quantile via moment method). The study found that Germany and Denmark experience the merit order effect. Wind and solar were found to have different impacts on electricity prices. Also, it was found that while the production of wind increases the amount of price variability when considering a case of low demand, there was price stabilization when high demand levels as a case were considered for Germany. Finally, the research also found that hourly time series fails to estimate the extent of the merit-order effect.

Cevik and Ninomiya (2022) investigated how green power sources, wind and solar, affected electricity prices at a granular level. The paper is panel data research of 24 countries. The paper was conducted by observing the data from 2014 to 2021. It also used a panel quantile regression approach to produce its findings. The paper found that renewable energy contributed to a decrease in wholesale prices in Europe. This is seen as a percent increase in renewable energy penetration led to a 0.6 percent price change. The research findings reveal that as the share of renewable energy increases, there is a corresponding increase in the effect on electricity prices. The quantile regression on the other hand, revealed a different result depending on the quantile. While a negative effect on electricity price volatility was observed for higher quantile, the reverse is true.

2.3.2 Summary of Previous Studies

Table 2.1: Summary of Previous Study

Author	Objective	Method	Result
Wiredemo (2017)	Relatiohship between price volatility in the Nordic Wholesale electricity exchange and Nord Pool due to Sweden producing more power	GARCH model	Increases in wind production induce electricity price volatility in the long run.
Pereira da Silva and Horta (2019)	investigated the relationship that exist between renewable energy supply and electricy price volatility	Regression and EGARCH models	wind power intersifies the volatility in price
Garland and Gjerde (2020)	To assess how an intermittent renewable energy source will affect the price of electricity	Two-time series regression analysis Augmented Dicky-Fuller unit root test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS)	a positive relationship exists between wind power production and intra-weekly volatility in electricity prices in
Sa Cunha's (2021)	To ascertain the association between day-ahead electricity prices in the market and production in the Nordic area	Balancing contribution, spectral analysis, correlation coefficient	day-ahead prices are associated with the product type and the production area
Oosthuizen et al. (2022)	Determine how increasing renewable	unit root and cointegration analysis	positive impact on retail electricity prices

	electricity percentage affects retail prices in 34 countries		as renewable energy share increases
Kyriaki Tselika (2022)	To find the impact of renewable energy generation on electricity prices and their variability in Denmark and Germany.	panel quantile approach (Quantile via moment method)	Wind and solar were found to have different impacts on electricity prices
Cevik and Ninomiya (2022)	investigated how green power sources, wind, and solar, affected electricity prices at a granular level	panel quantile regression approach	the share of renewable energy increases, there was a corresponding increase in the effect on electricity prices

Authors Construct (2023)

2.4 Theories

2.4.1 Merit Order Dispatch

In the era where most countries are diversifying the energy mix, looking at the source that will lead to minimum operation costs while safeguarding the environment by producing fewer carbons to reduce global warming is essential. In doing this, most countries try to meet the electricity demand by introducing renewable power sources into their total energy mix. These sources of energy come with different operating costs. Market operators resort to dispatching energy generation infrastructure in terms of merits to ensure the most effective operating cost of generating power and emitting lower greenhouse gases. Thus, the Merit Order Dispatch.

The Merit Order Dispatch, according to Bhattacharyya (2019), considers energy generation units by ranking them in a particular order of preference given the cost associated, which is mostly `"hourly fuel cost per megawatt" (Bhattacharyya, 2019). In this case, the energy generation facilities are ranked based on cost, the available units, and the existing demand (Bhattacharyya, 2019).

Initially, various generation and demand agents in the electricity market make multiple bids. The Market operator tends to arrange these bids in terms of price in ascending order for the supply bids and descending order for the demand bids. The market operator, therefore, initiates a market clearing point by matching the demand to the supply (Juan-Manuel Roldan-Fernandez et al., 2016, Bhattacharyya, 2019).

Renewable energy sources like wind and solar power generate electricity at low marginal cost while producing fewer greenhouse gases. Operators of renewable generation infrastructure submit bids with low costs for the energy they intend to supply. So, when these lower bids are offered from the renewable energy operators, the market operator inputs these bids by shifting rightward the merit order generation curve. According to Juan-Manuel Roldan-Fernandez et al. (2016), the rightward shift leads to a decrease in the market clearing and causes a marginal surge in the energy sold. They displaces other forms of energy which otherwise would have commanded higher operating costs and led to an increased emission of GHG. The merit order dispatch can be seen in the diagram below.

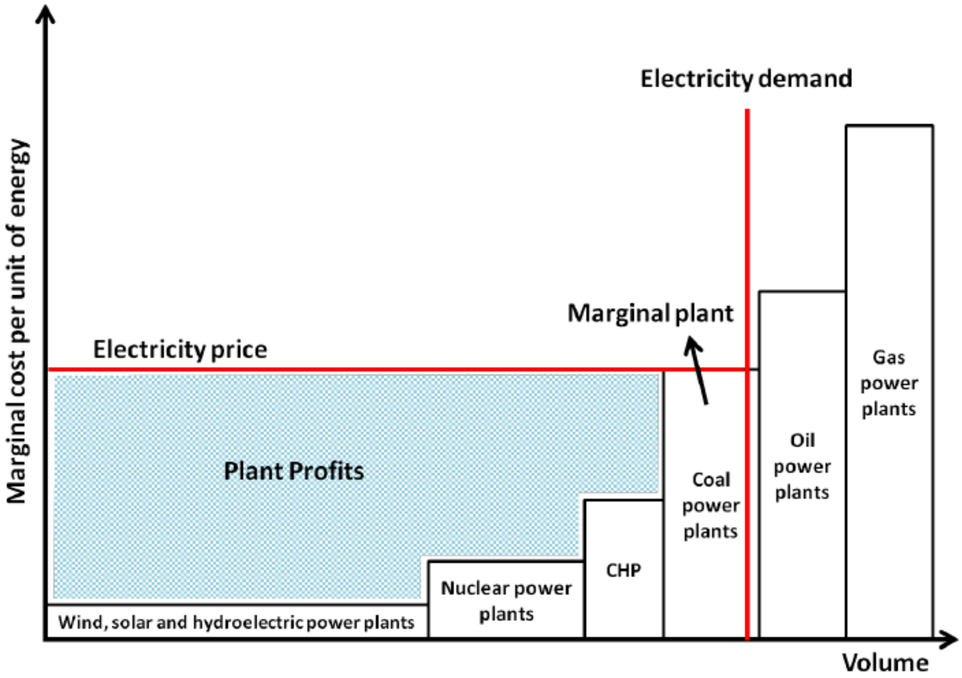


Figure 2.3: Merit Order Dispatch

Source: Bahar and Sauvage (2013)

The above diagram shows that the energy generation infrastructure with the least operating cost is initially matched to meet the existing demand. Here, wind, solar, and hydroelectric power plants are dispatched first, followed by the nuclear power plant, CHP, and coal power plants.

Chapter Three

Methodology

3.1 Introduction

This chapter examines the data and approaches developed to meet the study's objective. The chapter discusses the type and source of data, presents the data in graphical form by taking the trend, undertakes a unit root test, and comes up with an econometric model to analyse the data and arrive at a result.

3.2 Case Study Area

The research employs a case study approach to meet the study's objective. The study focuses on four Nordic countries: Norway, Sweden, Finland, and Denmark. Some countries have different electricity trading areas in the Nord Pool Trading Area. The research selects a single trading area for each country for this research. Thus, the study purposely sets the NO2 trading area for Norway, SE2 trading area for Sweden, DK2 from Denmark, and F1 from Finland based on integrating renewable energy in producing electricity in these trading areas.

3.3 Data

3.3.1 Types and Sources of Data

The research uses secondary data throughout this research, which is obtained from a secondary source. This data is collected from the ENTSO-E database using Python queries. Other sources of data include the Montel Online database. The data gathered ranges from the beginning of 2015 to the end of 2022. However, due to data wrangling issues and available data, the research focused on January 2018 to November 2022. The data went through various cleaning stages to ensure its usability for this research.

3.3.2 Description of Data

The description of the data the research uses in its analysis is as follows:

i. Electricity Price

Electricity prices represent wholesale prices of actual prices for the case study area. Other studies used day-ahead forecasts in their analysis. But since these are historical data and based on the period, the research uses the actual prices as a proxy for day-ahead prices in its analysis. These prices are all in Euros. As such, there is no need for conversion to a common currency before using it in this analysis.

ii. Renewable Energy

The renewable energy used in this study is Wind and Solar energy production. Wind and Solar energy are produced and fed into the various countries' energy mix. The Wind and Solar Power integration data for the Nordic countries understudy serve as independent variables in the analysis. The analysis uses wind and solar power data in megawatts for Finland, Norway, Sweden, and Denmark from the beginning of 2015 to the end of 2022.

iii. Power Consumption

Power consumption is an essential factor that may determine electricity price volatility. When power consumption increases, this means that there is a need for an increase in electricity production to meet the associated increase in demand. That is, bringing on board other sources of electricity to meet the demand. Hence this leads to price volatility as different sources of electricity generation come with their own cost of production. The study uses load as a measure of power consumption.

iv. Temperature

Temperature is considered an element that affects the production of electricity. Depending on the prevailing weather, the electricity demand could vary from a group of consumers in a particular geographical location. During winter, the need for electricity by consumers for heating homes increases; as such, there is an increase in production from power producers to meet the demand. Hence, electricity production increases during winter, and the reverse is true. Also, during the winter, weather conditions make some of the renewable sources' production vary. One such is solar, whose output in terms of electricity production falls during the winter and the reverse during summer. Hence temperature could be seen as an exogenous factor in determining electricity price volatility, especially in Europe. The study area's daily temperature is a control variable in determining how electricity prices vary because of the Nordic region's renewable sources. The temperature data consist of hourly temperature data in degree Celsius taken from various locations for Finland (EFHK-Helsinki), Sweden (ESKN-Stockholm), Norway (ENFB - Oslo), and Denmark (EKCH- Copenhagen).

V. Price of other Fuels (Gas)

The variation in the price of other fuels could affect the price of electricity. In Europe, electricity production in many countries depends on several energy sources. In our study area, the predominant fuel is using natural gas to produce electricity. Therefore, the study uses the natural gas price as an exogenous variable in evaluating how electricity prices vary. The research obtains the TTF day-ahead hourly price benchmark for Gas in Europe from Montel online database for its analysis.

VI. Water Level

Hydro is a primary source of electricity in the Nordic countries. The water level in the hydro dam affects the electricity production level differently. As the weather changes, the water levels in the Hydro dams also change. The study uses the water level of hydroelectric dams in Norway's NO2 pricing area.

Table 3.1: Summary Variable Data and Source

No.	Variable	Description	Source
1	Electricity Price	Electricity prices consist of hourly data for Finland (fi), Sweden (se_3), Norway (No_1), and Denmark (dk_2).	Entso-e
2	Power Consumption	The electricity power consumption data consist of hourly load data for Finland (fi), Sweden (se_3), Norway (No_1), and Denmark (dk_2).	Entso-e
3	Temperature	The temperature data consist of hourly temperature data in degree Celsius taken from various locations for Finland (EFHK-Helsinki), Sweden (ESKN-Stockholm), Norway (ENFB -	Entso-e

		Oslo), and Denmark (EKCH-Copenhagen).	
4	Gas Prices	Natural gas price in Euros.	
5	Water Level	The water level of the dam in Norway's NO2 trading area.	Entso-e

Source: Authors Construct

3.3.3 Summary of Data

The summary of the data is presented in Table 3.2 below. The data looks at the variables' mean, standard deviation, minimum, 50th percentile, and maximum.

Table 3.2: Summary of Data

	Mean	Std	min	50%	max
ln_So_Den	1.87072	2.89264	-4.6052	1.16315	7.13997
ln_Wi_Den	6.78797	1.0877	0.19885	7.04846	8.8689
ln_Wi_Fin	6.01904	1.08138	0	6.1097	8.35173
ln_Wi_Nor	1.73823	2.07338	-4.6052	0	5.87341
ln_So_Swe	0.19492	1.08479	-4.6052	0	6.09709
ln_Wi_Swe	6.32097	0.93092	0	6.4677	7.98778
ln_ETS_P	2.893	0.95361	1.39872	3.10205	4.56435
ln_Gas_P	3.07635	0.80898	1.2716	2.91271	5.65724
ln_PC_Fin	9.13685	0.16162	8.56121	9.12891	9.62278
ln_PC_Den	7.73735	0.2008	6.99485	7.7463	8.32239
ln_PC_Nor	8.25464	0.329	7.40001	8.25946	9.00369
ln_PC_Swe	9.17055	0.22137	8.47178	9.17066	9.78002
ln_WL_Nor	3.97421	0.59736	2.59214	4.25407	4.48413
ln_TP_Fin	1.48172	1.21164	-0.6931	1.79176	3.46574
ln_TP_Swe	1.56476	1.16441	-0.6931	1.8718	3.46574
ln_TP_Nor	1.42845	1.2125	-0.6931	1.79176	3.46574
ln_TP_Den	1.98361	0.93647	-0.6931	2.25129	3.46574
ln_VEP_Nor	0.06436	0.09549	0.00163	0.03462	1.23627
ln_VEP_Swe	0.16048	0.18773	0.00696	0.0885	1.95887

ln_VEP_Den	0.22041	0.30855	0.00517	0.11198	2.4505
ln_VEP_Fin	0.19459	0.18177	0.00733	0.14024	1.95887

Source: Authors Construct

3.4 Trend in the Data

A graphical plot of all the variables below shows how the data of the various variables have trended during the study. The graphs show the grouping of the variables according to type.

3.4.1 Trend of Hourly Electricity Prices

The graphs below present electricity prices for the four countries.

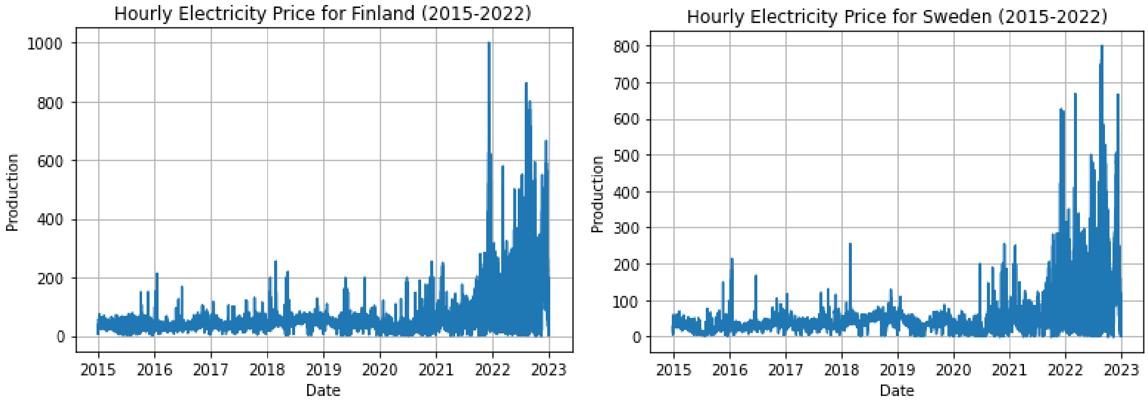


Figure 3.1 **: Hourly Electricity Price for Finland and Sweden**

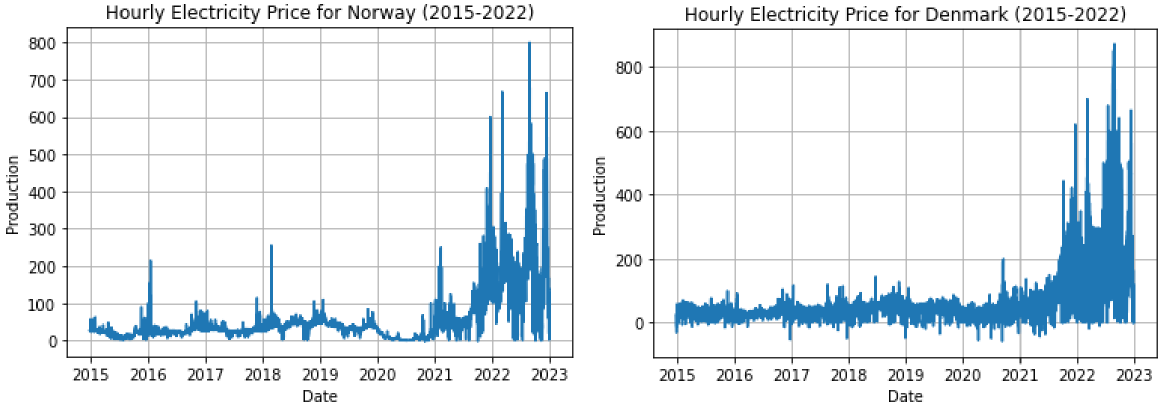


Figure 3.2**: Hourly Electricity Price for Norway and Denmark**

The graphical representation of the trend for the four countries exhibits a similar trend. That between 2015 to 2020, electricity prices in Finland, Sweden, and Denmark were relatively the same, with occasional high prices, mostly seen at the beginning and the end of the year. This shows that prices mainly increase during the winter and fall after that, with summer prices mostly lower. Norway's electricity prices are relatively lower during this period than the others. The lower cost could be because hydro's predominantly used as a power source and has a relatively lower cost of operations than other fuels.

Prices begin to spike after mid-year 2020 towards the end of 2021 and continue until the end of 2022. The price spike is mainly seen and sustained from 2021 for Sweden, Denmark, and Finland. Unlike Norway, these countries rely on other fuels, particularly hydrocarbons, to produce electricity. Therefore, with the rise in prices of fuels like Gas and Oil, due to the invasion of Ukraine by Russia, the cost of producing electricity went up, mainly affecting these countries. The impact of the war had a repealing effect on global prices of commodities, therefore also affecting the cost of electricity production for Norway and hence prices spiked in 2022.

3.4.2 Trend of Hourly Power Consumption (Load)

Hourly power consumption for the four countries is shown below from the beginning of 2015 to the end of 2022. From the diagram below, while Finland, Sweden, and Norway exhibit a similar trend in the load consumed for this period, Denmark, on the other hand, shows a little difference in its curve.

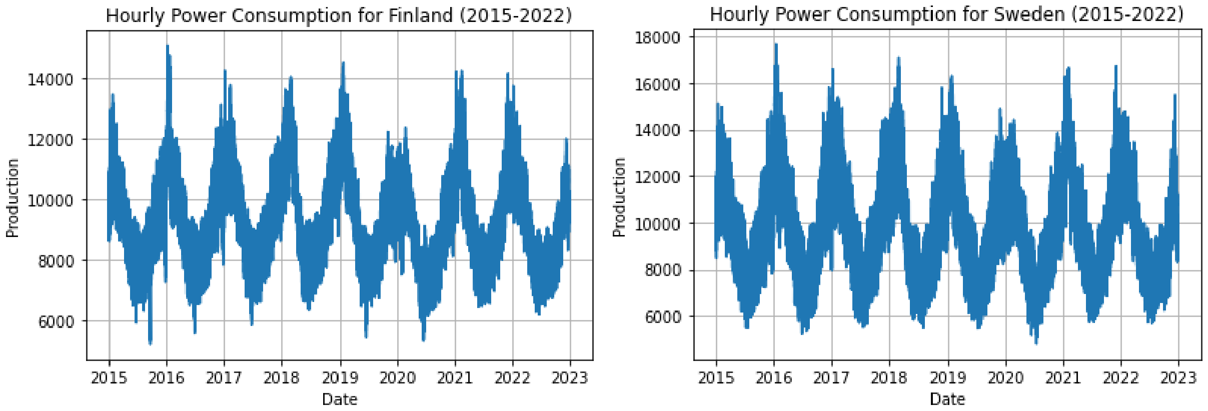


Figure 3.0.1: Hourly Power Consumption for Finland and for Sweden

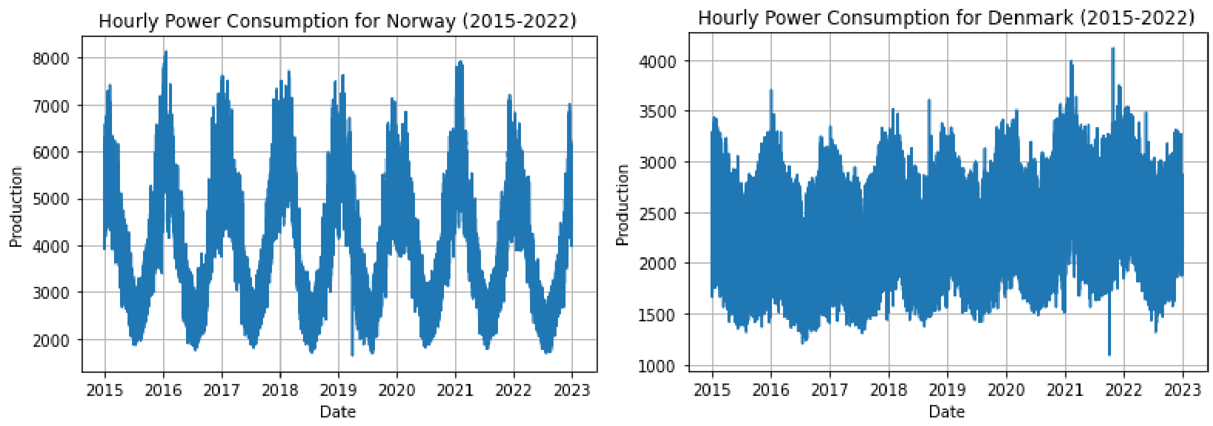


Figure 3.2: Hourly Power Consumption for Norway and Denmark

The difference is seen during the period after winter, while the load consumed for the other countries decreases till it is lowest during the summer and begins to increase after summer, the load consumed for Denmark also decreases marginally compared to the other countries.

3.4.3 Trend in Solar Integration

Among the four countries, Denmark and Sweden are the countries that use solar for electricity production.

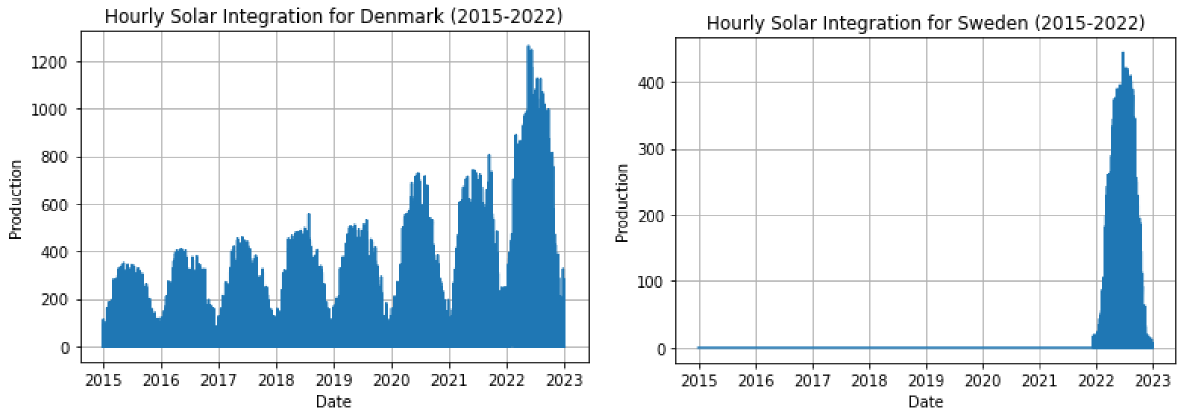


Figure 3.3: Hourly Solar Power Denmark and Sweden

From the graph, Sweden began using solar at the beginning of 2022. During this period, the hourly integration of solar into the total electricity mix of Sweden increased till it peaked in the middle of 2022 and started to fall till the end of 2022. Unlike Sweden, Denmark from 2015 has been integrating solar into the total energy mix for electricity production. The yearly trend has bell-shaped like a normal distribution curve. This is because the winter has low sunshine while the summer has more sunlight throughout the day. Hence, more solar is integrated into the electricity generation mix in the summer compared to the winter. Therefore, the bell is like the shape of the yearly trend. However, over the period, the load integrated has increased yearly. This results from increasing solar power in the total energy mix to generate electricity to meet continuous demand while helping to meet the global climate goal.

3.4.4 Trend in Wind Integration

Wind power integration into the total energy mix of the four countries from 2015 to 2002 is shown below.

The hourly integration of wind power into Finland and Sweden's total electricity generation mix has increased upwardly from 2015 to 2022. The graph shows a fall during the middle of the year. This may indicate low demand for electricity during that period as such low integration.

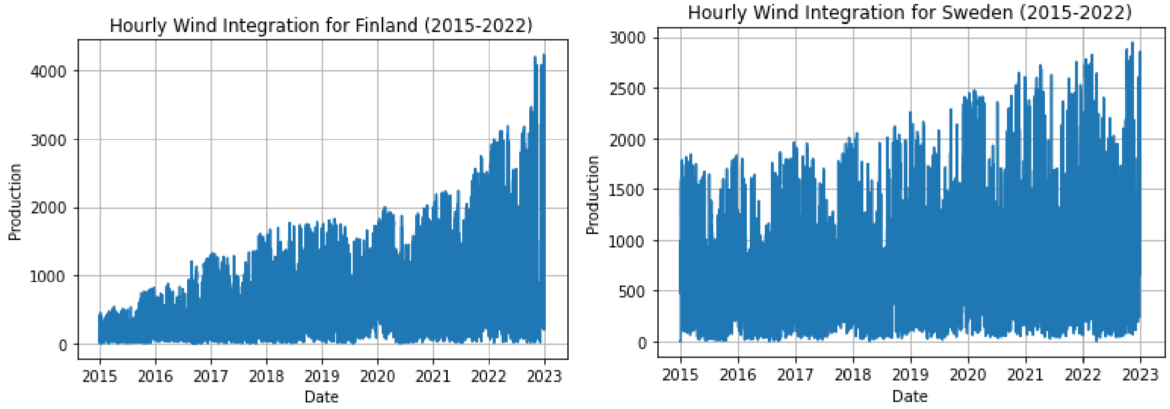


Figure 3.4: Hourly Wind Power for Finland and Sweden

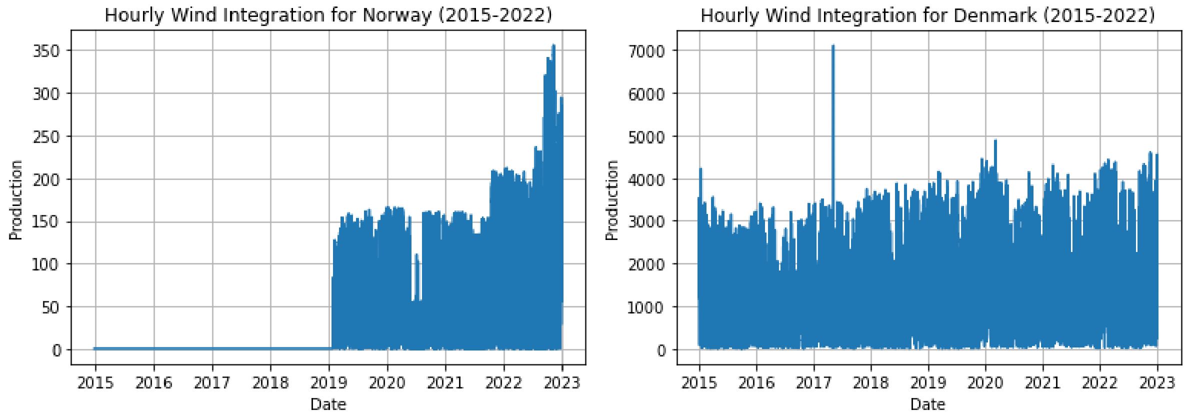


Figure 3.5: Hourly Wind Power for Norway and Denmark

For Norway, hourly wind power integration began in 2019 and was stable towards the third quarter of 2021 until it started to increase towards the end of 2021 and with a shot up in the third quarter of 2022. Hourly wind power integration has experienced an upward trend from the third quarter of 2021 till the end of 2022.

Hourly integration of wind power into the total energy mix in Denmark has been relatively stable even though there are periods of falls in the integration into the total energy mix, this can be seen to be seasonal.

3.4.5 Trend of Average Hourly Temperature

The temperature for the four countries exhibits a similar trend throughout the period under research. The temperature falls at the beginning of the year during winter, rises to its peak in summer in the middle of the year, and falls again as winter approaches.

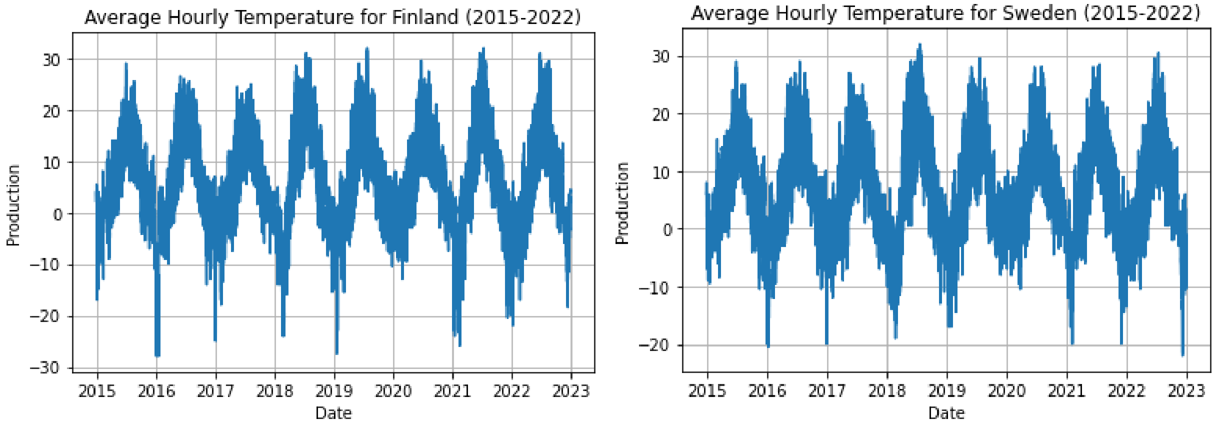


Figure 3.6:Average Hourly Temperature Finland and Sweden

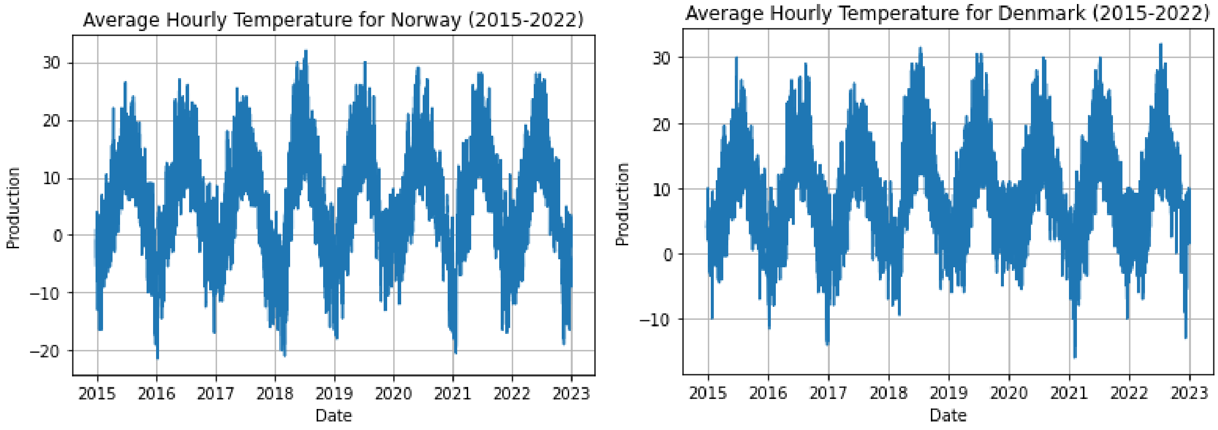


Figure 3.7: Average Hourly Temperature Norway and Denmark

3.4.6 Trend in Hourly Prices of Gas

Hourly gas prices from 2015 to 2022 exhibited a stable trend until middle of 2020, when they fell to their lowest due to the coronavirus and began to increase until they peaked in the middle of 2022 and started falling after.

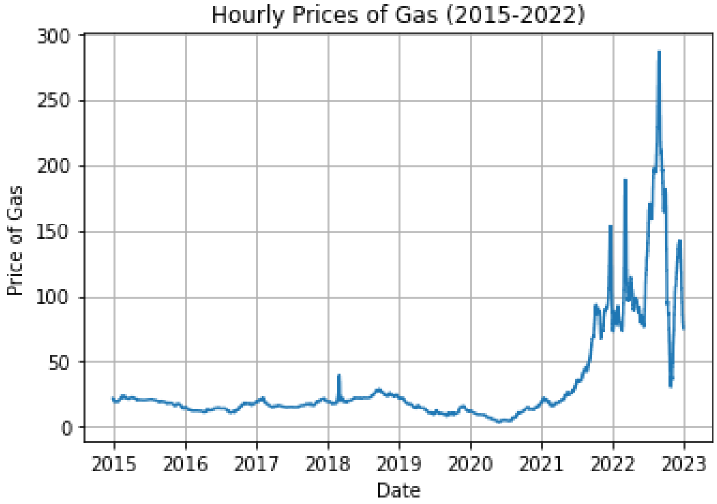


Figure 3.8: Hourly Gas Price

3.4.8 Water Level

The water level of Norway falls to its lowest at the end of the first quarter of and begins to rise to a peak towards the end of autumn and falls till the end of the year. This cycle is repeated throughout the year and impacts electricity production in Norway.

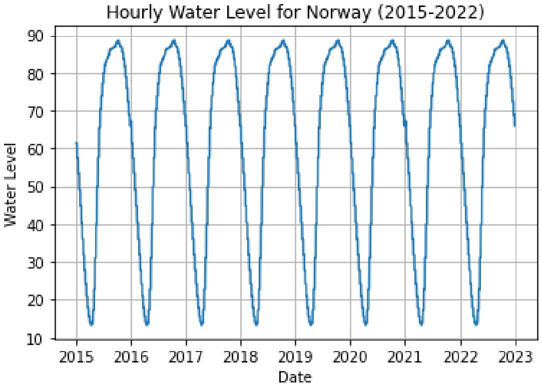


Figure 3.9: Hourly Water Level for Norway

3.4.9 Volatility of Electricity Price

Electricity Price Volatility is measured as a standard deviation of electricity prices. The standard deviation has been used to measure volatility because it can summarize the probability of seeing an extreme return value. Significant positive and negative returns are likely when a big standard deviation is used (Daley, 2007).

This research intends to use standard deviation to measure Electricity Price volatility. However, a rolling window of log return standard deviation is used to estimate the volatility in financial times series modeling involving large datasets like this research.

Thus, the daily natural log return of a rolling window of 24 (24 hours) of the electricity prices is taken to arrive at the volatility of electricity price volatility. The data with some missing observations was treated using a data cleaning and treating process, which included replacing periods of unobserved observation with zero and missing values with forward and backfill, among other data wrangling techniques, to make the resulting data conform to the normality assumption. This was done to ensure that the data was well structured and devoid of missing values, making analysis more accessible and more accurate. Therefore, the velocity of electricity prices is presented below.

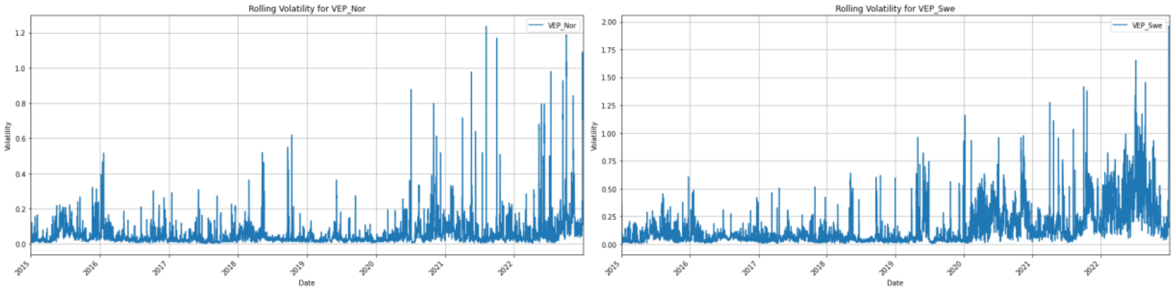


Figure 3.10: Rolling Volatility of Norway and Sweden

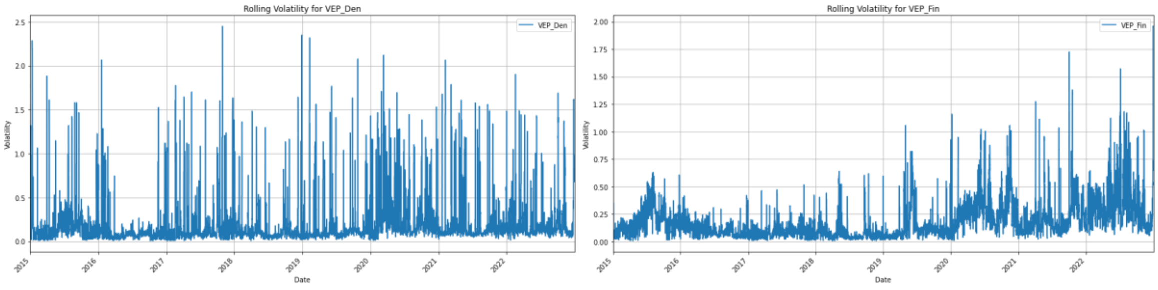


Figure 3.11: Rolling Volatility of Denmark and Finland

3.5 Test for Stationarity

In analyzing the data, it's essential to test it to ensure it is stationary. The study uses time series data in the analysis. As such, there is a need to undertake a stationary test on the data series to ascertain if it's stationary. This is to ensure that the results of the estimates and the research outcome are not spurious. Two forms of Unit root tests are performed below. These are the Augmented Dicky Fuller Unit Root test and the Phillips Perron Unit Root Test.

3.5.1 Augmented Dicky Fuller Test

The ADF regression is as follows:

$$\Delta y_t = \beta_1 + \beta_2 t + \beta_3 y_{t-1} + \sum_{i=1}^{m} \varphi_i \Delta y_{t-i} + \varepsilon_t$$

The Null hypothesis indicates no evidence of unit root in the data, while the alternative suggests otherwise.

The result of the test for unit root is carried out using the augmented unit root test is shown below in Table 3.2

3.5.2 KPSS Unit root test

Kwiatkowski–Phillips–Schmidt–Shin, commonly called the KPSS unit root test, looks at the time series in three categories. Namely: as a deterministic trend, a random walk, and a stationary error.

The tests hypothesis is given as follows:

H_0 = time series is level stationary

H_1 = time series have a unit root

This test is also conducted to ascertain whether the data is stationary. It acts as a complement to the ADF test. That is, in case the ADF states that a time series is stationary while it is not, it highlights.

The p-values of both unit root tests are shown below in Table 3.3.

Table 3.0.3: Augmented Dicky Fuller and KPSS Unit Root Results

Variable	ADF P-Values	KPSS P-Value	Order of Differencing
ln_So_Den	0.000	0.010	1
ln_Wi_Den	0.000	0.010	1
ln_Wi_Fin	0.000	0.010	1
ln_Wi_Nor	0.000	0.010	1
ln_So_Swe	0.000	0.010	1
ln_Wi_Swe	0.000	0.010	1
ln_ETS_P	0.898	0.010	1
ln_Gas_P	0.540	0.010	1
ln_PC_Fin	0.000	0.010	1
ln_PC_Den	0.000	0.010	1
ln_PC_Nor	0.000	0.030	1
ln_PC_Swe	0.000	0.100	0
ln_TP_Fin	0000	0.100	0
ln_TP_Swe	0.000	0.100	0
ln_TP_Nor	0.000	0.100	0
ln_TP_Den	0.000	0.100	0
ln_VEP_Nor	0.000	0.010	1
ln_VEP_Swe	0.000	0.010	1
ln_VEP_Den	0.000	0.010	1
ln_VEP_Fin	0.000	0.01	1
ln_WL_Nor	0.384	0.078	1

Authors Construct (2023)

From the above results, almost all the variables except ln WL_Nor, and Gas_Price were found to be stationary at order one due to the p-value being less than the critical values of 0.01 for the ADF test. This indicates that there is strong evidence against the null hypothesis. Therefore, this suggests that unit root does not exist in the data on the ADF Test.

Also, the KPSS test shows that ln PC_Swe and all the temperature variables were found to be stationary at order 0; the rest of the variables were found to be stationary at order one after the first differencing. Hence the data is stationary.

3.6 Econometric Model

3.6.1 Model Formulation

Electricity Prices are determined by several factors, which include the type of fuel and power consumption of electricity, among other factors. Renewable energy integration can affect electricity prices when introduced into the energy mix, as described by the theory of merit order dispatch. Therefore, the integration of renewable sources of power, along with other factors, could lead to changes in electricity prices. A continuous change in price leads to volatility in electricity prices. This is represented mathematically below:

$$\mathrm{VEP} = \mathrm{f}(\mathrm{RE}, \mathrm{X})$$

$$VEP_t = \beta_1 + \beta_2\, RE_t + \beta_3\, PC_t + \beta_4\, TP_t + \beta_5\, Gas_t + \beta_6\, WL_t + \varepsilon_t$$

Applying natural Logarithms to both sides,

$$ln\, VEP_t = \beta_1 + ln\, \beta_2\, RE_t + ln\, \beta_3\, PC_t + ln\, \beta_4\, TP_t + ln\, \beta_5\, Gas\_P_t + +ln\, \beta_7\, WL_t + \varepsilon_t$$

Where:

t is time

ln $\mathrm{VEP_t}$ is the natural log of Volatility of Electricity Price

ln $\mathrm{RE_t}$ is the natural log of Renewable Energy Production (Wind and Solar Production)

ln $\mathrm{PC_t}$ is the natural log of Power Consumption (Load)

ln $\mathrm{TP_t}$ is the natural log of temperature

$\mathrm{Gas_t}$ is the natural log of Natural Gas Prices

$\mathrm{WL_t}$ is the natural log of the Water Level

Following the discussions on the trend analysis conducted for the various data above, seasonal patterns can be seen in the data. Electricity prices are seen rising for all four countries during the winter and falling during the summer. The same can be said for the other variables, which also experience monthly increases and decreases depending on the time of the year. Therefore, It is essential to incorporate this seasonality into the model formulation.

Also, due to the patterns seen in the graphical representation of the data, it is crucial to control these patterns as uncontrolled may lead to the wrong inference, which will be biased and lead to a violation of the ordinary least square assumption. A model that incorporates seasonality and autocorrelation is therefore employed.

Seasonal Auto-Regressive Integrated Moving Average (SARIMA) is introduced into the model to remedy the underpinning. This will address the autocorrelation and seasonal correlation in the residuals. According to Adhikari and Agrawal (2013), SARIMA was introduced by Box and Jenkins as a variation to the ARIMA to remove the non-seasonal stationarity that may exist in a time series. To this end, an appropriate seasonal differencing order is used. The SARIMA is of order (p, d, q) × (P, D, Q) s. The s captures the seasonal pattern present in the model.

3.6.2 Model Selection

To develop a SARIMA Model, there is a need to determine the best ARIMA pattern and the best information criteria for the model. There are many forms of information criteria, but the three primary forms of information criterion primarily used in time series modeling are the Akaike information criterion (AIC), Bayesian information criterion (BIC), which is also referred to as the Schwarz information criterion, and Hannan–Quinn information criterion (HQC). These information criterion helps us to assess the various ARIMA patterns that could give the best-performing outcome of the model.

Using Python codes, the following ARIMA order and the best information criteria were found for each model.

Table 3.0.4: Best ARIMA Model and Information Criterion

	AIC	BIC	HQC
Norway	(1, 0, 2)	(1, 0, 2)	(1, 0, 2)
Sweden	(2, 0, 1)	(2, 0, 1)	(2, 0, 1)
Denmark	(1, 0, 1)	(1, 0, 1)	(1, 0, 1)
Finland	(2, 0, 1)	(2, 0, 1)	(2, 0, 1)

Authors Construct (2023)

Based on the above ARIMA pattern information criterion, AIC patterns are chosen for the SARIMA model.

3.6.3 Seasonality Patterns

An ACF and PACF of the various data are plotted to identify the seasonal pattern. The seasonal pattern is determined for each variable using the visual inspection method. Below is a plot of the ACF and PACF of the variables.

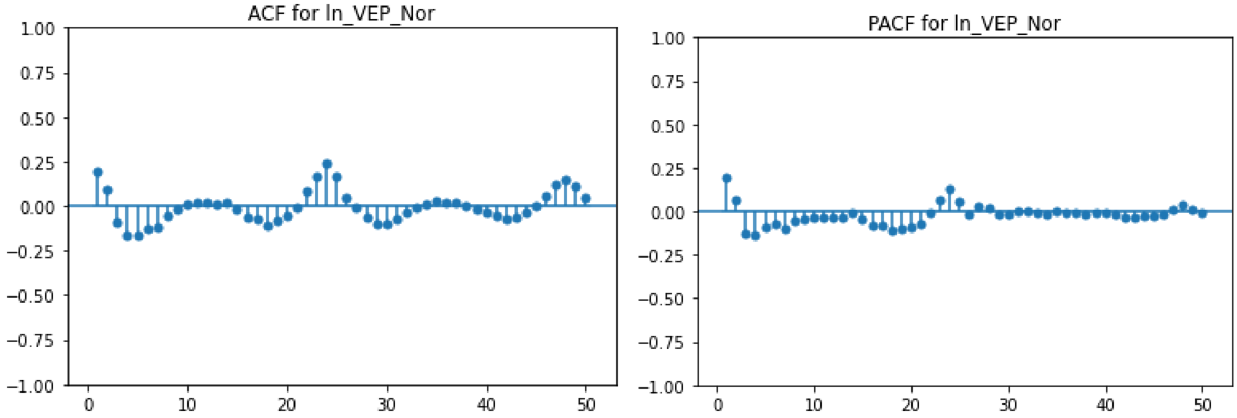


Figure 3.12: ACF and PACF for ln_VEP_Nor

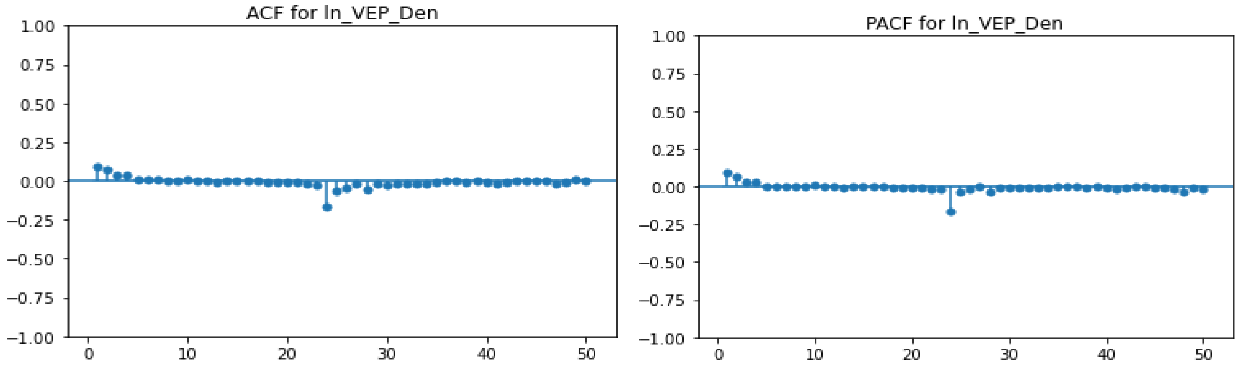


Figure 3.13: ACF and PACF for ln_VEP_Den

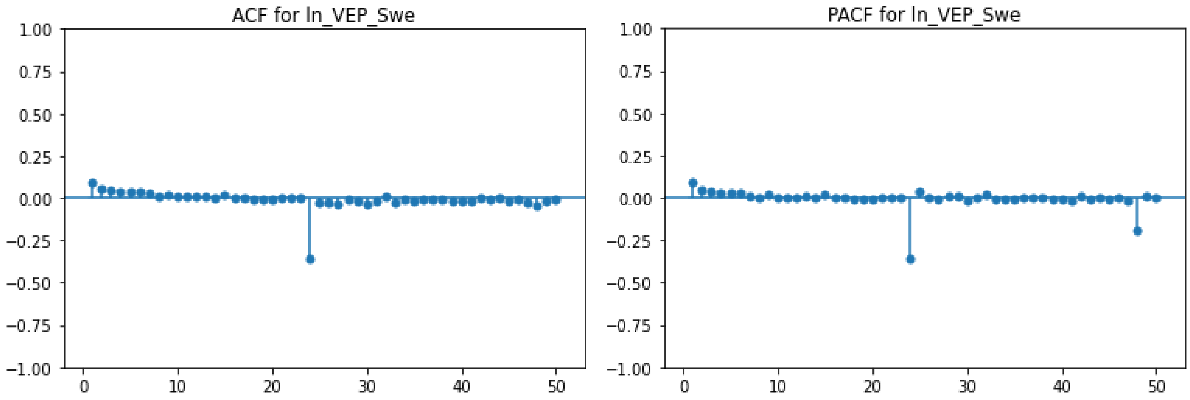


Figure 3.14: ACF and PACF for ln_VEP_Swe

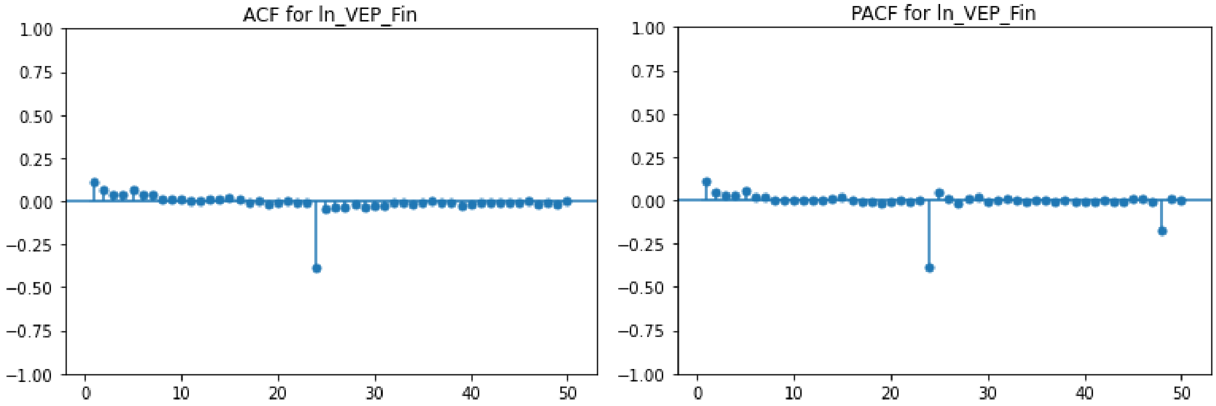


Figure 3.15: ACF and PACF for ln_VEP_Fin

Based on the plot and the frequency of data being used, we can deduce that there is a recurring seasonality is 24 hourly differences. Hence, the s is 24. Therefore, the following is used to determine the SARIMA model that will be used for analysis.

Table 3.0.5: SARIMA Pattern

Country	SARIMA Pattern
Norway	(1, 0, 2) (1,0,2,24)
Sweden	(2, 0, 1) (2,0,1,24)
Denmark	(1, 0, 1) (1,0,1,24)
Finland	(2, 0, 1) (2,0,1,24)

Authors Construct (2023)

3.7.4 EGARCH Model

In answering the research questions, the research uses an EGARCH Model. An EGARCH model is a short form of the Exponential Generalized Autoregressive Conditional Heteroskedasticity model. The EGARCH model was propounded by Nelson and Cao (1992) in their paper titled "*Inequality constraints in the univariate GARCH model*." In this paper, they argued that the constraint of inequality typically imposed on conditional variance to make it nonnegative does not adhere. This is because the parameter estimated violets this constraint when set as required by the GARCH model (Nelson and Cao, 1992). Due to this, they proposed a non-restrictive approach that allowed for no constraints on the parameters, thus, the EGARCH model.

The EGARCH model assumes that a conditional variance is a function of an asymmetric lagged disturbance term. Thus, this model looks at leverage's impact on an asset's returns (Morawkage, 2015). It is essentially used in financial econometrics to capture either negative or positive shocks that may arise from volatility. The EGARCH model is mainly used for time series analysis.

A few researchers have used the EGARCH model to analyze electricity price volatility. Pereira da Silva and Horta (2019) used this approach in their research focused on " investigated the effect of variable renewable energy sources on electricity price volatility in the Iberian market. "This research thus adopts this approach as used by Pereira da Silva and Horta (2019) in its analysis of electricity price volatility in Nordic countries. However, instead of the AR structure and the seasonal dummies used by Pereira da Silva and Horta (2019), this research uses the SARIMA pattern to develop a SARIMA model upon which an EGARCH conditional volatility is derived and used for the analysis.

$$ln\, VEP_t = \beta_1 + ln\, \beta_2\, RE_t + ln\, \beta_3\, PC_t + ln\, \beta_4\, TP_t + ln\, \beta_5\, Gas\_P_t + +ln\, \beta_7\, WL_t + \varepsilon_t$$

$$log(\sigma_t^2) = \omega + \alpha_t \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \gamma \frac{\varepsilon_{t-k}}{\varepsilon_{t-k}} + \beta \ln\,(\sigma_{t-1}^2) + \tau\, ln\, RE_t + \tau\, ln\, PC_t + \tau\, lnTP_t + \tau\, ln\, Gas\_P_t +$$

$$+\tau\, ln\, WL_t$$

The omega (γ), alpha (α), and beta (β) coefficient will be estimated to see if the model fit. Based on that, conditional volatility residuals will be used for further estimation.

3.6.5 Multivariate Ordinary Least Square

The relationship between Nordic countries' wind and solar production and electricity price volatility is analyzed using a multivariate Ordinary Least Square method. Also, the impact will help to know how an increase in renewable production, that is, wind and solar, has affected electricity volatility in the past. The resulting relationship will help to accept the Null or Alternative hypothesis of hypothesis. The conditional volatility will be the dependent variable for the multivariate models below. However, depending on the country's characteristics, some variables will be added or subtracted.

$$Cond\_ln\, VEP_t = \beta_1 + ln\, \beta_2\, Wi_t + ln\, \beta_3\, So_t + ln\, \beta_4\, PC_t + ln\, \beta_5\, TP_t + ln\, \beta_6\, Gas\_P_t + ln\, \beta_7\, WL_t + \varepsilon_t$$

3.7 Tools for Data Analysis

All the above analyses and data visualization will use Python as the data analysis tool.

Chapter Four

Data Analysis

4.1 Introduction

This chapter undertakes data analysis and data diagnostics. The data collected is analyzed in this chapter by considering the study's objectives. Various tests are undertaken here, including unit root tests for serial correlation and autocorrelation. This chapter also examines decisions based on the hypothesis to meet this research's objective.

4.2 Pearsons Correlation Matrix

To ascertain the relationship between the variables, the correlation of the variables with each other is taken. This is also done to avoid the study's outcome being spurious due to multicollinearity. The Pearson Correlation Matrix heat map was taken for the variables of the four countries. The result is illustrated in the figures below.

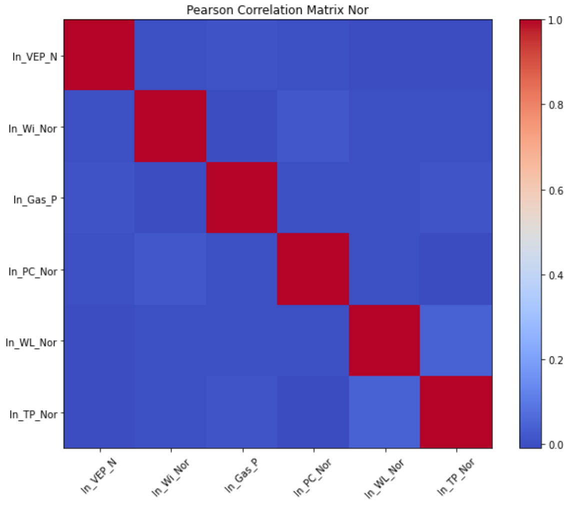


Figure 4.1: **Correlation Matrix Norway**

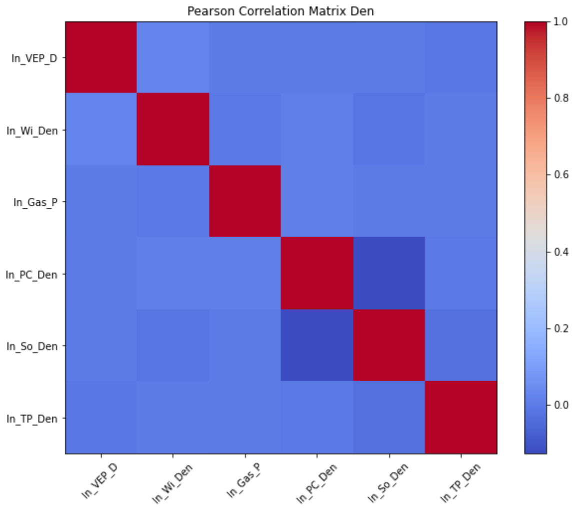


Figure 4.2: Correlation Matrix for Denmark

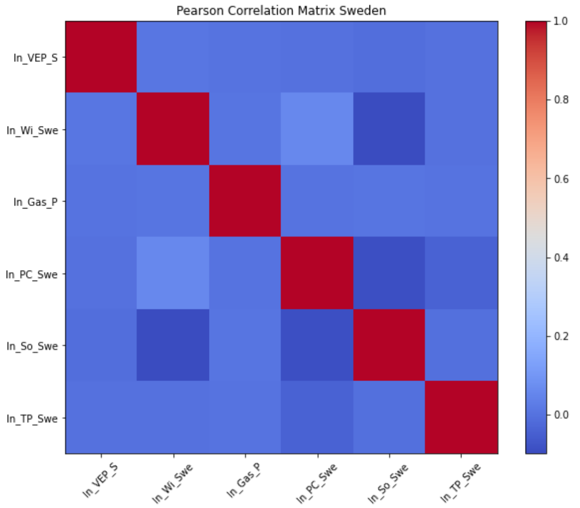


Figure 4.0.3: Correlation Matrix Sweden

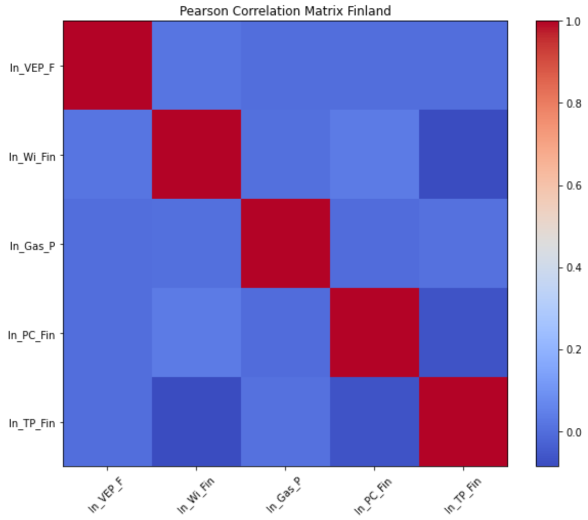


Figure 4.4: Correlation Matrix for Finland

All the above figures have some strongly correlated variables, while the others are with each other. At the same time, some of the variables show a negative correlation with each other. The only exception of strong positive correlation is the variables and themselves, shown in a diagonal form in red in all four Figures.

The relationship between wind and solar power integration and the volatility of electricity prices for the various countries are also expressed as follows. For Norway, shown in Figure 4.1, a strong negative correlation is seen between the integration of wind power and the volatility of electricity prices in Norway. On the other hand, Finland exhibits a negative correlation between wind power integration into the electricity mix and the volatility of the electricity prices. For Denmark, a negative correlation is observed between solar and wind power integration and the volatility of electricity prices. This color is not as deep blue as the strong negative relationship seen with wind power integration and volatility of electricity prices for Norway and Finland. This is the same for Sweden, which exhibits a negative correlation between solar and wind power integration and the volatility of electricity prices.

Therefore, in terms of the correlation heat map, there is a correlation between solar and wind integration into the energy mix.

4.3 SARIMA Models Results

The output of the SARIMA models is presented below for the four countries. Two countries' models are combined in a table each. The coefficients and the P-values are used to explain the outputs of the respective models below.

4.3.1 SARIMA Model for Norway and Denmark

Table 4.1 shows the coefficient and P-values of the SARIMA models for Norway and Denmark.

Table 4.1: SARIMA Model for Norway and Denmark

Country	**Norway**			**Denmark**	
Variable	ln_VEP_Nor			ln_VEP_Den	
Model	SARIMA (1, 0, 2) (1, 0,2,24)		SARIMA (1, 0, 1)(1, 0, 1, 24)		
	Coefficient	**P-Value**		**Coefficient**	**P-Value**
ar.L1	0.8692	0.000	**ar.L1**	-0.1878	0.000
ma.L1	-0.8776	0.000	**ma.L1**	-0.3272	0.000
ma.L2	0.0457	0.000	**ar.S.L24**	0.1150	0.000
ar.S.L24	0.0110	0.861	**ma.S.L24**	-0.2350	0.000
ma.S.L24	-0.2580	0.000			
ma.S.L48	-0.0356	0.023			
sigma2	0.0003	0.000	**sigma2**	0.0049	0.000

Authors Construct (2023)

Table 4.1 shows that Norway used SARIMA (1, 0, 2) (1, 0,2,24), while Denmark used SARIMA (1, 0, 1) (1, 0, 1, 24). These were based on the best-performing AIC model and seasonal pattern used to arrive at the models' output. Both models also show various lags for AR and MA.

Norway

The **ar.L1** for Norway shows a strong positive correlation of 0.8692 for the current price and its past values. This was found to be significant under the 1 percent significance level. This implies that the past values of electricity prices strongly influence the current volatility of electricity prices for Norway. In the case of the **ma.L1** an **ma.L2** for Norway, a strong negative correlation was found between the past forecast errors and the current volatility of electricity prices. At the same time, a weak positive correlation was found between the past forecast errors, the second lag, and it predicts the current volatility of electricity prices in the case of ma.L2, which was 0.0457. Both were found to be significant under a 1 percent significance level.

Another aspect of the SARIMA is that it looked at how seasonality affected volatility. A value of 0.0110 for **ar.S.L24** shows that the current value of the electricity price volatility in Norway positively influences the current by a small margin in 24 hours, which means that the past 24 hours' price weakly affects current prices. However, this is not significant under 0.05 significance level.

Regarding the moving average of seasonal lag, a value of -0.2580 for **ma.S.L24** shows that the influence of past forecast errors in electricity prices in the last 24 hours on current electricity prices will be negative but small. Also, the value of -0.0356 for ma.S.L48 shows a minimal negative influence of past forecast errors of electricity price 48 hours ago on the current price. Even though these values were found to be minimal, they were also found to be significant under 5 percent significant levels. Finally, the model has 0.0003 as its sigma value which is almost zero, in other words. This implies that the SARIMA models' predictions are closer to the actual point and hence a better fit.

Denmark

In the case of Denmark, a weak negative correlation value of -0.1878 was found between the past values of electricity prices and the current value of electricity prices in the case of lag one of the autoregression. This was found to be significant under the 5 percent significance level. Regarding the moving average, ma.L1 value of -0.3272 exhibits a negative correlation between past forecast errors and current electricity prices. ma.L1 is found to be significant under 1 percent significant level. In the case of seasonal influence on current price, a value of 0.1150 for ar.S.L24 indicates that the past 24 hours price has a weak influence on current price. Also, ma.S.L24 value of -0.2350 shows that the past forecast error in the last 24 hours has a weak negative influence on current electricity prices. A sigma of 0.0049 shows the model is a better fit as it is close to zero. All the values in the above for Denmark's SARIMA model were found to be significant under 0.01 significant level, given 0.000 as the p-values.

4.3.2 SARIMA Model for Sweden and Finland

Using AIC ARIMA of (2, 1, 2) seasonal pattern of (2,1,2,24) for Sweden and AIC ARIMA of (2, 1, 2) and seasonal pattern of (0,1,0,24) for Finland to arrive at SARIMA models for Sweden and Finland, respectively. The models are found in Table 4.2 below.

Table 4.2: SARIMA Model for Sweden and Finland

Country	**Sweden**			**Finland**	
Variable	ln_VEP_Swe			ln_VEP_Fin	
Model	SARIMA (2, 0, 1)(2,0,1,24)			SARIMA (2, 0, 1) (2,0,1,24)	
	Coefficient	**P-Value**		**Coefficient**	**P-Value**
ar.L1	0.8248	0.00	**ar.L1**	0.8707	0.000
ar.L2	0.0725	0.00	**ar.L2**	0.0267	0.000
ma.L1	-0.8860	0.00	**ma.L1**	-0.8761	0.000
			ar.S.L24	0.0730	0.000
ar.S.L24	-0.0475	0.00	**ar.S.L48**	0.0177	0.000
ar.S.L48	-0.0202	0.00	**ma.S.L24**	-0.4606	0.000
ma.S.L.24	-0.3774	0.00			
Sigma2	0.0008	0.00	**sigma2**	0.0007	0.000

Authors Construct (2023)

Sweden

The ar.L1 and ar.L2 for Sweden showed a strong negative correlation and weak positive influence of the past values on its current values. The ma.L1 showed a strong negative correlation between past forecast errors and the current volatility of electricity prices. All these were found to be significant under 1 percent significant level.

In terms of the seasonal influence, the ar.S.L24 and ar.S.L48 had a weak influence when looking at how the past 48 hours influenced current prices. However, the reverse is the case for the moving average seasonal value. The ar.S.L24 showed that the past 24 hours' forecast of error of price has weak minimal influence on determining the current price. A sigma of 0.0008 shows that the model is a better fit. They were all found to be significant under a 1 percent significance level.

Finland

Finland also had a strong positive ar.L1 and weak positive ar.L2 of past price influence its current prices. In the case of the moving average variables, a weak negative and negative correlation is found between past forecast error values and the volatility of prices for ma.L1.

In terms of the seasonal influence on the current price, 24 hours ago price and 48 hours prices had weak positive influence on determining the current price. However, ma.S.L24 showed that the past 24 hours' forecast error negatively influenced determining current electricity prices. These were all found to be significant under a 1 percent significance level.

The ARIMA residuals are graphically shown in Figure 4.5, Figure 4.6, Figure 4.6, and Figure 4.7 for Norway, Denmark, Sweden, and Finland, respectively.

4.3.3 Fitness of the Model

The Mean Square Error and Mean Absolute Errors are estimated to determine the model's performance. A lower MSE and MAE imply that the model is a better fit, and the reverse is true. The estimation of the models for the various countries is shown below in Table 4.3.

Table 4.3: Fitness of the Model

	MSE	**MAE**
Norway	0.0003	0.0029
Denmark	0.0049	0.0131
Sweden	0.0008	0.0078
Finland	0.0007	0.0007

Authors Construct (2023)

The MSE and MAE values estimated for all the countries are very low, approaching zero. This implies that the models used to predict the residuals fit well.

4.3.4 SARIMA Residuals

Based on the above models, the following residuals are obtained and plotted as seen below.

SARIMA Residuals for VEP Norway

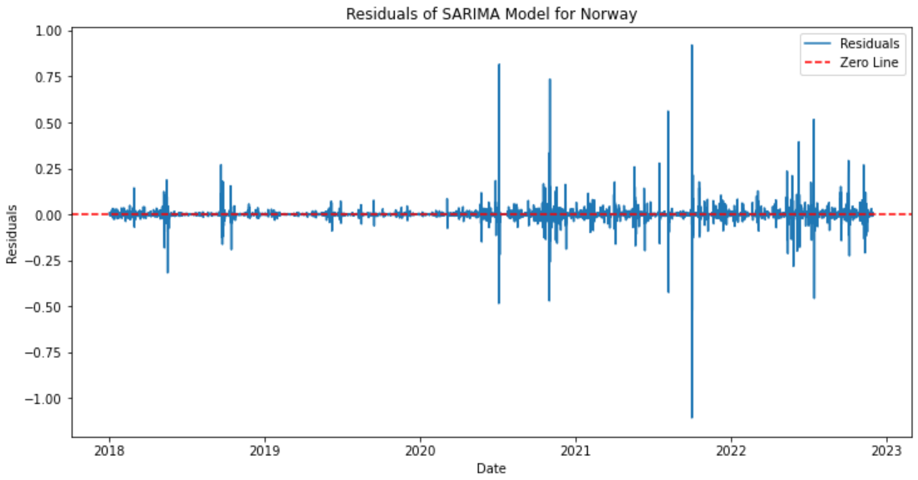


Figure 4.5: SARIMA Residuals VEP Norway

SARIMA Residuals for VEP Finland

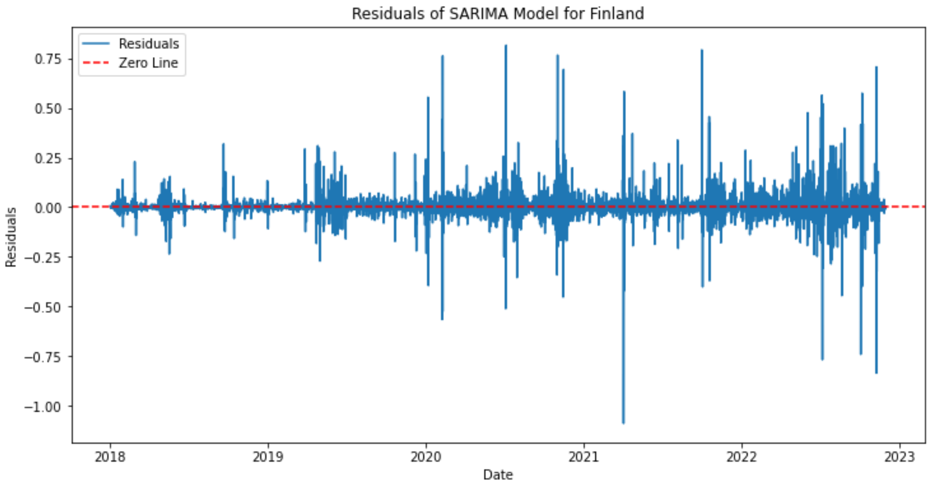


Figure 4.6: SARIMA Residuals for VEP Finland

SARIMA Residuals for VEP Denmark

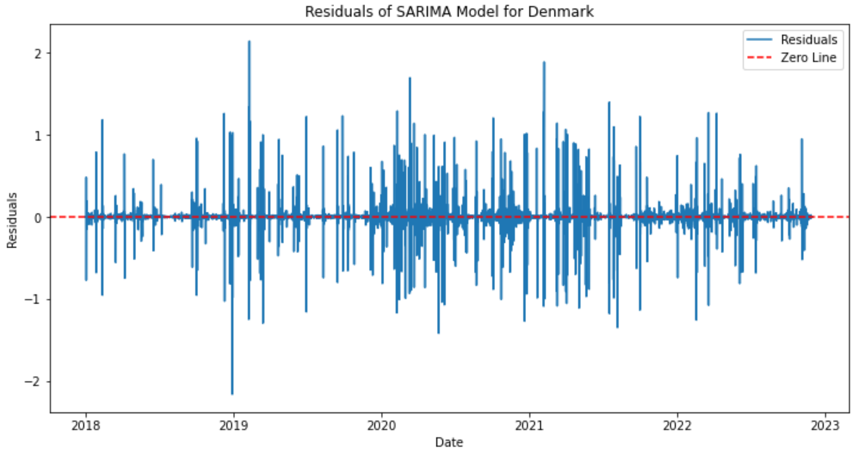


Figure 4.7: SARIMA Residuals VEP Denmark

SARIMA Residual for VEP Sweden

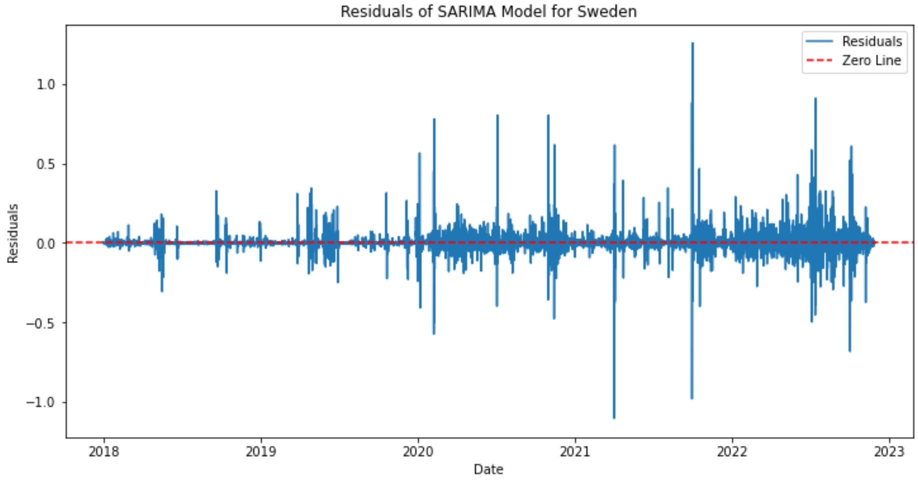


Figure 4.8: ARIMA Residuals VEP Sweden

4.4 EGARCH Model Results

The EGARCH results based on the SARIMA models for the countries are presented and explained below.

Table 4.4 shows the EGARCH results for Norway and Denmark. Also, Table 4.5 shows the EGARCH model results for Sweden and Finland.

Table 4.4: Constant Mean and Volatility EGARCH Results Norway and Denmark

	Norway		**Denmark**	
	Coefficient	**P>|t|**	**Coefficient**	**P>|t|**
Mean Model				
Mu	-0.0002	0.003	-0.002	0.000
Volatility Model				
Omega	0.0083	0.763	-0.2857	0.396
alpha (1)	0.3421	0.000	1.2922	0.000
beta (1)	0.9855	0.000	0.8232	0.000

Authors Construct (2023)

Table 4.5: Constant Mean and Volatility EGARCH Results Norway and Denmark

	Sweden		**Finland**	
	Coefficient	**P>|t|**	**Coefficient**	**P>|t|**
Mean Model				
Mu	0.00003	0.565	0.0002	0.386
Volatility Model				
Omega	-0.1424	0.012	-0.1447	0.011
alpha (1)	0.0975	0.000	0.0786	0.000
beta (1)	0.9800	0.000	0.980	0.000

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4.4.1 Mean model

From Table 4.4, the constant mean (mu) for the volatility of electricity prices for Norway is negative 0.0002, and that of Denmark is -0.002. This indicates that the average volatility of electricity prices in Norway and Denmark is negative. These values are close to zero. The constant mean coefficients are statistically significant for Norway and Denmark at a 0.01 significance level.

From Table 4.5, the volatility of electricity prices of Sweden's mean is 0.00003, while that of Finland is 0.0002. The constant mean for Finland and Sweden were found not to be significant under 0.05 significant level. This indicates that the average volatility of the electricity prices for Sweden and Finland is nearly zero.

4.4.2 Volatility Model

Also, Table 4.4 shows the volatility model for Norway and Denmark. For the omega, 0.0083 and -0.2857 coefficients show that the experience of the shock by Norway and Denmark led to the volatility decay over time. They were all found to be insignificant.

For the volatility, which looks at how past shocks account for current volatility, the alpha values of 0.3421 and 1.2922 for Norway and Denmark, the value for Norway indicates that past values have little effect on current prices. At the same time, Denmark suggests that past shocks significantly impact current volatility. While Denmark's value is above 1, Norway's value is close to zero. The alpha values for the two countries were all significant at a 1 percent significance level.

The beta coefficient of 0.9855 for Norway and 0.8232 for Denmark, which are close to 1, indicates a robust asymmetric relationship. These are all significant under 0.01 significant levels.

Table 4.5 also shows the volatility model for Sweden and Finland. An omega coefficient of -0.1424 and -0.1447 for Sweden and Finland shows a weak negative shock of the past values on the current volatility of prices. This shock may decay over time. This indicates a lower baseline for both volatility in the electricity price value of Sweden and Finland.

The alpha values of 0.0975 and 0.0786 for Sweden and Finland, respectively, show that past values of volatility in electricity prices weakly positively account for the current electricity prices. Both alpha coefficients are found to be significant under a 1 percent significance.

The beta coefficient values of 0.980 for Finland and Sweden show a strong symmetric relationship. The positive beta shows that adverse price shocks have a higher impact on the volatility of electricity prices.

In summary, the EGARCH model has been fitted to the volatility of electricity prices for Norway, Denmark, Sweden, and Finland. It can be inferred that past shocks may influence the current volatility of electricity prices in the countries under consideration. An asymmetric reaction because of negative and positive shocks can be implied. The original data is plotted against the fitted values and shown in the appendix for the various countries.

4.4.3 EGARCH Conditional Volatility and Standard Residuals Plots

The conditional and standardized residuals for Norway, Denmark, Sweden, and Finland are graphically shown below.

A. EGARCH Conditional and Standardized Residuals for Norway

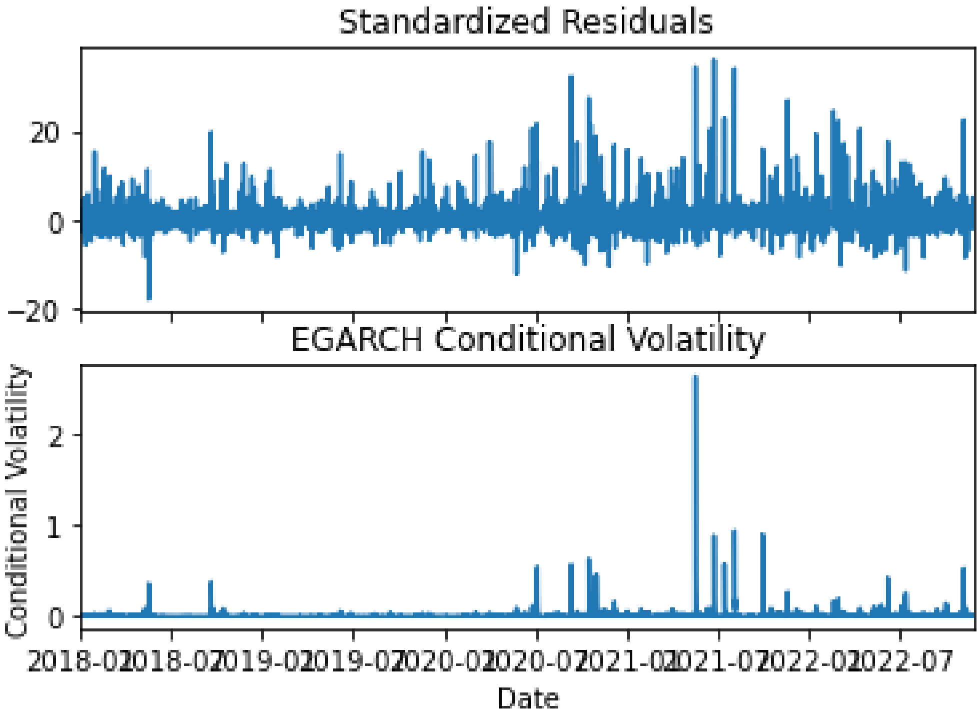

Figure 4..9: Standardized Residuals Conditional Volatility Norway

B. EGARCH Conditional and Standardized Residuals for Denmark

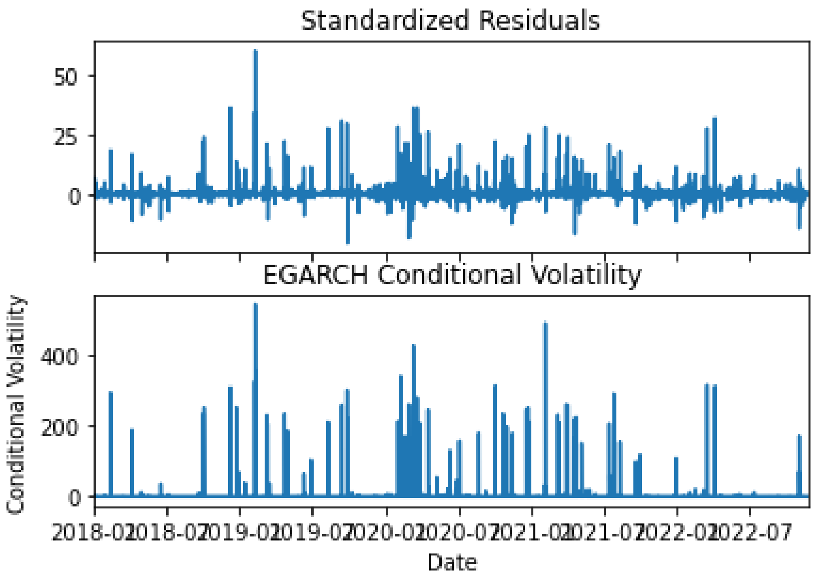

Figure 4.10: Standardized Residuals and Conditional Volatility Denmark

C. EGARCH Conditional and Standardized Residuals for Sweden

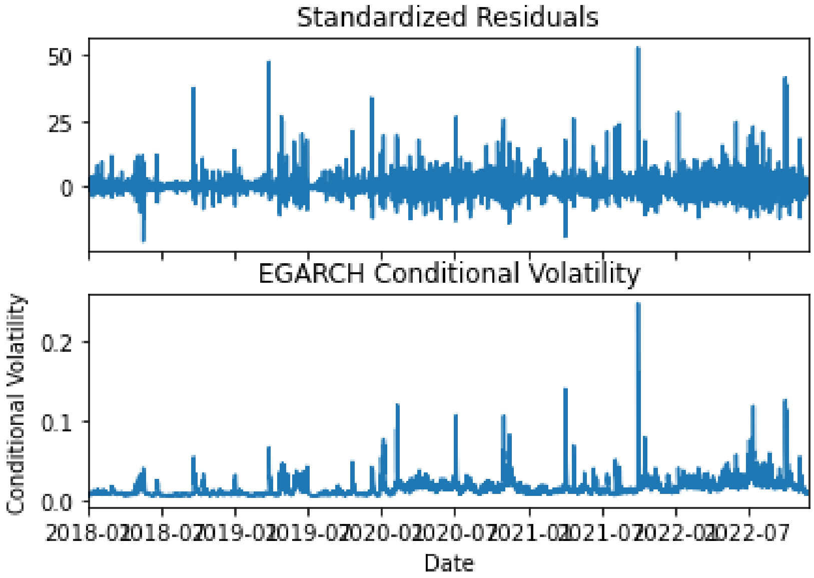

Figure 4..11: Standardized Residuals and Conditional Volatility Sweden

D. EGARCH Conditional and Standardized Residuals for Finland

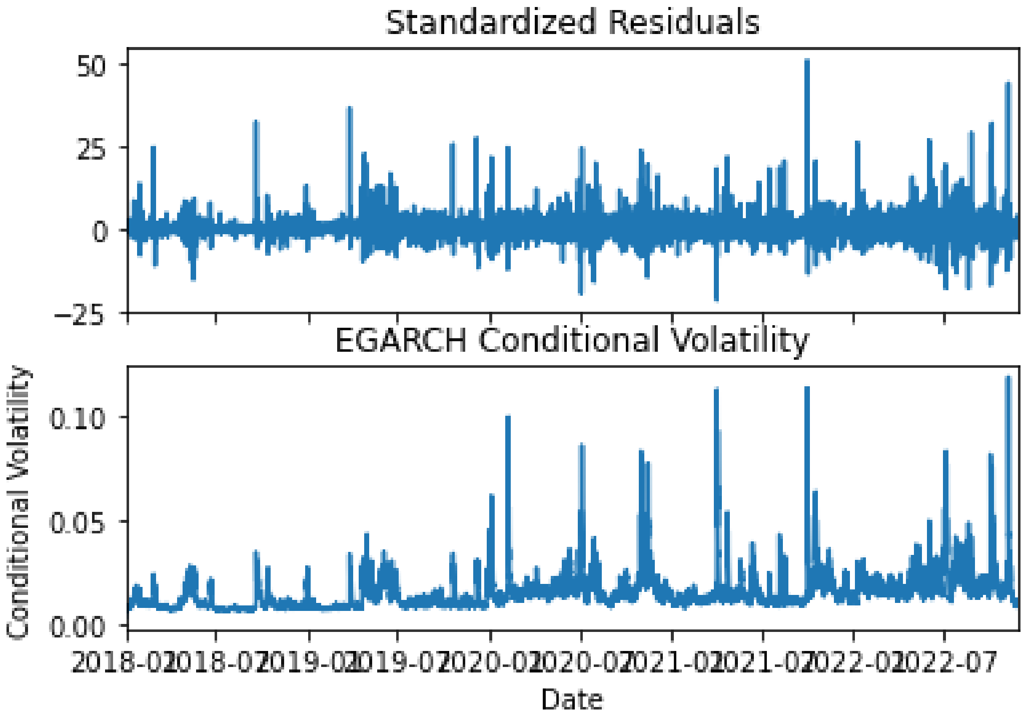

Figure 4.12: Standardized Residuals and Conditional Volatility Finland

4.5 Multivariate Ordinary Least Square Results

The research used a multivariate Ordinary Least Square regression to examine the effect of the exogenous variables on the conditional volatility of electricity prices for each country. The results are presented below in Table 4.6 and Table 4.7.

Table 4.6: OLS Results for Norway and Finland

	Norway		Finland	
	Coefficient	**P-Value**	**Coefficient**	**P-Value**
Constant	0.0088	0.000	0.0150	0.000
ln_Wi	0.0003	0.494	0.0003	0.106
ln_Gas_P	-0.0072	0.846	0.0119	0.116
ln_PC	-0.0170	0.000	-0.0078	0.000
ln_TP	0.0014	0.000	0.0003	0.180
ln_WL	0.0366	0.022		
Dependent Variable	Cond_Vol_Nor			Cond_Vol_Fin

R-Square	0.002	0.001
Adj. R-Squared	0.002	0.001
F-Statistics	20.00	8.864
Prob (F-Statistics)	0.000	0.000

Authors Construct (2023)

Norway

Table 4.6 shows a positive relationship between wind production, temperature, and water level in Norway. In contrast, a negative relationship between Gas prices and Power consumption is observed. A percentage increase in the integration of wind power into the energy mix leads to a 0.00003 percent increase in the conditional volatility of electricity prices. Also, a percent increase in water level and temperature leads to a 0.0366 percent increase and a 0.0014 percent increase in conditional volatility of electricity prices. On the other hand, a percentage increase in Gas price and Power Consumption leads to 0.0072 and 0.0170 percent decrease in conditional volatility of electricity prices. While Power Consumption, Temperature, and Water Level were all significant under 1 percent and 5 percent significance level, Gas price and wind were not significant.

Finland

Also, from Table 4.5, there is a positive relationship between wind power integration into the energy mix, Gas prices, temperature, and conditional volatility of electricity price. At the same time, a negative relation is observed between power consumption and conditional volatility of electricity prices in Finland. Also, a percent increase in wind power integration into the energy mix will increase the conditional volatility of electricity prices by 0.0003 percent. A percentage increase in Gas Prices and Temperature will result in a 0.0119 and 0.0003 percent increase in conditional volatility of electricity prices for Finland. Conditional volatility of electricity prices will reduce by 0.0078 percent when there is a percentage increase in power consumption in Finland. Wind power integration into the energy mix and Power Consumption were found n significant under a 0.10 significance level, and the rest of the variables were not significant under a 0.01 significance level.

Table 4.7: OLS Results for Sweden and Denmark

	Sweden		Denmark	
	Coefficient	**P-Value**	**Coefficient**	**P-Value**
Constant	0.2536	0.000	-0.6941	0.020
ln_Wi	0.0002	0.562	0.1766	0.000
ln_So	-0.00001	0.132	-0.0655	0.057
ln_Gas_P	-0.0009	0.929	-0.6030	0.948
ln_PC	-0.0056	0.000	-0.8453	0.329
ln_TP	0.0009	0.000	-0.1485	0.579
Dependent Variable	Cond_Vol_Swe			Cond_Vol_Den
R-Square	0.010			0.000
Adj. R-Squared	0.010			0.000
F-Statistics	90.27			4.270
Prob (F-Statistics)	0.000			0.000

Authors Construct (2023)

Sweden

From Table 4.7, a positive relationship is observed between wind power integration into the energy mix and conditional volatility of electricity prices. The exact relationship between temperature and conditional volatility of electricity prices is observed. A negative relationship is observed between Gas price, Solar Power and Power Consumption, and the Conditional volatility of electricity prices. A percentage increase in wind power integration will lead to a 0.0002 percentage reduction in the conditional volatility of electricity prices. Also, a percentage increase in solar power integration into the energy mix will lead to a 0.0001 percentage reduction in the conditional volatility of electricity prices. A decrease of 0.0056 percentage is expected in conditional volatility of electricity prices because of a percentage increase in Power consumption. Also, a percentage increase in Gas price and Power Consumption will lead to a 0.0009 and 0.0056 decrease in the Conditional volatility of electricity prices. Apart from temperature and Power Consumption, which were found to be significant under a 5 percent significance level, the rest of the variables were not significant.

Denmark

Table 4.7 shows a positive relationship between wind power and the conditional volatility of electricity prices. At the same time, a negative relationship is seen between Gas Price, Power consumption, and temperature. A percentage increase in solar power integration into the energy mix will lead to a 0.0655 percent decrease in the conditional volatility of electricity prices. Also, a percentage increase in wind power integration into the energy mix will lead to a 0.1766 percent increase in conditional volatility of electricity prices for Denmark. However, the Conditional volatility of electricity prices is expected to decrease by 0.6030 percent, 0.8453 percent, and 0.1485 percent because of a percentage increase in Gas price, Power Consumption, and Temperature, respectively. Solar and wind power integration were significant under a 5 percent significance level, while the rest of the independent variables were insignificant.

4.6 Relationship Between Wind and Solar Power Integration and Volatility of Electricity Prices

Firstly, we discuss the inference made from the correlation coefficient heat map used to ascertain the relationship between wind and solar power integration and volatility. The result shows a strong negative correlation between wind power integration and the volatility of electricity prices for both Norway and Finland. Also, a negative correlation exists between wind and solar power, integration into the energy mix, and the volatility of electricity prices in Denmark. This shows a relationship between solar and wind power integration into the grid and the volatility of electricity prices. However, this relationship is negative. This implies that an increase in the integration of solar and wind power into the grid will reduce the volatility of electricity prices, and the opposite is true. But it's inconclusive to make this decision by just looking at the correlation heat map outputs.

To determine the relationship, we look at the results from the multivariate ordinary least square of the conditional volatility of electricity prices as dependent against wind and solar and other endogenous variables that affect electricity prices, as seen above. The results are summarized as follows.

- A positive relationship is seen between wind power integration and conditional volatility of electricity prices in Norway. This was not significant under the 5 percent significance level.

- A positive relationship is seen between wind power integration and conditional volatility of electricity price in Finland. This was significant under 10 percent significance level.
- A positive relationship was found between wind power integration and conditional volatility of electricity prices in Denmark. A negative relationship was also found between solar power and Conditional volatility of electricity prices in Denmark. These were all found to be significant under a 5 percent significance level.
- A negative relationship was found between solar power integration and conditional volatility of prices for Sweden. This was found to be insignificant under a 5 percent significance level. A positive relationship was found between wind power integration and conditional volatility of electricity prices. This was found to be insignificant under the 1 percent significance level.

From the above, there is a relationship between solar power and wind power integration, and this is significant in most cases, apart from the case of Norway and Sweden, which had wind and solar power integration into the energy mix as insignificant.

Therefore, the null hypothesis that no relationship exists between wind and solar power integration and the volatility of electricity prices in Denmark is rejected. Also, the null hypothesis that no relationship exists between wind power integration and the volatility of electricity prices in Norway is not rejected. Regarding Finland, the null hypothesis that no relationship exists between wind power integration and the volatility of electricity prices in Denmark countries is rejected. The null hypothesis that no relationship exists between wind and solar power integration and the volatility of electricity prices in Sweden is not rejected.

4.7 Impact of Hourly Integration of solar and wind power electricity price volatility.

To find the impact of hourly integration of solar and wind power on the volatility of electricity prices, the following was as part of the multivariate OLS results.

- A percentage increase in wind power integration will lead to a 0.0003 percent increase in conditional electricity prices for Norway. This was, however, found not to be significant.
- A percentage increase in wind power integration will lead to a 0.0003 percent increase in conditional volatility of electricity prices for Finland. This was found to be significant.
- A percentage increase in wind power integration will lead to a 0.0002 increase in the conditional volatility of electricity prices for Sweden. Also, a percentage increase in solar

power integration will lead to a 0.00001 reduction in the conditional volatility of electricity prices in Sweden. While the impact of wind power integration was found to be insignificant, the impact of solar power integration was found to be statistically significant.

- A percentage increase in wind power integration will lead to a 0.1766 percent increase in conditional volatility of electricity prices. Also, a percentage increase in solar power integration will lead to a 0.0655 percent decrease in conditional volatility of the price. These were all found to be significant.

From the above, a little impact is seen by renewable energy on the conditional volatility of electricity prices. While some were significant under the various significance levels others remain insignificant. Therefore, integrating wind and solar power does affect the volatility of electricity prices.

The second null hypothesis of hourly integration of wind and solar power integration does not affect electricity price volatility is rejected for Denmark. Also, the null hypothesis of hourly integration of wind power integration does not affect electricity price volatility is rejected for Finland. For Sweden, the null hypothesis of hourly integration of wind and solar power integration does not affect electricity price volatility is not rejected. And finally, for Norway, the null hypothesis of hourly integration of wind power integration does not affect electricity price volatility is not rejected.

4.8 Discussion of Results

The results show varied relationships and effects based on country-specific. In the case of Norway, the result of no relationship and effects differs from the findings by Garland and Gjerde (2020), who found a positive relationship between wind and electricity price volatility. The variation in this result could be due to the methodology used and the study period. However, no significant relationship is expected between wind integration and the volatility of electricity prices in Norway. This is due to the percentage of wind power brought on board to complement the power from the hydro dams, which account for almost 96 percent of the total energy mix. Hence, the result is valid, looking at the above factors.

The no significant relationship results of wind power integration and electricity price volatility also vary from the findings of Wiredemi (2017), which found a long-term effect of wind on electricity price volatility. This difference may also emanate from the research period and methodology employed. While this research used an EGARCH approach to observing seasonal and autoregressive effects on the research outcome, Wiredem (2017) used a GARCH model. A disadvantage of the GARCH model is that it fails to account for adverse shocks, while the EGARCH accounts for the negative shock and can use that to generate a more robust estimate. Also, Sweden relies on other forms of fuel in addition to the wind to generate electricity. Therefore, with the result showing that an increase in power consumption and temperature account for volatility, it implies that the power generation authority in Sweden, the Swedish National Energy Administration, will call upon or highly depend on other forms of fuel when there is an increase in demand for electricity and or when the temperature changes. Regarding solar for Sweden, its integration into the Swedish national grid began in 2021. As such, looking at the research period, it was expected to have an insignificant effect on electricity price volatility.

In the case of wind production and its relationship and impact on Finland's electricity price volatility, a positive significant result shows that the wind is essential in their total energy mix, as such a recent investment into wind power production by Finland. The result also somehow agrees with Fränti (2009), who, among the results from research on large-scale wind effects on the electricity market, indicates that wind production and integration into the electricity market will lower spot prices. Meaning that wind integration has a significant impact in Finland, resulting in spot price decreases. This implies that lowering the spot price because of wind integration may reflect lower wholesale prices, all other equal things.

Finally, a positive relationship and impact of wind and solar on electricity price volatility for Denmark also differ from findings by Kyriaki (2022), who had differing outcomes. This could also be due to the difference in methodology. This research reflects the expected outcome due to the length of time Denmark has been using solar and wind power to produce electricity.

The outcome of the relationship between wind and solar power integration and electricity price volatility varies from country to country in the Nordic region. This could be because of several factors, including the period for the analysis, the composition of the electricity generation mix in the national grids, the electricity of power consumption, or demand for load, among others.

4.9 Variance Inflation Factor

To ensure that the models do not have multicollinearity, the independent variables do not correlate with each other, a Variance Inflation Factor is carried out for the independent variables used in the respective countries. The results are shown below in Table 4.8.

Table 4.8: Variance Inflation Factor

Variable	Norway	Denmark	Sweden	Finland
ln_Wi	1.00027100	1.000688	1.005172	1.00007
ln_Gas_P	1.000131	1.000118	1.000107	1.00015
ln_PC	1.000328	1.001207	2.681697	1.00029
ln_So	NA	1.000497	2.681802	NA
ln_TP	1.000829	1.000075	1.005163	1.00044
ln_WL	1.000688	NA	NA	NA

Authors Construct (2023)

The result from the variance inflation factor indicates that's, the correlation between the variables which could lead to multicollinearity of the model is very minimal for all the variables used to estimate the effect and impacts in the various models.

Chapter Five

Summary, Conclusions, and Recommendation

5.1 Introduction

This chapter summarizes the whole work from the first chapter to the fourth chapter and makes conclusions and recommendations based on the study's findings.

5.2 Summary

The research sought to look at how the integration of renewable energy, that is, wind and solar power, affect the volatility of electricity prices in Nordic countries. The study mainly assesses the relationship between wind and solar power integration and volatility of electricity prices and how hourly integration of solar and wind power impacts electricity price volatility in Nordic Countries.

The study employs a case study approach by purposively selecting the following trading areas: NO2, SE2, DK2, and F1, representing Norway, Sweden, Denmark, and Finland. The study uses secondary data collected from the ENTSO-E database using Python queries and TTF day-ahead benchmark natural Gas prices in Europe from Montel online database. The data underwent cleaning and preparation to ensure its usability. The volatility of electricity prices was estimated using a 24-hour rolling window as used in financial modeling.

To ensure that the data is stationary, an Augmented Dicky-Fuller unit root test and KSPP test were carried out. The research used the identified ARIMA pattern, best information criterion, and seasonal pattern to develop the SARIMA model. Based on the developed SARIMA model, an EGARCH model was used to estimate the conditional volatility of electricity prices. The conditional volatility of prices was used as the dependent variable for the multivariate OLS estimation.

The result showed that while solar power integration had a statistically negative relationship and effect in Denmark, it had no relationship in with electricity price volatility in Sweden. In the case of wind power, it had a significant positive relationship with volatility of electricity prices in Denmark and Finland. At the same time, insignificant relationships and effects were found for Sweden and Norway.

5.3 Conclusions

In conclusion, there is a varying relationship between wind and solar power integration and electricity price volatility. Also, even though an impact is seen, it is minimal. Therefore, even though the integration of renewable energy, a cheaper source of fuel, theoretically is supposed to lead to lower prices whenever it's integrated into the energy mix leading to volatility, it seems in the case of the Nordic countries under review over the stated period, its contribution to electricity price volatility is minimal. +

5.4 Recommendation

Countries that want to increase renewable energy in their energy mix should invest heavily to have the desire to lower prices, as the impact on electricity price volatility is negligible. Research should also look at how it impacts spot prices and affects consumers in the Nordic region. Also, future research using hourly data should invest in data wrangling as it may affect the outcome of the result.

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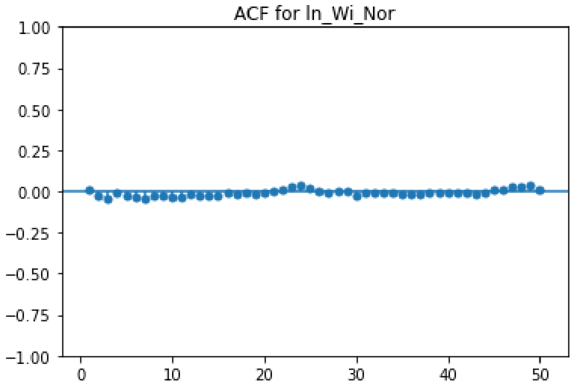
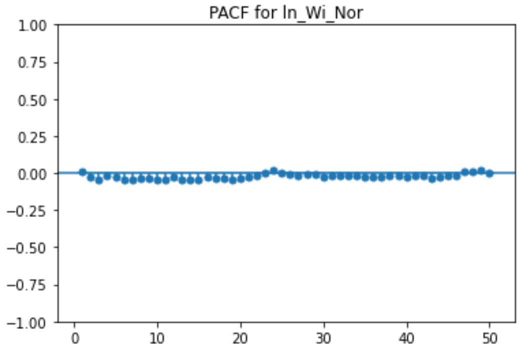
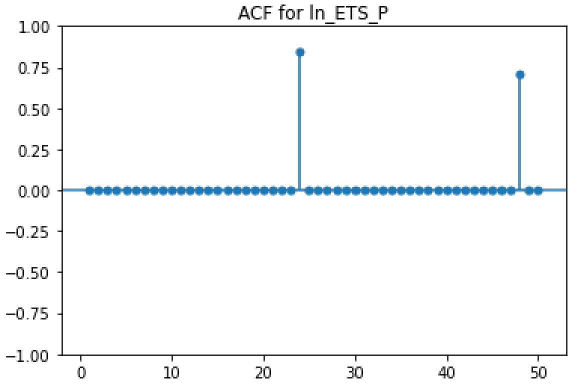
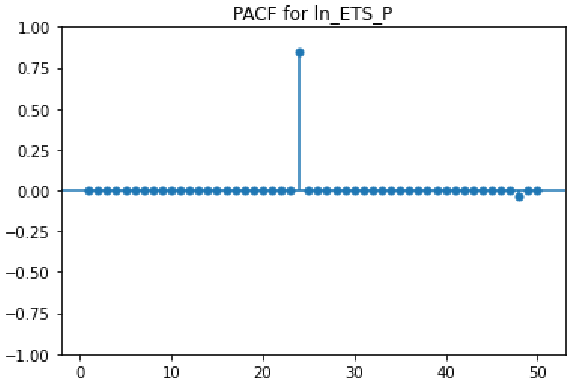
Appendix

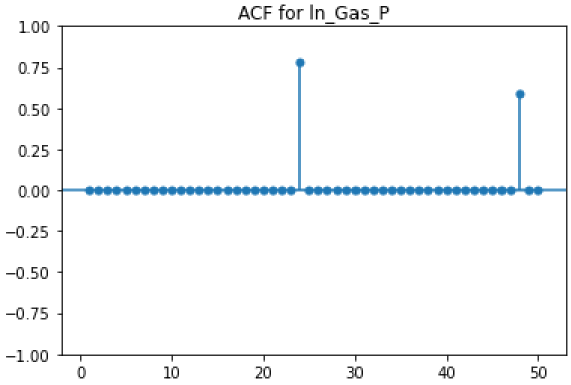
Appendix 1: ACF and PACF Plots

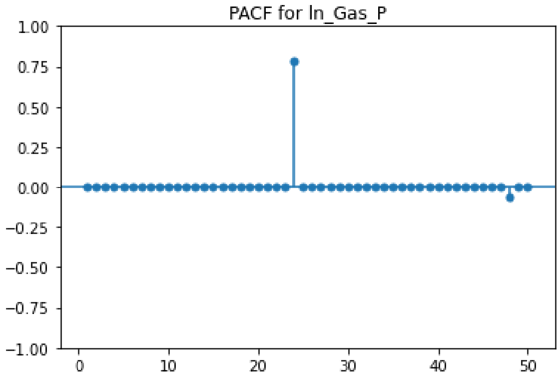


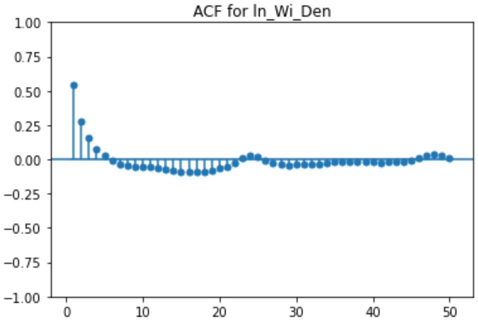








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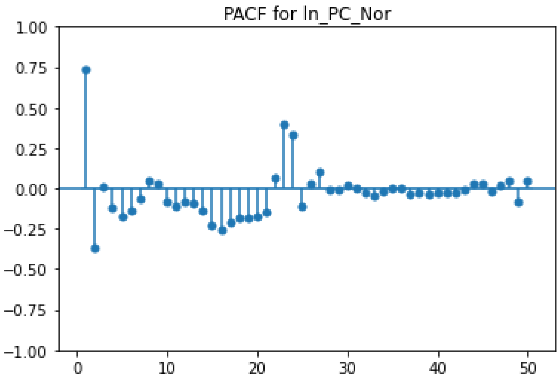
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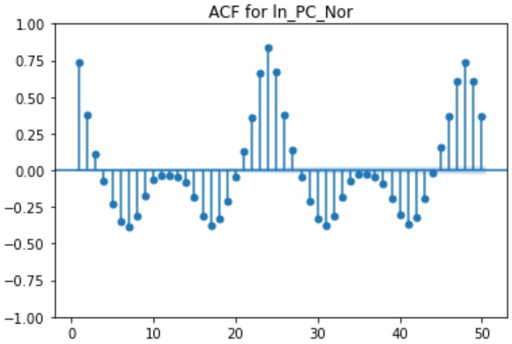
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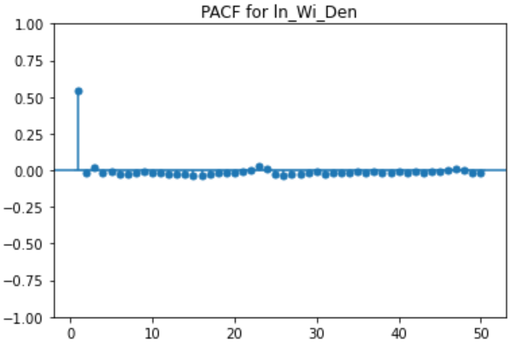
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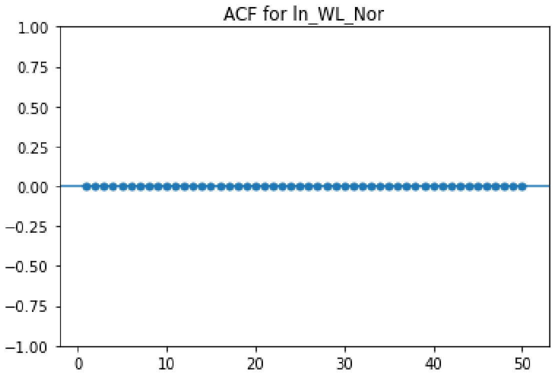
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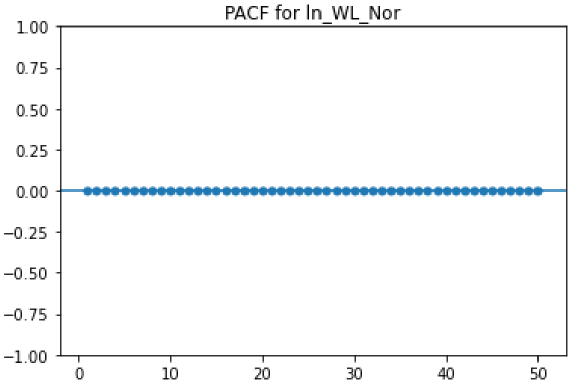
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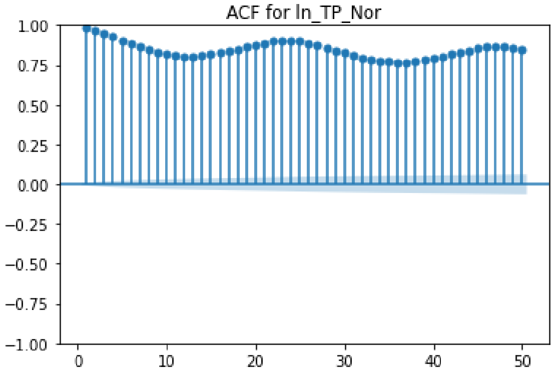
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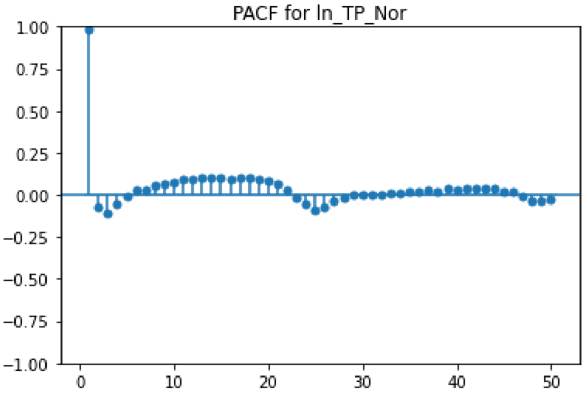
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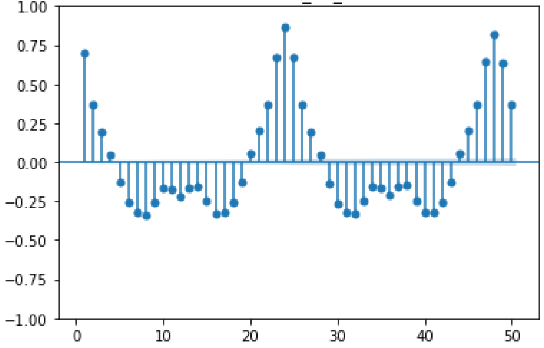
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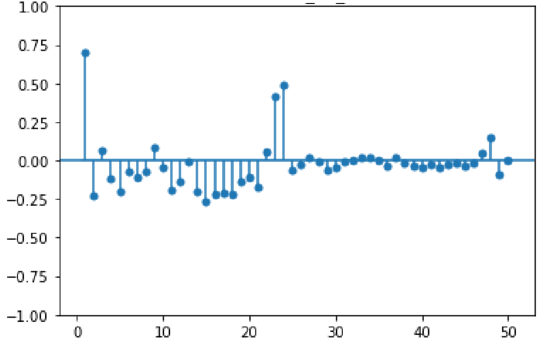
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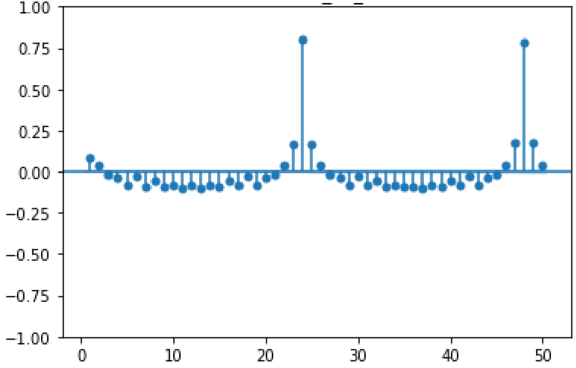
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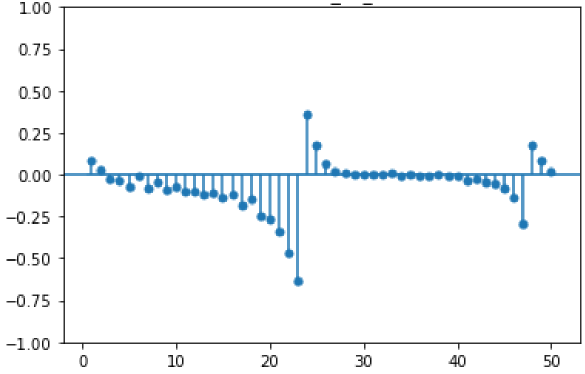
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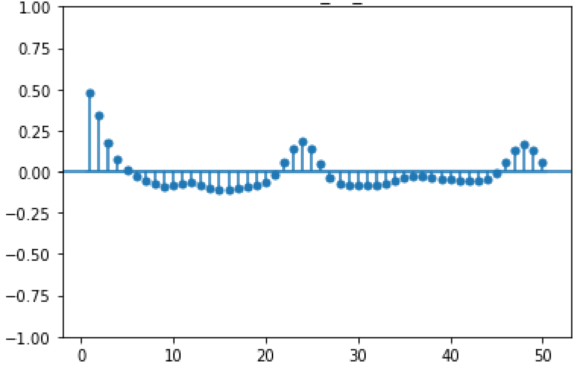
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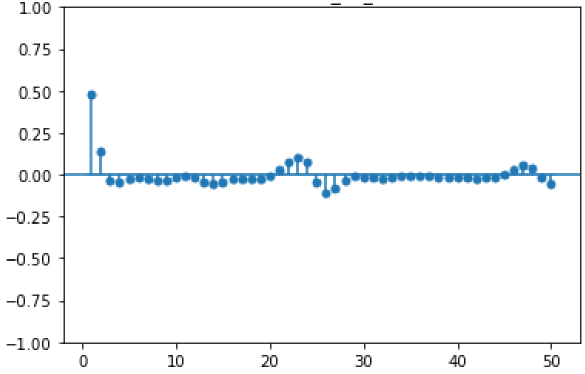
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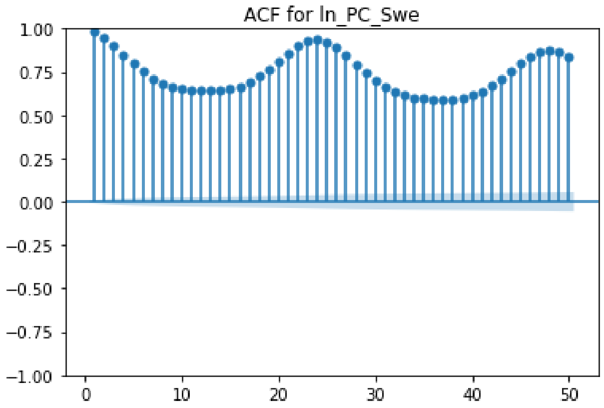
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0.00
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−1.00
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40
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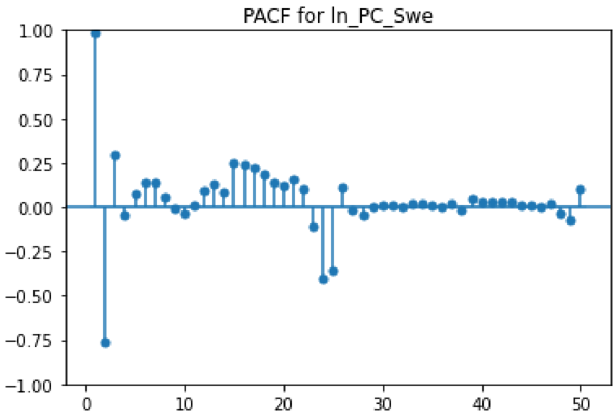
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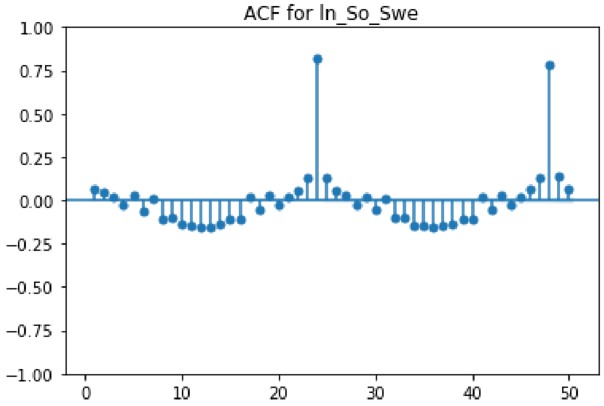
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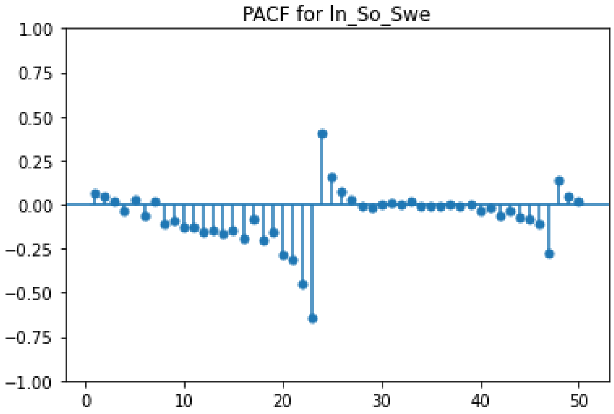
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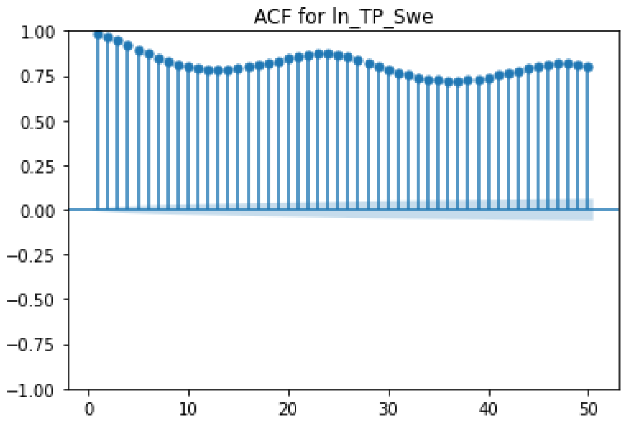

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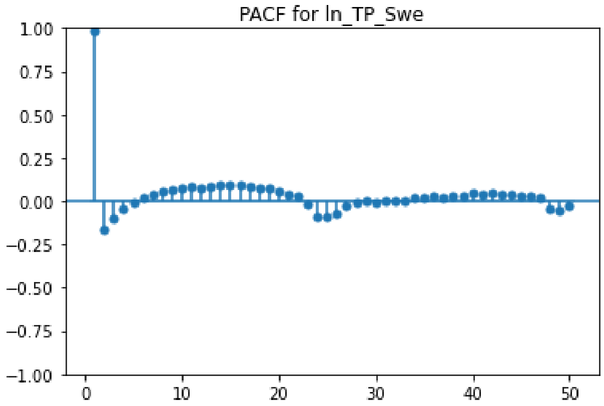
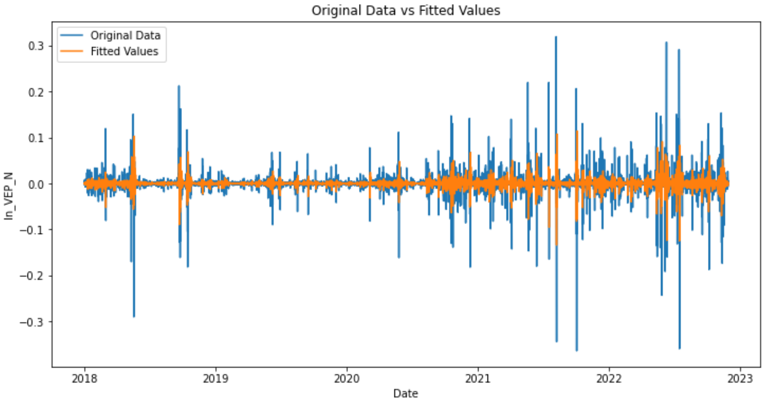


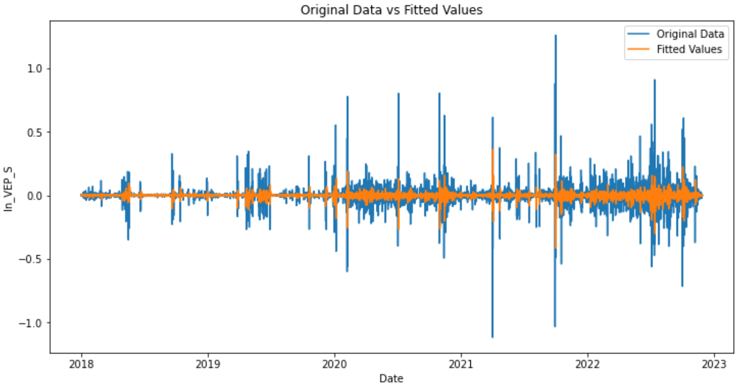
PACF for ln_TP_Swe

Appendix 2: Original versus Fitted Plots

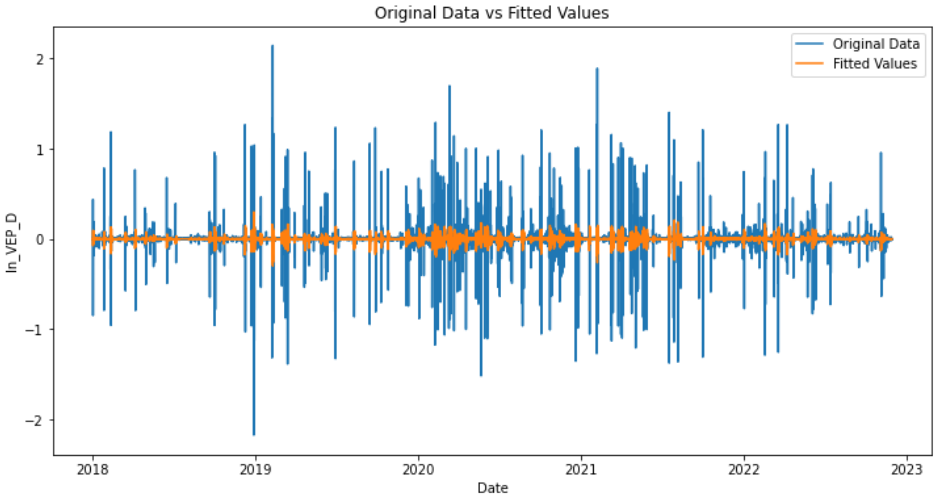
Original versus Fitted for Norway



Original versus Fitted for Sweden



Original versus Fitted for Denmark



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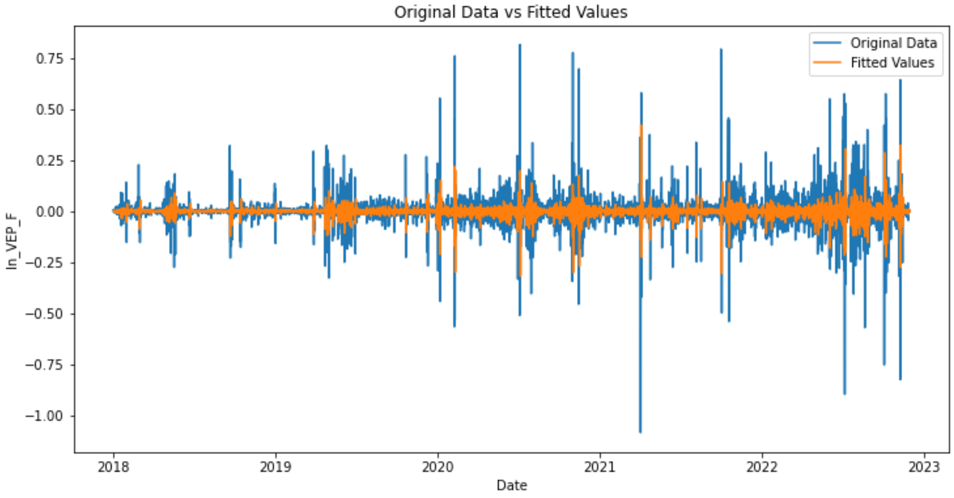

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