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Exploring the Impact of Brent Spot Prices, Interest Rates, and Electricity Costs on Vehicle Registrations in Norway

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Thank you!

Abstract

This thesis investigates the correlations and potential long-term relationships between vehicle registrations in Norway and several economic indicators, including Brent spot prices, interest rates, and electricity costs. Utilizing Vector Autoregressive (VAR) and Vector Error Correction Model (VECM) analysis, this study explores how these economic variables influence the fluctuations and trends in the registration of vehicles, particularly electric vehicles, in the Norwegian market. The analysis confirmed the existence of at least one long-term relationship, with some models indicating up to two, demonstrating significant impacts of these economic factors on vehicle registrations. The most robust findings were produced by models that excluded outliers, which not only showed the strongest long-term relationship between vehicle registrations and interest rates but also offered the highest forecasting accuracy. This study not only illuminates the dynamics between economic factors and vehicle registrations but also contributes to the understanding of consumer behavior in response to the shift from fossil fuel vehicles to electric vehicles.

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1 Introduction

1.1 Motivation

The impetus for this research originated from an interview discussing the importation of vehicles into Norway, which piqued an interest in examining the interplay between vehicle registrations and various economic variables. As noted by the interviewee, Jon Winding-Sørensen co-founder of Bilforlaget AS, in the podcast “Tid er penger” (2023), there exists a notable gap in scholarly inquiry focused on the dynamics of vehicle imports in Norway. This gap in research is particularly significant in light of recent developments, including the inundation of Norwegian docks with newly imported cars at the onset of 2023, coupled with the government’s incentives aimed at fostering the adoption of electric vehicles. These factors collectively underscores the necessity to delve deeper into how vehicle registrations correlate with multiple economic indicators.

Norway’s vehicle market presents a unique case study distinct from global trends, primarily due to its accelerated transition towards electric vehicles. According to the trend analysis shown in Figure 2.2, electric vehicles constituted approximately 81% of all new vehicle registrations in 2023, a shift largely attributed to the Norwegian government's robust policies promoting electric vehicle adoption (Alsaadi, 2019). The government’s ambitious target is for all new vehicles registered in Norway to be zero-emission by 2025 (Samferdselsdepartementet, 2019). The subsequent chapter will explore the mechanisms through which the government has achieved such high rate of electric vehicle integration alongside the historical and current examination of the trends in the Norwegian vehicle market.

This study aims to ascertain the presence or absence of correlation between the registration of new vehicles and a variety of economic factors deemed pertinent to the Norwegian vehicle market. By doing so, it intends to establish a foundational reference that will facilitate future research endeavors within this specific market context.

1.2 Research Question

This thesis investigates the interactions between vehicle registrations in Norway and various economic indicators, including electricity prices (*NOK/MWh*), Brent spot prices (*Brent_Price*), and interest rates (*Interest_Rate*) - the latter serving as a proxy for the overall economic climate and lending rate in Norway. The focal point of this analysis is to determine the relationship between the electricity price and vehicle registration, given the rapid increase in electric vehicle uptake and the significant surge in electricity prices in the later years. We will also incorporate other variables that seem significant and beneficial for trying to answer our research question:

What relationships exist between vehicle registrations in Norway and key economic factors such as Brent spot prices and interest rates, and have the recent increases in electricity prices become a significant influencing factor?

We aim to explore the relationship between new vehicle registrations and various economic factors, with a primary focus on identifying any long-term relationship among the selected variables. To achieve this, we will develop vector autoregressive models (VAR) and vector error-correcting models (VECM). VAR models will be used to understand the concurrent fluctuations and mutual influences of these variables. Meanwhile, VECM models will be specifically employed to analyze how temporary changes in these variables may affect the long-term trends of vehicle registrations in Norway. This approach will highlight the factors that significantly influences vehicle registrations over time.

In consequence, the hypotheses for this study are defined as follows:

H_0: *There is no long-run relationship between the variables*

H_1: *There is at least one long-run relationship between the variables*

The thesis is organized as follows: Chapter two explores the evolution of the Norwegian vehicle, oil, and electricity markets from the early 2000s to the present day, emphasizing the significant changes that have occurred over the past fifteen years. This chapter also includes a literature review that examines various papers and studies that have researched similar topics, providing a thorough analysis of previous research and methodologies applied in the field covering vehicles. Chapter three presents descriptive statistics and data exploration, alongside discussions on pertinent findings. The construction and analysis of models are the primary focus of chapter four. Finally, chapter five synthesizes the conclusion drawn from the analyses conducted the preceding chapters.

2 Background and Literature

2.1 Norwegian Vehicle Market

The evolution of Norway's vehicle market reflects a strategic shift towards a more sustainable car-park, driven by a series of progressive policy changes aimed at promoting electric vehicles in the later years. The Norwegian market has been, like all the other markets in the world, predominantly consisting of fossil fuel vehicles all the way up until the early parts of the 2010's, this is when the electrification of the Norwegian vehicle market got traction. The Norwegian government's goal for reducing emissions from road transports consists of:

- All new passenger cars and light vans sold should be zero-emission by 2025.
- All new city buses should be zero-emission or use biogas by 2025.
- All new heavy vans, 75% of new long-distance buses and 50% of new lorries sold should be zero-emission by 2030.
- Distribution of most goods in major city areas should be emission free by 2030.

These goals are dependent on technological development making the necessary technology competitive with the combustion engine, as the government states (Samferdselsdepartementet, 2021).

Norsk Elbilforening (2024) reported in their statistics that in 2010 the number of electric vehicles registered in Norway was at a modest 3 347 vehicles, dominated by a few manufacturers like Nissan and Mitsubishi (Dalløkken, 2011). At that time, the infrastructure for electric vehicles was considerably underdeveloped, with only 20 fast charging stations available nationwide by 2011, which, along with limited vehicle range, posed a significant challenge to wider adoption. Concurrently, Norwegian legislators advocated for enhanced government support through proposals such as creating a subsidy scheme for electric vehicles in public fleets and attempting to remove VAT on electric vehicle leasing, although the latter did not materialize until 2015 (Stortinget, 2010; Lothe, 2011). These incentives included exemptions from the one-time vehicle tax, zero-rated VAT on purchases, reduced annual fees, free municipal parking, toll exemptions, and access to public transport lanes. This extensive package significantly contributed to the growth electric vehicle market, with over 10 000 vehicles sold shortly thereafter.

By April 2015, the number of registered electric vehicles surged to 50 000 and reached 80 000 by March 2016. During this period, nearly a quarter of all new car sales were electric vehicles. Subsequently, a shift in subsidy regulation occurred, transitioning some nationwide incentives to be controlled at the municipal level, capped at a max 50% of the rates for fossil-fueled vehicles.

In the recent years, particularly from 2020 to today, there has been a significant shift in the automotive industry towards the production and adoption of electric vehicles. Major vehicle manufacturers globally have initiated their own electric vehicle lines, and China is starting to find footing as well in the European market (Webster, 2024), but the enthusiasm towards electrical vehicles from China has not yet reached Norway (Norheim, 2024). This period has also been subject of changes in regulations affecting the electric vehicle market, notably the reduction of benefits for driving electric vehicles.

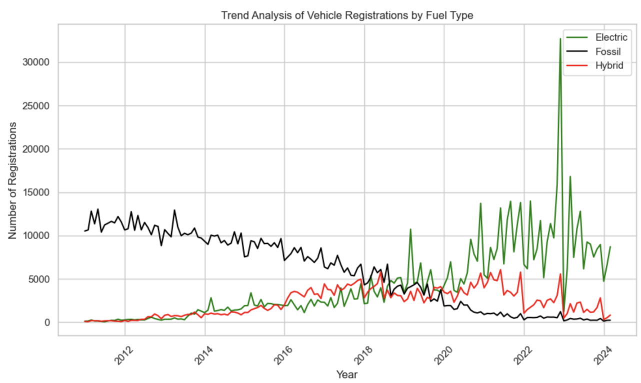
By 2023, electric vehicles constituted almost 82% of all newly registered vehicles in Norway, (NAF, 2023b), a significant increase from just over 50% in 2020, around 65% in 2021, and approximately 79% in 2022. This rapid growth in electric vehicle adoption has necessitated an expansion in infrastructure, notably in public charging facilities. As of November 2022, Norway boasted 3 300 public changing stations, with Tesla providing an additional 1 200 fast charging points. However, to accommodate the increasing amount of electrical vehicles, Statens Vegvesen (2022) projected that between 10 000 and 14 000 new fast chargers will be required for light vehicles before 2030, an increase of 7 000 from what already exists.

The Norwegian economy has been subject to high inflation and higher interest rates in the latter years. Due to higher interest rates and a general price increase on goods, the demand for vehicles has dropped as well. This and the new regulations on VAT lead to a high inventory surplus for the distributors (Ghaderi, 2023).

Regarding incentives to encourage the purchase of electric vehicles to accelerate the transition to electric mobility, traditional fossil-fueled vehicles in Norway are subject to a one-time tax calculated based on the vehicles weight, CO2 emissions, NOx emissions, and engine displacement - a levy not applied to electric vehicles. Prior to 2023, electric vehicles were exempt from VAT; however, starting in 2023, VAT is applied to electric vehicles costing more than 500 000 NOK . Additionally, a new weight tax has been introduced on electric vehicles, which could cost between 20 000 and 30 000 NOK (Handagard, 2024). Since 2003, electric vehicles have also been permitted to use bus lanes in Norway. However, the high volume of electric vehicles in these lanes has started to delay the public transport, according to officials from Statens Vegvesen (NTB, 2024), hence the new regulation prohibits the electric vehicles of using the public transport lane under rush hours.

Local benefits also exist, such as reduced toll rates for electric vehicles. Previously, electric vehicles paid a maximum of 50% of the tolls when passing a toll ring compared to fossil-fueled vehicles, a rate decided by local municipalities and county councils. From 2023, this rate has been adjusted to a maximum of 70%, with the specific rates still being determined locally (NAF, 2023a)

However, there are still a lot of incentives to buy electric vehicles after the regulation changes. Despite the fluctuations in electricity prices, the cost of powering an electric vehicle remains lower than fueling a vehicle with gasoline or diesel. With an average electricity price of 1.50 NOK per kWh in 2022, operating an electric vehicle continues to be more cost-effective over the course of a year (NAF, 2023a)



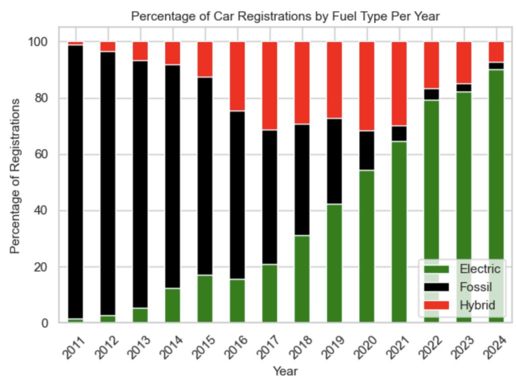


Figure 2.1: Trend Analysis of Vehicle Registration by Fuel Type
Figure 2.2: Percentage of Car Registrations by Fuel Type per Year

The huge fluctuations in vehicle registration from 2018 and onwards, seem to correlate nicely with the graphic above, figure 2.1, where we can see that electrical vehicles overtakes fossil fuel vehicles as the most registered vehicle types. At the same time there is more fluctuations in the registrations of electric vehicles compared with fossil fuel vehicles. Hence, we can state that the registration of electrical vehicles causes the huge fluctuations from 2018 until present day, in the plot showing total vehicle registration, Figure 3.

The graphs illustrates the significant evolution within the Norwegian vehicle market from the period 2011 to 2024, highlighting a pivotal shift away from fossil-fuel vehicles towards electric vehicles. The bar chart reveals a steady decrease in the registration of fossil-fuel vehicles coupled with a substantial increase in electric vehicle registrations, reflecting the effectiveness of the incentives the Norwegian government presented, aimed at promoting electric vehicle adoption and the increased production of electrical vehicles (NBF, 2024). These incentives include tax exemptions, free parking, and the usage of bus lanes, significantly shaping consumer preferences and accelerating the transition to sustainable transportation (Holtsmark & Skonhoft, 2014). The line graph complements this data showing the rise in electric vehicle registrations, particularly after 2020, indicating the strong influence of policy measures on market dynamics and consumer behavior.

2.2 Brent Crude Oil

The discovery and exploration of oil along the Norwegian continental shelf began tentatively in the 1950s and gained momentum following significant gas discoveries in the Netherlands. The Norwegian government plays a pivotal role, asserting control and setting up regulatory frameworks essential for managing the resource (Olje-og Energidepartementet, 2019). The discovery of the Ekofisk oil field in 1969 marked a significant turning point, leading to the exploration and development of other major fields like Statfjord and Troll. These developments not only increased Norway’s oil output but also positioned it as a key player in the global energy market. The oil sector emerged as a cornerstone of the Norwegian economy, influencing various aspects of economic policy and contributing significantly to the country’s GDP and the welfare state (Olje-og Energidepartementet, 2019).

The relationship between crude oil prices and consumer fuel prices is complex in Norway due to high taxations and other market factors. Korlyuk et al., (2015) highlight some of the factors that affect fuel prices are taxes, exchange rates, and international fuel prices. Crude oil prices is still one of the primary and most important factors for setting the consumer fuel prices because oil is the primary commodity in the production of fossil based fuel. Korlyuk et al., (2015) show that the price evolution of fossil fuels over a ten year period followed the crude oil price movements, although not all the time likely due to the other influencing variables stated above. Mjønerud (2019) states that Norwegian oil mainly ends up as fuel, whereas earlier it was mostly used to produce electricity. As of 2019, oil alone stood for approximately 94% of the energy consumption within the transport sector, which means that oil is one of the main factors in the world energy consumption.

As Norway witnesses a significant shift in vehicle registrations with electric vehicles surpassing fossil fuel registrations in 2020, ref Figure 2.2, understanding the broader economic factors influencing this trend becomes increasingly relevant. While the primary focus of this thesis is on the relationship between electricity prices and vehicle registrations, it is also insightful to examine how Brent crude prices interact with vehicle registrations. Historically, Brent crude prices have been linked to consumer fuel costs, with implications for the registration trends of fossil fuel vehicles, as we will see in the literature review. Given that electric vehicles do not rely on petroleum fuels, the analysis of Brent prices in this new vehicle landscape could reveal changing relationship dynamics between the variables. This examination will complement the main analysis by providing a broader view of the economic influences on vehicle registrations, especially under shifting energy consumption patterns and economic conditions in Norway.

2.3 Electricity Market

Electricity prices in Norway have been subjected to substantial volatility, influenced by a variety of factors ranging from global energy markets to regional policy decision and environmental conditions. Historically, Norway has benefited from relatively stable and low electricity prices due to its abundant hydroelectric power resources. However, recent years have seen significant fluctuations that are important to understand within the scope of this thesis.

The trajectory of electricity prices in Norway has shown remarkable highs and subsequent stabilization over the past few years. In 2021, Norway experienced unprecedented electricity prices, with the average household rate in the fourth quarter reaching 1.081 NOK/kWh, approximately 0.69 NOK/kWh higher than the average of the same quarter over the previous five years. Following year, 2022, saw even higher rates, with prices before subsidies reaching as high as 2.353 NOK/kWh, which was 66% higher than 2021 (Holstad, 2022; Holstad, 2023). However, by 2023, there was a notable reduction in electricity prices, with a 42.5% decrease from the previous yearly average price, though still maintaining levels among the highest historically recorded. This price reduction reflects a combination of shifts in the global energy market and regional energy supply adjustments (Holstad, 2023).

Several key factors influence electricity prices in Norway. The country's reliance on hydroelectric power means that electricity prices are closely tied to hydrological conditions; years with low precipitation can significantly reduce water levels in reservoirs, leading to higher prices. Additionally, Norway's electricity market is interconnected with broader European energy markets making it susceptible to fluctuations in these markets.

Recent trends in the gas market have had substantial impact on electricity prices. A sharp reduction in Russian gas supplies to Europe in response to the economic sanctions in February 2022, led to a significant increase in electricity prices (NRK, 2024).

Moreover, the NordLink interconnectors between Norway and Germany has facilitated price convergence, linking Norwegian prices more closely with those of continental Europe where gas and carbon prices play a significant role (Myrvoll & Undeli, 2022). This integration highlights the dual impact of domestic conditions and broader market dynamics on Norway's electricity pricing.

As we explore the potential influence of electricity prices on vehicle registrations, a clear understanding of these pricing trends and their underlying factors is essential. This insight is particularly relevant as we consider the shift from fossil fuel vehicles to electric vehicles, where electricity essentially becomes the fuel for these types of vehicles. Understanding whether electricity prices significantly affect vehicle registrations could offer valuable perspectives on consumer behaviors and future policy directions in Norway.

2.4 Literature Review

This literature review explores various studies that examine the dynamics of vehicle adoption, in particular electric vehicles, and the import patterns of motor vehicles, focusing on the influence of economic factors like energy prices, government subsidies, and global commodity prices.

A significant body of research, including Bushnell et al., (2022), has investigated the impact of energy prices on the adoption of electric vehicles, focusing on California between 2014 and 2017. The study reveals that gasoline prices have a disproportionately strong influence on electric vehicle adoption compared to electricity prices. A change in gasoline prices affects the demand for electric vehicles four to six times more than an equivalent percentage change in electricity prices. This difference is attributed to a behavioral bias where consumers tend to undervalue future electricity costs while overvaluing immediate gasoline savings. This suggests a lack of consumer understanding about how electricity prices are set and their impacts, compared to more familiar gasoline prices. The findings advocates for policy measures that account for these perceptions, suggesting adjustments in subsiders to effectively enhance the adoptions of electric vehicles buy better aligning consumer behavior with long-term energy cost realities. From Bushnell et al., (2022), we draw on the significant impact of energy prices on vehicle adoption, applying this understanding to how electricity prices might influence vehicle registrations in Norway, especially given the vast amount of electric vehicles in Norway and the recent fluctuations in electricity prices.

In Norway the government has had an extensive subsidies policy to promote electrical vehicles, Holtsmark and Skonhoft (2014) has examined the efficiency of these policies. These policies, which include various incentives such as exemptions from VAT and tolls, have significantly increased electric vehicle adoption in Norway. However, the study questions whether these policies have translated into a net environmental benefit or merely shifted the burden of emissions. The Norwegian approach demonstrates that while subsidies can dramatically increase electric vehicle adoption, they also may lead to increased vehicle usage, potentially offsetting some of the environmental gains. This analysis complements the findings by Bushnell et al., (2022), highlighting the complexity and potential unintended consequence of economic incentives on consumer behavior. Bushnell et al., (2022) provides a perspective on the behavioral shifts in vehicle adoption due to policy changes, which is pertinent given Norway's aggressive subsidy policies highlighted by Holtsmark and Skonhoft (2014)

Ashan Tishler (1982) study, "The Demand for Cars and the Price of Gasoline: The User Cost Approach" similarly analyzes the impact of operating costs, specifically gasoline prices, on the demand for cars. The empirical results indicate a substantial negative relationship between gasoline prices and car demand, particularly for cars with larger engines which are less fuel-efficient. The study finds that cars of different engine sizes are not perfect substitutes, with larger, less fuel-efficient cars being more sensitive to changes in gasoline. Tishler concludes that operating costs, especially gasoline prices, are crucial determinants of car demand. This insight is relevant for policy discussions on fuel taxation and energy conservation, and it resonates with the findings from Bushnell et al., (2022) about energy prices influencing vehicle adoption rates.

Further integrating the economic dimensions of vehicle technology choices, Berthelsen and Arteaga (2016) explore the relationship between oil prices, lithium prices, and electric vehicle sales. Their study employs vector error correction models (VECM) and vector autoregressive models (VAR) to analyze these relationships. Findings indicate a positive correlation between oil prices and electric vehicle sales, suggesting that higher oil prices may motivate increased interests in electrical vehicles as alternatives to traditional fuel-powered vehicles. Conversely, rising lithium prices could dampen electric vehicle sales by increasing the cost associated with electric vehicle batteries. The econometric techniques used in Berthelsen and Arteaga (2016), specially VAR and VECM, directly influence our approach to modeling the relationship between vehicle registrations and economic indicators. We will elaborate on these models later in the thesis.

Moore and Walkes (2009) analyze the factors influencing motor car imports in Barbados over the period from 1994 to 2008. They employed an ordinary least square model (OLS) to examine the responsiveness of the aggregate demand for motor cars to change in income, interest rate, price of the motor car, the change in fuel price, and the relative price of non-durables (food, clothing, toiletries etc.). The findings show that car imports are positively correlated with real income and negatively affected by car prices and interest rates. Their study underscores the sensitivity of car purchases to monetary policy measures, where higher interest rates decrease vehicle imports due to increased financing costs. Moor and Walkes

(2009) reinforces the importance of including a broader set of economic factors, such as the interest rate as an indicator of the cost of lending in the country.

Similarly, Humbativ and Hajiyev (2020) assess the impact of oil exports and oil prices on car imports in Azerbaijan. The study employs an autoregressive distributed lag model (ARDL) to assess the long-term relationship between the variables, they check for stationarity by using tests like ADF and KPSS, and checks for cointegration to identify any long-term relationships. Their findings reveal a significant positive long-term effect of oil prices and oil exports in car imports, which emphasizes the economic dependency Azerbaijan has on the oil sector. Our thesis will employ some of the same test stationarity, but we will use the Johansen test for cointegration.

In summary, the literature review not only provides a theoretical backdrop to what we should be able to find in our study, but also shapes the empirical framework of the thesis.

3 Data

The data used in the study were collected from different sources, such as Opplysningsrådet for Veitrafikken AS (OFV), Nord Pool AS, Norges Bank, and U.S. Energy Information Administration (EIA). Some of the sources are public and some are private sources.

The data underpinned this analysis is derived from OFV, which maintains a comprehensive database among them being automotive sales, registrations, and vehicle fleet in Norway (OFV, n.d). The time frame covered by the data extends from January 2000 to October 2023. The data is compiled on a monthly basis, encompassing variables such as year, month, brand, model, and number of the specific model registered. The data will be aggregate to get the total number of vehicles registered each month.

To enhance the dataset for modeling and analysis, additional economic factors that is known to influence vehicle imports - namely interest rates and oil prices - have been integrated, as well as factors not known to influence vehicle imports - namely electrical prices - has also been integrated, ensuring that all variables share the same monthly frequency for consistent temporal analysis.

Interest rate data is collected from Norges Bank (Styringsrenten) and is free online data. The data is arranged on a monthly basis and the timeframe is consistent with the dataset from OFV.

Brent crude oil prices are obtained from the EIA (Europe Brent Spot Price FOB (Dollars per Barrel)) for free. EIA get their data from Thomson Reuters, which is the world's leading provider of news and information-based tools to professionals (Thomson Reuters, n.d.). The data has a monthly frequency and span from January 2000 until October 2023. Note that the data is stated in USD/barrel, to convert this into NOK/barrel we obtained the historical exchange rate on NOK/USD from Norges Bank (Norges Bank - valutakurser).

Data on electricity prices were handed over from Nord Pool AS, which was the first international exchange for trading electrical energy. The data is the average electricity price for Oslo in NOK/MWh, with a monthly frequency from January 2000 until October 2023. We will not convert the data into NOK/kWh, but note that one MWh of energy is equivalent to thousand kWh of energy (Richardson, 2019).

Reg_Vehicles	Newly Registered Vehicles in Norway per month	OFV per e-mail
Interest_Rate	Interest rate in Norway	Styringsrenten
Brent_Price	Brent Spot Price	Europe Brent Spot Price FOB (Dollars per Barrel)
NOK/MWh	Average electricity price	Nord Pool per e-mail
NOK/USD	Exchange rate to convert Brent_Price	Norges Bank - valutakurser

Table 3.1: Data and Internet Sources

3.1 Descriptive Statistics

In the preceding quantitative exploration, a meticulous examination of the descriptive statistical measures across various financial variables was undertaken to discern the underlying patterns and variability inherent within the dataset, pertinent to vehicle registrations. This analysis aims to furnish a foundational understanding of the dataset's characteristics, serving as a preliminary step towards more sophisticated economic modeling.

From the descriptive statistics we see that we have quite different volatilities (relative std. dev.[1]) in our variables. Registered Cars (New Reg. Cars) has a relative standard deviation of approximately 30%, while the electricity price (*'NOK/MWh'*) seem to have significantly higher volatility with a relative standard deviation at 112%.

Looking at the kurtosis, we see that both variables exceed a kurtosis of 3, which means that they are not normally distributed. Using the Jarque-Bera test, we check to see if the time series in our dataset is normally distributed again. As we observe that the p-values are 0.00 this means that we reject the null hypothesis (Khadka, 2023), hence the data does not follow a normal distribution confirming the prior observation. The skewness tells us that none of the time series are symmetric and are positively skewed, meaning that most data points are clustered around the left-tail of the distribution and that the right-tail is longer (Taylor, 2022).

	New Reg. Cars	NOK/Mwh	Interest Rate	Brent Spot
Count	286.00	286.00	286.00	286.00
Mean	10776.26	373.56	2.49	474.37
Std.Dev.	3222.53	418.22	2.09	200.43
Minimum	1859.00	11.21	0.00	167.55
Maximum	39495.00	3586.88	7.00	1198.20
Relative. Std. Dev.*	29.90%	111.96%	83.80%	42.25%
Skewness	2.85	4.50	0.97	0.71
Kurtosis	21.50	25.63	-0.29	0.56
Jarque-Bera	5896.60	8792.98	46.33	27.87
p-value	0.00	0.00	0.00	0.00

Table 3.2: Description Statistic
Relative Standard Deviation: Calculated as Rel. Std. Dev = (std/mean)

3.1.1 "Newly Registered Cars "

Taking a look at the Figure 3.1 depicting the total numbers of vehicles registered over time we observe that the registrations vary largely from each month, but looking closer we see that the variations fluctuate from 2017 and onwards, with an all time high 2022-12 at 39 000 vehicles registered. This is largely due to new regulation regarding car taxation when

[1] Relative Standard Deviation: Calculated as Rel. Std. Dev = (std/mean)

importing vehicles over a certain weight, the CO2-component regulation was tightened and a VAT on electric vehicles over 500.000 NOK was introduced from 01.01.2023 (Bilnytt, 2022) as stated earlier. With this in mind we believe that we will detect multiple breaks in the registered vehicle dataset.

The number of registered vehicles from the timespan of 2000-01 to 2023-10 have had an exponential growth, clocking in at just above three million vehicles as of October 2023. A lot of the registered vehicles in the later years have been electric vehicles, which have had an explosive growth in the Norwegian market in the last years, seen in Figure 3.3. Much thanks to the government's incentives for buying electric cars, e.g. cheaper toll rings, no VAT on imports up until 2023, and also no one-off fee upon purchase, etc (Nesheim, 2021).

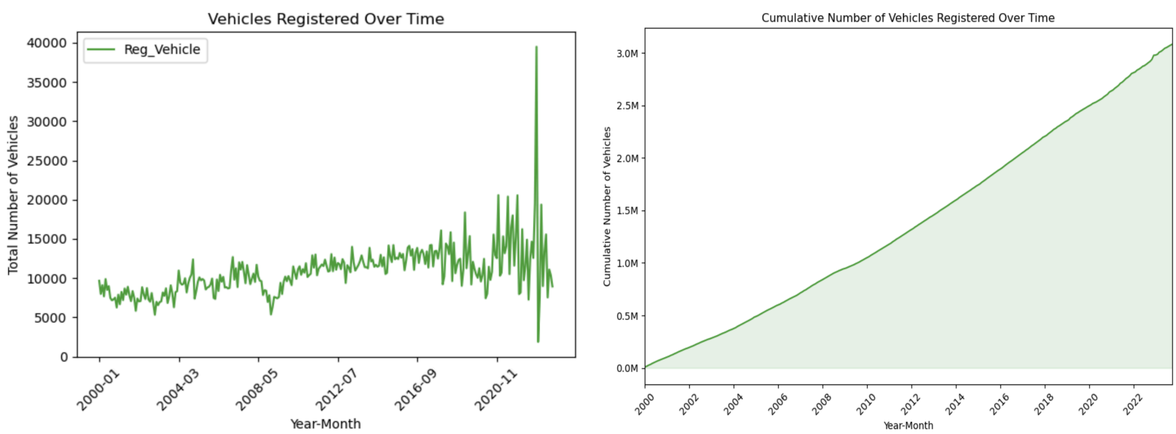
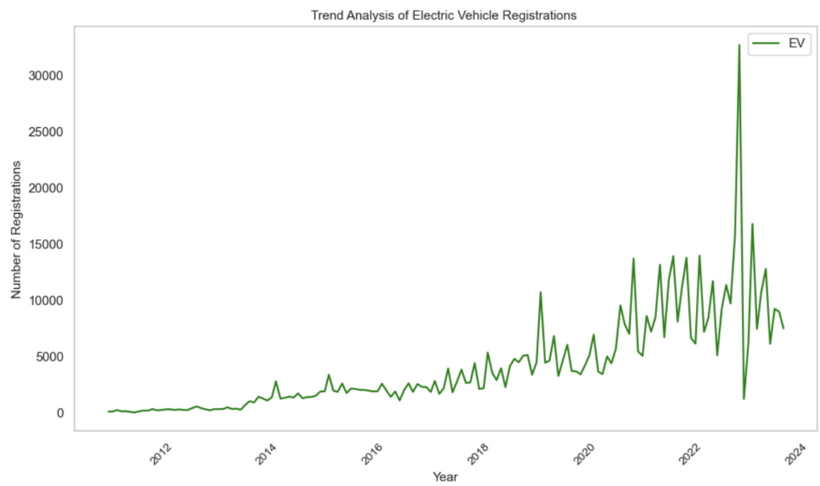


Figure 3.1: Vehicle Registration Over Time

Figure 3.2: Cumulative Number of Vehicles Registered Over Time

It seem like much of the variation in the plot for "Vehicle Registration Over Time", Figure 3.3, can be attributed to electrical vehicles entering the market mix.



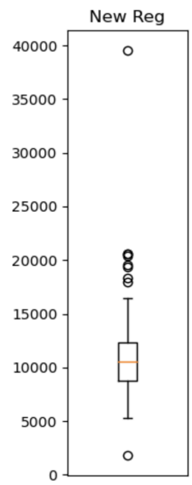


Figure 3.3: Trend Analysis of Electric Vehicle Registrations
Figure 3.4: Distribution of *New_Reg*

Figure 3.4 also represents the distribution of new vehicle registrations over the time period 2000-01 to 2023-10. The bulk of the data lies within the interquartile range, between approximately 5,000 and 16,000 new registrations, with the median value close to 10,000, indicating a symmetric distribution of values around the median. Notably, there are several outliers; these are data points that significantly deviate from the rest of the distribution (Wikipedia Contributors, 2019). Above the upper whisker, which marks the boundary for the highest expected registration value within the typical range, there are numerous outliers that suggest exceptional months where registrations were unusually high, peaking near 40,000. Additionally, there are outliers below the lower whisker, indicating months with unusually low registrations, close to zero.

3.1.2 Interest Rate

Conversely, the interest rate variable demonstrates markedly lower volatility, with its RSD positioned at 11.58%. This relative stability in interest rates, juxtaposed against the volatility observed in *Reg_Vehicle*, intimates the factors beyond mere interest rate fluctuations are at play in influencing vehicle registration dynamics. Figure 3.5 tracks the changes in interest rates from 2000 until October 2023. The plot shows significant fluctuations over time, with rates peaking at above 6%, dropping to 0%, and then surging again in the latter years. The sharp increase at the end of the timeline is explained by the current economic situation in

Norway where the inflation has been high and Norges Bank has increased the interest rate to fight the inflation (Husøy, 2023).

The box plot shows a median interest rate just under 2%, with an interquartile range extending from approximately 1% to just over 3.5%. This indicates that the middle 50% of the interest rate values are spread within this range. The "whiskers" of the box plot suggests that the majority of the data falls between 0% and 4.5%, while there are no outliers present in the plot, indicating that all interest rates lie within a reasonable range from the median.

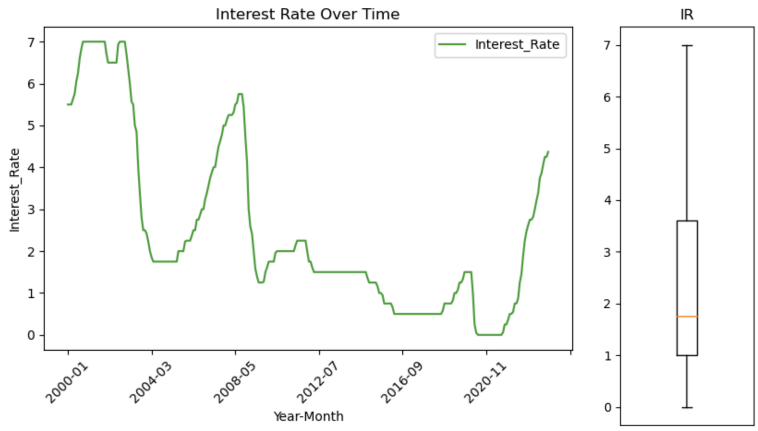


Figure 3.5: Interest Rate Over Time and Box of the Interest Rate

3.1.3 Electricity prices (NOK/Mwh)

Figure 3.6 is a time series plot displaying the "Electricity Price Over Time" with the price measured in *NOK/MWh*. It spans from January 2000 until the start of 2021. The line plot shows relatively stable prices with some fluctuations up until a sharp spike towards the end of the plot. This spike represents a significant increase in electricity prices, reaching a peak far above previous historical levels. The graph's y-axis scale and the spike's magnitude suggest an extraordinary event or series of events that drastically affected electricity prices during this period, which is consistent with the increased price convergence where Norway got somewhat higher electricity prices and Germany god somewhat lower prices (Myrvoll & Undeli, 2022). Note that the electricity prices are influenced by several variables.

The second graph is a box plot for the electricity prices (*NOK/MWh*). The central box shows the interquartile range, the median price is indicated by the line within the box, and the "whiskers" extend to the highest and lowest prices that are still within a reasonable range. Points above the top whisker represent outliers. These are months when electricity prices were exceptionally high compared to the rest of the dataset. The cluster of outliers at the upper end further suggests that there were multiple instances where the electricity prices were significantly higher than typical, corresponding with the spikes seen in the time series plot.

Note that this variable is stated as *NOK/MWh* as mentioned earlier. One MWh of energy is equal to thousand kWh of energy. The most typical notation to use regarding electricity prices in Norway is kWh, but we are continuing forward with "*NOK/MWh*".

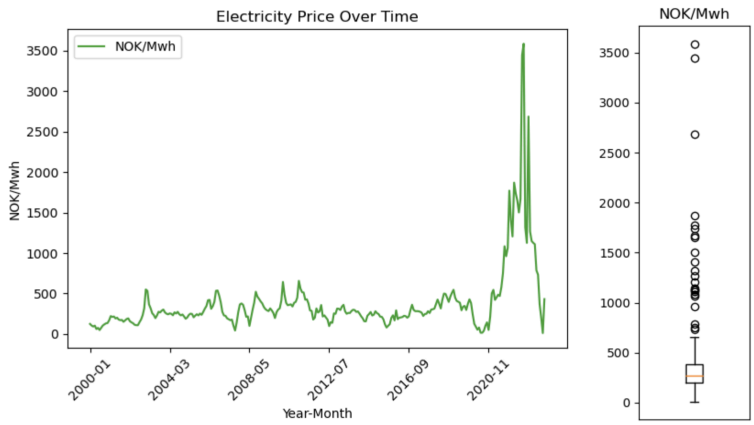


Figure 3.6: Electricity Price Over Time and Box plot of *NOK/MWh*

3.1.4 Brent Spot Price (NOK per Barrel)

The plot shows a volatile trajectory of prices with several peaks and troughs. A notable rise in prices is observed starting from around 2021, suggesting a significant upwards trend in the Brent oil spot prices after the Covid-19 shock, where demand for oil had fallen sharply as e.g traveling stopped, and the producers couldn't stop the production at a fast enough rate to match the demand. On top of that Russia and Saudi Arabia, the two biggest members of OPEC+, had a supply war (Gaffen, 2022). Add this together and we have a surging Brent spot price. The rise in the later years is also a complex situation, as Russia invaded Ukraine. This conflict led to sanctions on Russian oil (Utenriksdepartementet, 2022), further increasing the gap between supply and demand after the Covid-19 lockdown (Gaffen, 2022).

Figure 3.7 display a box plot for the Brent oil spot price. The median of the distribution is shown by the horizontal line within the box, situated just above 400 NOK per barrel, indicating the central tendency of the prices. The box itself represents the interquartile range, spanning from approximately 300 to 600 NOK, which contains the middle 50% of the price data points. The whiskers extend from the bottom and top of the box to the minimum and maximum price values within a typical range, excluding outliers. A few outliers are visible above the upper whisker, indicating specific instances where the Brent spot price was exceptionally high, surprising the typical price range observed.

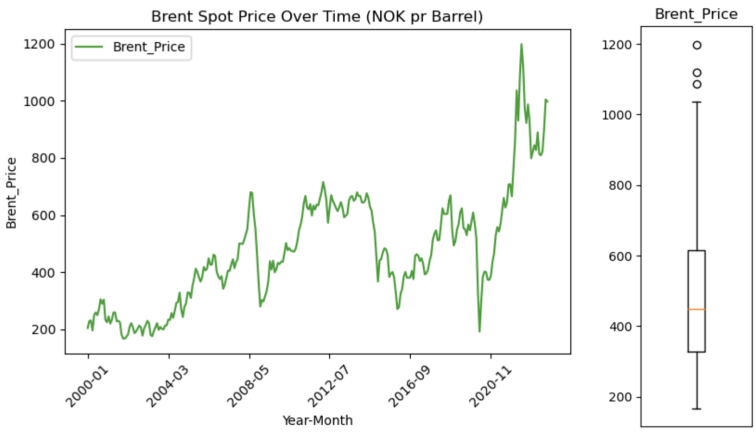


Figure 3.7: Brent Spot Price Over Time and Box plot *Brent_Price*

3.1.6 Correlation

The correlation matrix heatmap depicted is a display of the interrelationship between the variables: vehicle registration (*'Reg_Vehicle'*), electricity prices (*'NOK_Mwh'*), Brent crude oil prices (*'Brent_Price'*), and interest rates (*'Interest_Rate'*). The heatmap color gradient, ranging from blue (negative correlation) to red (positive correlation), visually underscores the strength to the relationships, with more intense colors indicating stronger correlations.

Starting with vehicle registrations, there is a moderately positive correlation with electricity prices, signifying a potential tendency for registrations to rise with increasing electricity prices costs, albeit the correlation is not strong. Interestingly, vehicle registrations also have a moderately positive correlation with Brent oil prices, perhaps indicating that oil price fluctuations have a perceptible impact on the automobile market. Electricity prices show a substantial positive correlation with Brent oil prices, which suggests a possible link between energy markets and oil prices. Cojocaru and Myrann (2017) found that the Norwegian energy prices are affected by the oil prices, which correspond with what we can see from the correlation matrix. Interest rates exhibit a notable negative correlation with vehicle registrations, indicating an inverse relationship where higher interest rates might discourage new vehicle purchases, likely due to higher borrowing costs. Conversely, interest rates have a generally negative correlation with the other variables as well, implying that if the interest rate falls, prices of energy and commodities may tend to rise.

Despite the insight offered by the matrix, it is essential to remember that correlation does not necessarily mean causation. The observed correlations could result from a variety of underlying economic forces. To probe the causal relationship further we will perform a Granger causality test later in our study.

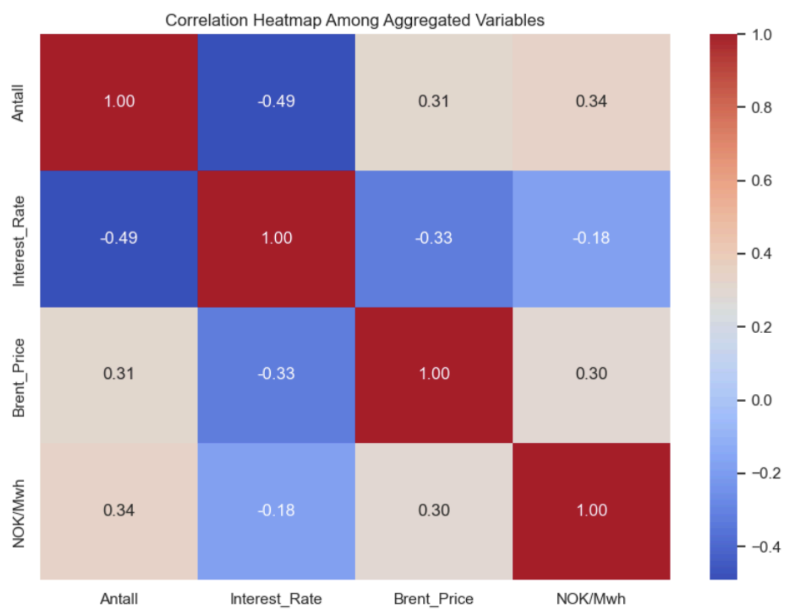


Figure 3.8: Correlation Heatmap Among Aggregate Variables

3.1.8 Granger Causality

This test is used to determine if one time series can predict another. Note that this test does not imply true causality but indicates whether past values of one variable help predict future values of another (Eric, 2021). Here we explore the relationship between vehicle registrations (*'Reg_Vehicle'*) and the other economic indicators in the dataset. The test involves checking for statistical significance over different maximum lags to observe variations on predictive power across time. The p-value threshold was set at 0.05 for determining statistical significance.

3.2 Stationarity and Cointegration

In the analysis of time series data, several key characteristics are essential for stationarity. First, the mean of the series must remain constant over time, indicating that the average value does not change as time progresses. Secondly, the variance of the series should also be constant, suggesting that the dispersion or spread of the data does not vary throughout the observed period. Lastly, the series should not exhibit trends nor seasonality, meaning that there are no systematic increases or decreases in the data, and no recurring seasonal patterns over the time interval (Singh, 2023). Shocks hitting a variable that exhibit non-stationarity will never die out, hence non-stationarity in a variable would be undesirable. To check for trends and stationarity in our variables, we perform the Augmented Dickey-Fuller (ADF) test for unit root and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for stationarity around a deterministic trend. Unit root indicates if there is any stochastic trend that drives the time series data away from the mean. Presence of unit root in the time series indicates non-stationarity and would result in difficulties in deriving statistical inferences from the time series data (Santra, 2023). When encountering mixed results in non-stationary from the tests, we differentiate to confirm stationarity. Additionally, we use the Zivot-Andrews test to determine if there are structural breaks in the dataset. This test allows for one break at an unknown point in the dataset, which means that there might be more breaking points (Statistics How To, 2016). We later use a Bai-Perron method to look for several breaks in our dataset. Looking at the figures above we would expect many breaks in the time series data.

4 Analysis

The focus of our analysis shall be on how vehicle registration is dependent on the price of electricity, Brent oil price, interest rate, fuel price and its relation to these. This will be done through the statistical tool known as the Vector Autoregression (VAR).

By using the Granger causality test, we will get an understanding of whether changes in one variable can predict changes in another. An example would be how changes in Brent oil prices can point out changes in vehicle registrations.

Whenever our data are not constant but linked in the long term, we will apply what is referred to as a Vector Error Correction Model (VECM). This model explains the pace of return of variables to the relationship course after a disturbance, normally. This model however typically requires that the variables are non-stationary for which there could be a potential long-term cointegration relationship to explore.

4.1 Model Introduction

Vector Autoregression (VAR) model is a fundamental tool for econometrics that captures linear interdependencies among multiple time series data (Urade, 2023). Unlike models assuming unidirectional influences, VAR treats all variables in the system as endogenous, allowing for a multidirectional dynamic interaction among them. This framework is particularly effective in scenarios where variables influence each other reciprocally (Hyndman & Athanasopoulos, 2018).

The VAR model with p lags and K endogenous variables are shown in equation form below. Each equation in the VAR system estimates the current value of one of the endogenous variables as a function of the lagged values of all K endogenous variables.

Let Y_t be a $K \times 1$ vector of endogenous variables at time t. The VAR(p) model for Y_t is given by:

$$Y_t = C + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + ... + \Phi_p Y_{t-p} + \epsilon_t$$

Where:

- C is a $K \times 1$ vector of constants (intercepts)
- $\Phi_1, \Phi_2, \dots, \Phi_p$ are $K \times K$ coefficient matrices corresponding to the 1st through p-th lags of the endogenous variables.

- ϵ_t is a $K \times 1$ vector of error terms at time t, which are assumed to be white noise with a multivariate normal distribution with zero mean and a constant covariance matrix Σ.

We will apply the VAR(p) model for the following set of equations in our analysis:

The individual equations:

$$Reg\_Vehicle_t = c_1 + \Sigma_{k=1}^{p}(\phi_{11,k}Reg\_Vehicle_{t-k} + \phi_{12,k}NOK/MWh_{t-k} + \phi_{13,k}Interest\_Rate_{t-k} + \phi_{14,k}Brent\_Price_{t-k}) + e_{1,t}$$

$$NOK/MWh_t = c_2 + \Sigma_{k=1}^{p}(\phi_{21,k}Reg\_Vehicle_{t-k} + \phi_{22,k}NOK/MWh_{t-k} + \phi_{23,k}Interest\_Rate_{t-k} + \phi_{24,k}Brent\_Price_{t-k}) + e_{2,t}$$

$$Interest\_Rate_t = c_3 + \Sigma_{k=1}^{p}(\phi_{31,k}Reg\_Vehicle_{t-k} + \phi_{32,k}NOK/MWh_{t-k} + \phi_{33,k}Interest\_Rate_{t-k} + \phi_{34,k}Brent\_Price_{t-k}) + e_{3,t}$$

$$Brent\_Price_t = c_1 + \Sigma_{k=1}^{p}(\phi_{41,k}Reg\_Vehicle_{t-k} + \phi_{42,k}NOK/MWh_{t-k} + \phi_{43,k}Interest\_Rate_{t-k} + \phi_{44,k}Brent\_Price_{t-k}) + e_{4,t}$$

By incorporating more lags in the model, we need a robust dataset to ensure reliable estimations. A complex model has the potential of overfitting so carefully checking for stationarity, serial correlation, and model stability is important.

Vector Error Correction Model (VECM) is an advanced statistical method that extend the VAR model to include cointegration relationships among multiple time series data, which makes it especially valuable for data that are non-stationary in their levels but stationary in their differences. Like the VAR model, VECM treats all variables endogenously interacting, but also integrates error correction terms to capture the long-term equilibrium relationships among the variables (Urade, 2023).

For a system of cointegrated variables, the VECM model introduces error correction dynamics to adjust the short-term deviations from the long-term equilibrium. Consider K cointegrated variables with one cointegration relationship and $p - 1$ lags for simplicity in the difference terms. The VECM model can then be expressed as:

$$\Delta Y_t = \mu + \Pi Y_{t-1} + \Sigma_{i=1}^{p-1}\Gamma_i \Delta Y_{t-i} + \epsilon_t$$

Where

- ΔY_t is the difference of the K-vector of endogenous variables at time t.

- μ is a vector of constraints.
- Π is a $K \times K$ matrix representing the speed of adjustment to the long-term equilibrium (loading factors of the error correction term).
- Γ_i are $K \times K$ matrices of short-term coefficients.
- ϵ_t is a K-vector of white noise error terms.

The cointegrating equation (error correction term), Y^*_{t-1}, is often specified as a linear combination of the levels of variables that correct the short-term disequilibrium to bring the variables back to equilibrium. The term ΠY_{t-1} thus reflects how deviations from the long-term equilibrium relationship among the variables in period $t - 1$ influence the changes in ΔY_t.

4.2 VAR and VECM Modeling

In order to determine the optimal lag length, we fit a VAR model using our four variables, *Reg_Vehicle, NOK/MWh, Brent_Price* and *Interest_Rate* after differentiation. We calculate measures for various lag lengths using different information criteria. As our data is monthly and contains 286 observations, we believe a maximum lag length of at least 12 would be feasible. We chose to focus on the lag lengths suggested by AIC, BIC and HQIC.

Our whole dataset with all observations are first estimated, as this helps us see the behaviour of the model when all the coefficients are estimated. Our data on vehicle registrations are clearly increasing in volatility starting from around 2016-2017 and onwards, which leads to difficulties in forecasting as the model is trained on relatively stable data. Below we present a VECM model showing the actual vehicle registrations together with the forecast for different lags. In later sections, we aim to create two new datasets, whose purpose is to correctly model the volatile part of the data from 2016-2023 as well as the more stable period from 2000-2016.

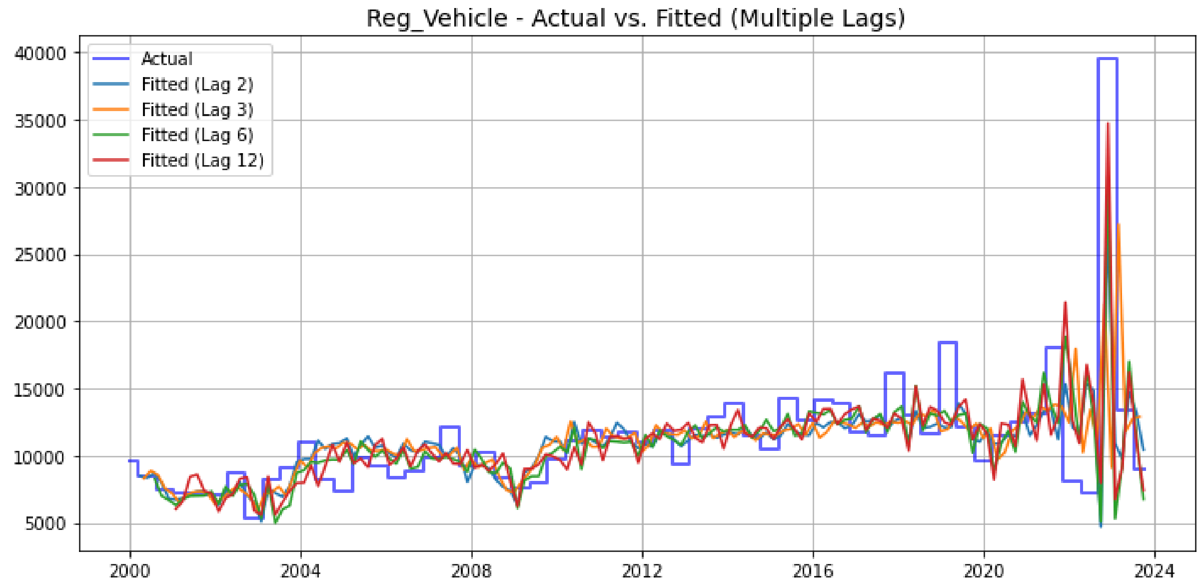


Figure 4.1: VECM Actual vs. Fitted with multiple lags (Full Model) - In-sample forecast

The best performing model in this case was the model using 12 lags. It yielded both the best performance metrics with the lowest MAPE, highest R^2 and no serial correlation. However, while the model with 6 lags performed the best in terms of significant coefficients, it proved to suffer from serial correlation.

When checking for cointegration, we have chosen to use the Johansen test to ensure the best results as this test is better suited for systems consisting of more than two variables. The test gave a result of three co-integrated equations at a 95% confidence interval.

The model will use three error correcting terms. The coefficient for the first error correcting term indicates the speed of adjustment towards long-term equilibrium relationship between the variables in the equation. This is negative and significant, indicating a tendency for *Reg_Vehicle* to correct short-term deviations from its long-term equilibrium. It will adjust downward if above the long-term equilibrium value given by the error correction term. The second error correcting term however, is negative and insignificant, indicating an unreliable estimate and a variable that might not impact the adjustment process in any meaningful way. The third error correcting term is also negative and insignificant, with a high standard error relative to the coefficient, which results in a low p-value. *Reg_Vehicle* has several significant lags, with two lags at 1% level and five lags at 10% level. Cointegration relations show that

Reg_Vehicle has a significant positive long-term relationship with *Interest_Rate*, while the effect of the other variables are negligible.

Residual diagnostics:

We perform residual diagnostics to determine the normality, heteroscedasticity and serial correlation of our residuals. Jarque-Bera is used to determine normality, where we find that the null-hypothesis is rejected and we do not detect any normally distributed residuals. Ljung-Box test fails to reject null-hypothesis, meaning no sign of serial correlation. Both White and Breusch-Pagan tests reject null hypothesis, confirming that we have heteroscedasticity present.

Coefficient diagnostics:

The Granger causality test results provide insights into the predictive relationships between the variables in the short-term. With *Reg_Vehicle* as the target variable, the relationship between *NOK/MWh* and *Reg_Vehicle* is statistically significant. This indicate that past values of *NOK/MWh* significantly help predict future values of *Reg_Vehicle*.
Similarly, historical values of *Brent_Price* are shown to have predictive power over future values of *Reg_Vehicle*. The test results suggest that changes in crude oil prices significantly influence the demand for new vehicle registrations.
In contrast, the relationship between *Interest_Rate* and *Reg_Vehicle* is not statistically significant. This implies that past values of Interest_Rate do not significantly help in predicting future values of *Reg_Vehicle*.

The Wald test is used to find joint significance in the model, proving that the model is joint significant at all confidence levels.

Full Model	Number of lags	Cointegrated Equations	R-squared	MAPE	Normality	Serial-Correlatio	Heteroscedasticity
Reg_Vehicle	12	3	0.78	11.36%	No	No	Yes

Table 4.1: VECM Full Model Result

4.2.1 Structural Breaks

To detect structural breaks in the *Reg_Vehicle* series, we used the Bai-Perron test, a dynamic programming-based method designed to identify multiple structural breaks in a linear regression model. This robust statistical approach allows us to detect multiple breaks by minimizing the residual sum of squares for each segment.

We applied the Bai-Perron test to the *Reg_Vehicle* time series, aiming to identify up to three breakpoints. For implementation, we used the ruptures package, specifically the Dynp algorithm, which uses dynamic programming as Bai-Perron is not directly available in Python. We can see from Figure 4.2 below, we have several breaks that may affect our results. In line with the data split mentioned previously, we will attempt to improve the model by splitting at breakpoint two, 1st of June 2010, deviating from our original plan to split at 2016. This will give the model enough data points to work with.

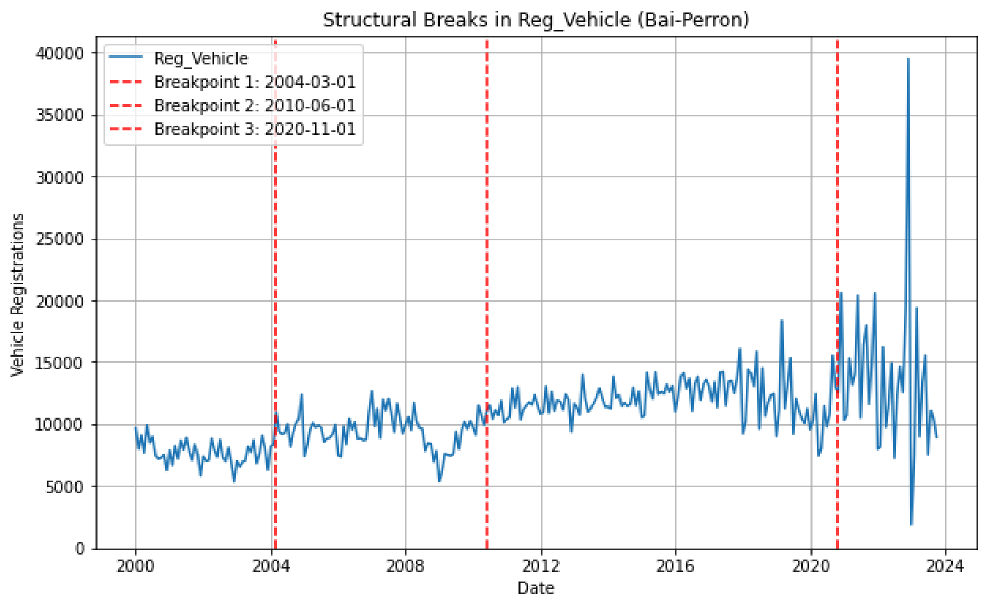


Figure 4.2: Structural Breaks in *Reg_Vehicle* (Bai-Perron)

We fit two new models, splitting our initial dataset before and after the break in June 2010. The models are fitted with the optimal number of lags based on AIC, as well as a new cointegration rank based on Johansen test.

4.2.2 Estimation Results

The model before the break uses 5 lags according to AIC, and we identify two co-integrating equations according to Johansen test. We observe negative and significant coefficients for the lagged *Reg_Vehicle* at first-lag. This implies a negative short term adjustment. Interest rate shows a positive and significant impact on *Reg_Vehicle*.

Before break	Number of lags	Cointegrated Equations	R-squared	MAPE	Normality	Serial-Correlatio	Heteroscedasticity
Reg_Vehicle	5	2	0.49	10.15%	Yes	No	No

Table 4.2: VECM Model Result (Before Break)

The first error correction term is negative and significant, which means the model has a strong adjustment towards long-term equilibrium. It does not have issues regarding heteroscedasticity or serial-correlation, however there is still no normality present. The MAPE shows a good prediction accuracy. Coefficient relations show that both brent price and interest rate is highly significant. The negative coefficient suggests that increases in *Brent_Price* are associated with decreases in *Reg_Vehicle* in the long term, while the positive coefficient of interest rate suggests a strong long-term relationship where increases in *Interest_Rate* are associated with increases in *Reg_Vehicle*. *NOK/MWh* only exhibits a significant short-term relationship.

After break	Number of lags	Cointegrated Equations	R-squared	MAPE	Normality	Serial-Correlatio	Heteroscedasticity
Reg_Vehicle	12	1	-0.07	11.92%	No	No	Yes

Table 4.3: VECM Model Result (After Break)

The model after the break uses 12 lags and proves to only have one co-integrating equation. Reg_Vehicle is negative and significant at several lags, implying a consistent negative short term adjustment. Both *NOK/MWh* and *Interest_Rate* also show significance at multiple lags, while *Brent_Price* show a more pronounced impact on vehicle registrations in later years. The error correction term is also significant, although it is lower than the model before the break. It also performs poorly on the residual diagnostic tests, including a very low R^2.

The coefficient relations tells us that the oil price is positive and significant at 1% level. An increase in oil price will increase vehicle registrations, showing a strong long-term relationship. The interest rate is negative and significant at 5% level indicating a decrease in registrations as interest rate increases. The electricity price is not significant at any level.

4.2.3 Forcasting Accuracy

Our forecasting model employs a 15% trim in an attempt to mitigate the impact of extreme values and volatility. We did this for both our full model, as well as the models split at the break in 2010.

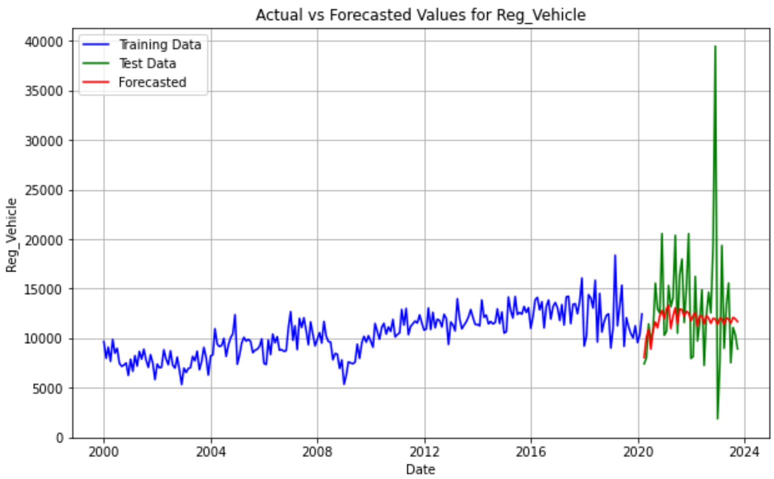


Figure 4.3: VECM Forecast (Full Model)

The out of sample forecast for the full model shows that it follows the general trend, but it struggles in capturing the volatility that occurs in the later period of the time series. It shows a reasonable ability to capture the trend over longer periods.

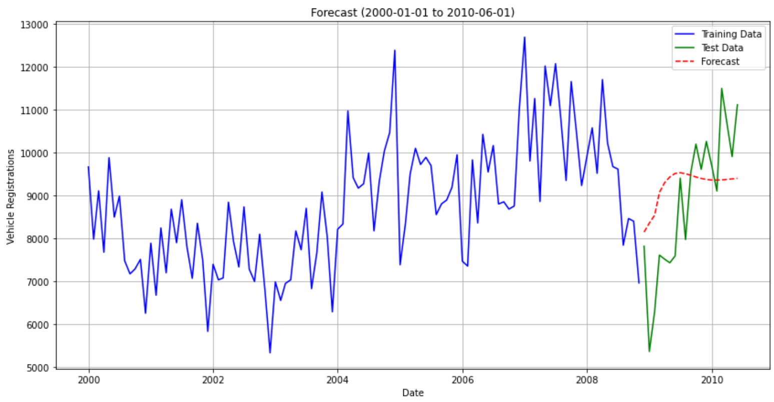


Figure 4.4: VECM Forecast (Before Break)

For the first subperiod, the forecast model generally captures the trend of pre-2010 vehicle registrations, but with certain differences. The forecast captures the fluctuations and downward trend with moderate error but sees noticeable deviations in periods of high volatility. The low MAPE shown in Table 4.2 indicate the model doing reasonably well in predicting vehicle registrations in this period.

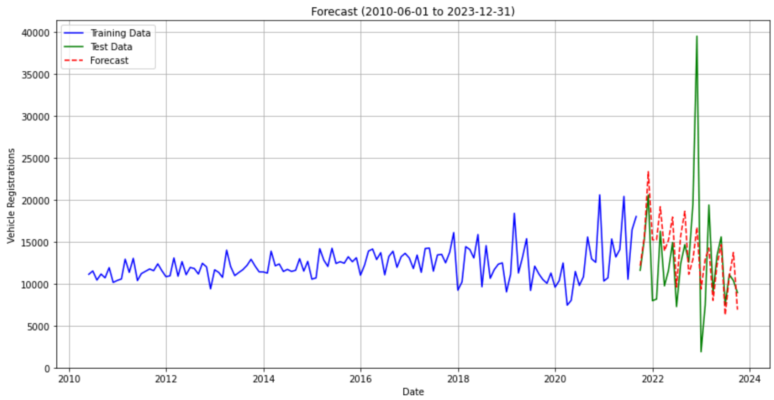


Figure 4.5: VECM Forecast (After Break)

The forecast shows a more mixed accuracy the second period. The model captures some of the peaks and troughs but not the magnitude of the exact fluctuations but, as with the full model, those noticeable spikes in actual data show periods of intense volatility, which are not captured that well by the forecast. The low R^2 also tells us that a simple mean prediction would likely perform better. MAPE is still acceptable, but lower than both the full model and the forecast before the break as shown in Table 4.1 and 4.3.

This volatility in the last period is what needs to be addressed if we are to improve the forecast. Our next attempt will then be to remove the extreme values in this period.

4.2.4 Outliers

The approach to managing outliers in the vehicle registration data involved a systematic outlier detection process followed by their removal. The detection method used was based on the interquartile range (IQR), a statistical technique that is robust to extreme values in data with skewed distributions. Specifically, outliers were defined as observations that fell below the first quartile minus 1.5 times the IQR or above the third quartile plus 1.5 times the IQR.

The application of the IQR method led to the identification of several outliers, particularly in the upper tail of the distribution, which corresponds to unexpectedly high vehicle registration numbers. Removal of these outliers was performed to prevent them from exerting undue influence on the statistical analysis of the dataset. The removal of outliers from the vehicle registration dataset underscores the necessity of meticulous data preprocessing in statistical analysis. By eliminating these atypical observations, the analysis became more robust, with models showing improved predictive performance and increased reliability of inference statistics. In this case, the vehicle registrations had an extreme outlier in December 2022 where 39000 cars were imported.

4.3 Modeling VECM without outliers

Following the removal of outliers with *Reg_Vehicle* as target variable, we see an improvement in the model, both in an improved MAPE as well as the model no longer suffering from heteroscedasticity. When looking at breaking points we can see a slight shift compared to the full model with outliers.

This model uses the number of lags suggested by AIC, which is seven. This results in a co-integration rank of two. The predictive performance, as reflected by the mean absolute percentage error (MAPE), indicates a reasonably good fit with an error margin of 9.25 %. This suggests that the model is capable of delivering practical predictions, aligning well with typical expectations in economic forecasting and decision support in the automotive sector.

The refined model, now cleansed of anomalies that could skew results, better captures the underlying trends and relationships within the data. Despite this improvement, the mean squared error (MSE) remains relatively high, signaling that while the model is robust in terms of explaining a significant portion of variability in vehicle registrations, it still struggles with some predictive challenges. This could stem from the variability inherent in the data not captured by the model or from potential model specification issues. The issue of non-normality still exists.

We find that Granger causality in this model is only significant for *Brent_Price* and *Interest_Rate* on *Reg_Vehicle*, while *NOK/MWh* is non significant and has a weaker or non-causal relationship with car registrations. The model suggests that negative influences of lagged vehicle registration values are felt on subsequent registrations, suggesting a peak-and-fall pattern of registration. On the other hand, some positive correlations can be observed with vehicle registrations and a delay in the trend of interest rates at the fourth lag. This might imply that consumers anticipate further rate increases and take such measures as purchasing cars at discounted rates. The relationship between Brent oil prices and vehicle registrations is dynamic in the sense that it shows both the positive and negative effect, possibly reflecting weak or strong economic conditions and how positive or negative consumer confidence is. Similarly, the effect of *NOK/MWh* on registrations is also dynamic and reflects the same positive-negative relationship, hence possibly indicating the changing economic activity on the consumer's decisions.

Only the first error correcting term is significant. It is negative and tell us that vehicle registrations corrects deviations from long-term equilibrium. The coefficient relations display a strong significant long-term relationship between *Reg_Vehicle* and *Interest_Rate*, further confirmed by the Granger causality. *Brent_Price* and *NOK/Mwh* does not show a significant long term relationship with *Reg_Vehicle*, but the significant Granger causality for *Brent_Price* displays a short-term relationship.

Removed Outliers	Number of lags	Cointegrated Equations	R-squared	MAPE	Normality	Serial-Correlatio	Heteroscedasticity
Reg_Vehicle	7	2	0.68	9.25%	No	No	No

Table 4.4: VECM Model Result (Removed Outliers)

4.3.1 Impulse Response and Variance Decomposition

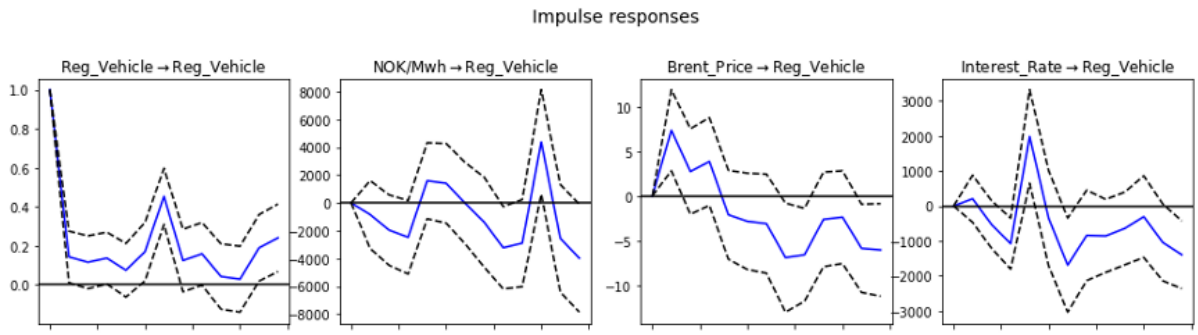


Figure 4.6: Impulse Responses (Without Outliers)

Figure 4.6 show how shocks in the variables affect vehicle registrations over a period of 12 months for the VECM model. Initially, the response of a shock in vehicle registrations in itself is strong and positive, suggesting that a shock to vehicle registrations leads to a substantial increase in registrations, but the effect diminishes over time and will gradually stabilize around zero.

A shock in the electricity price on the vehicle registrations initially leads to a decline, indicating that a higher operating cost affects consumer behavior. Electricity prices have a significant impact initially, but the long-term effect becomes more transient.

The initial response to a shock in brent prices is positive, increasing vehicle registrations. This could be an increased demand for EV vehicles. It then declines further before it stabilizes.

Interest rate shocks have a significant increase in vehicle registrations which is followed by a negative response. The reason for this could be an urge to secure financing at current rates.

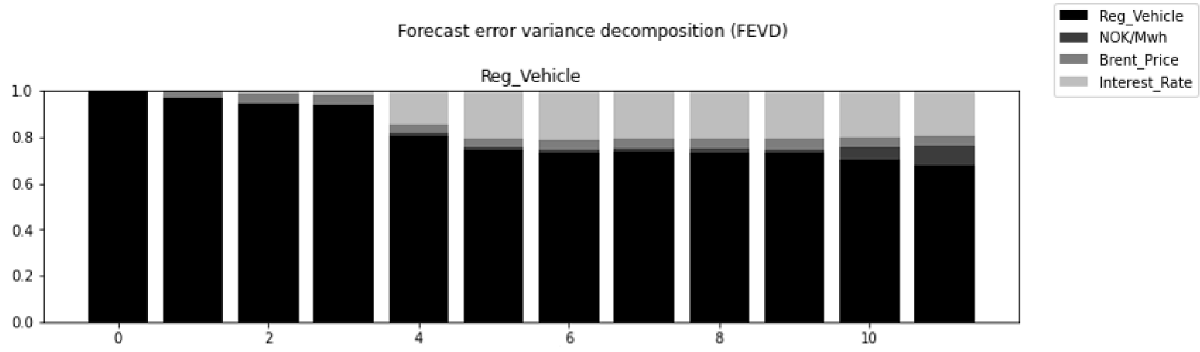


Figure 4.7: Forecast Error Variance Decomposition (Without Outliers)

Figure 4.7 shows a FEVD model for the VAR, visualizing how much each variable contributes to the forecast error variance of vehicle registrations over a period of 12 months. In the early months, most of the variance is attributed to vehicle registration itself. The other variables start to impact the variance after around four months. The influence of interest rate shows the most significance for the rest of the period with the other variables growing in impact over time, especially the electricity price for the later months. The figure implies that the short-term variance in vehicle registrations is mainly influenced by their own past values. In the long-term, other variables will start becoming more significant.

4.4 Modelling with Electric Vehicle Dataset

We also thought it would be interesting to look at the electric vehicle registrations, using a similar approach as earlier. The reason for this is that EV registrations are causing the majority of the volatility in our dataset. We decided to attempt using interest rate as an exogenous variable as the volatility in the EV imports are a result of policies, causing a spike in electric vehicles in a time with a rising interest rate. A higher interest rate would according to Moore and Walkes (2009), lower the number of vehicle registrations. We assume this is the case for electric vehicles as well.

We fit a VECM model according to AIC criteria, resulting in twelve lags and one cointegrating equation. The coefficients of lagged variables of EV suggest a possibly negative relationship with its current values, hence suggesting mean-reverting characteristics within the series.

With setting the interest rate as an exogenous variable, we get a negative coefficient for interest rate. This suggests that a potential decrease in interest rates will stimulate more electric vehicles to be registered. However, this coefficient is not statistically significant, indicating it might not strongly influence electric vehicle registrations. In contrast, the Brent oil price shows a positive and significant coefficient, suggesting that increases in oil prices correlate with an increase in electric vehicle registrations. Conversely, the electricity price exhibits a negative and significant coefficient, indicating a decline in electric vehicle registrations as electricity prices increase.

However, the residual diagnostic test results being significant for the normality and heteroscedasticity tests, respectively, would lead to problems and thus influence the robustness of the model estimates and inference. This is the case with our models which include the volatile spikes in registrations the last few years.

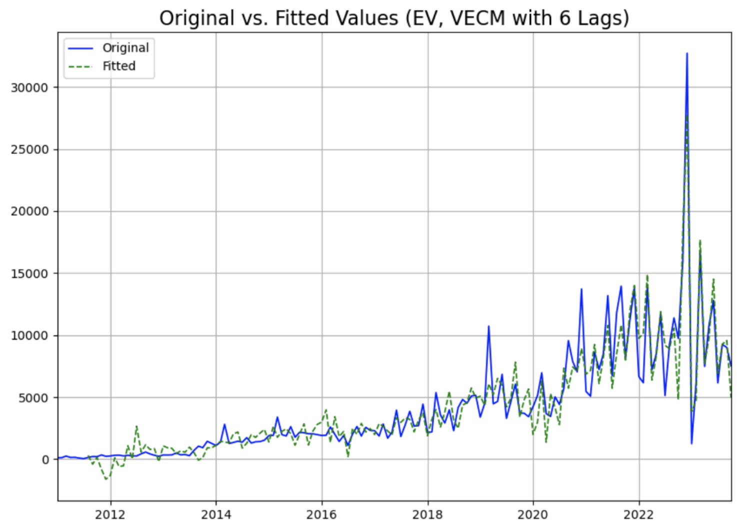


Figure 4.8: Original vs. Fitted Values (EV, VECM with 6 Lags)

EV dataset	Number of lags	Cointegrated Equations	R-squared	MAPE	Normality	Serial-Correlatio	Heteroscedasticity
Reg_Vehicle	12	1	0.91	45.36%	No	No	Yes

Table 4.5: VECM Model Result (EV dataset)

4.4.1 Impulse Response and Variance Decomposition

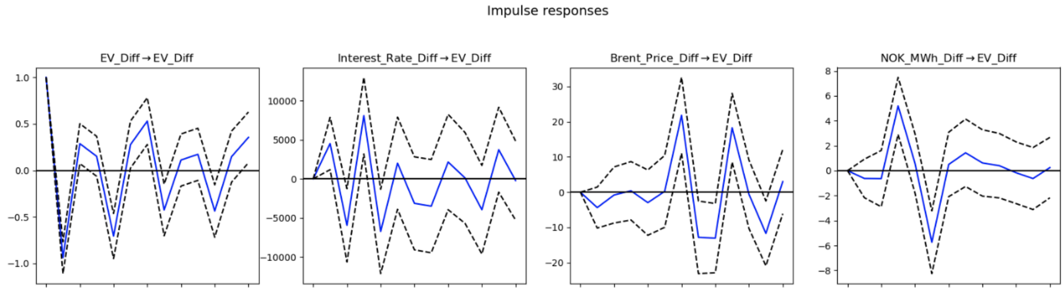


Figure 4.9: Impulse Responses

Impulse responses on the electric vehicles

Looking at the impulse response for the VECM model to gain insight into the more long-term relationship, here also set to 12 months, we can see that a shock in the electric vehicle registrations has a stabilizing impact on itself, indicating a certain level of resilience moderating fluctuations within the industry. The electricity prices show a short-run impact on electric vehicle registration, suggesting a correlation where higher electricity costs might briefly deter or influence electric vehicle registrations. In contrast, the effect of changes in the interest rate and Brent oil prices on electric vehicles registrations appears more pronounced and sustained, reflecting how these economic factors potentially sway consumer decisions over a longer period.

Interestingly, the response of electric vehicle registrations to shock in electricity prices quickly diminishes, which could imply that the initial deterrence caused by higher electricity costs may be offset by other long-term favorable conditions or policies promoting electric vehicle usage. These dynamics underscores the complex interplay of economic incentives and market conditions on the adoption of electric vehicles.

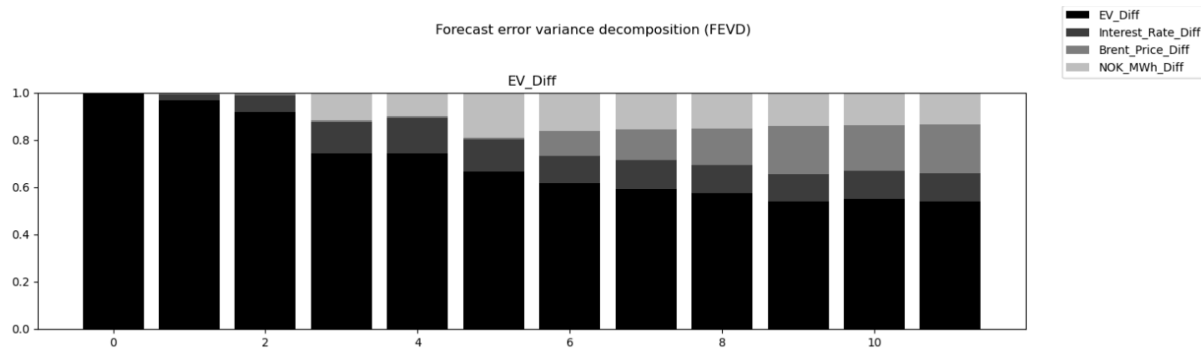


Figure 4.10: Forecast error variance decomposition (FEVD)

The forecasted error variance decomposition (FEVD) plot is used to analyze how much the forecasted error of variance of each variable in a VAR model can be attributed to its own shocks versus shocks to other variables in the model. The model used for *EV_Diff* has six lags and by taking a look at Figure 4.10 we find the contribution each variable has on *EV_Diff*. The black area, representing the proportion of the forecast error variance of *EV_Diff* attributed to its own shock, is the dominant factor. It appears to take up more than half of the bar, around 60%. This indicates that over six periods ahead, the majority of the variance in the forecast error can be explained by its own past values. *NOK/MWh_Diff*, the light gray area, appears to be the largest contributor after *EV_Diff* itself. Both *Interest_Rate_Diff* and *Brent_Price_Diff* seem to be approximately the same size. Hence, the dominance of its own shocks suggest that internal dynamics or inherent characteristics of *EV_Diff* play a larger role in shaping its own future values than the external economic factors at this specific lag.

4.6 Model Summary

Our analysis ends up consisting of several models aiming to capture the long-term relationship between vehicle registrations, electricity, oil prices and interest rate. This section will provide a summary of the findings

Reg_Vehicle	Forecast Evaluation		Significance	Residual Diagnostic		
	MAPE	R2	Jointly	Serial Correlation	Heteroscedasticity	Normality
Full model	11.36%	0.78	Yes	No	Yes	No
Split before break	10.15%	0.48	Yes	No	No	Yes
Split after break	11.92%	-0.07	Yes	No	Yes	No
Outliers removed	9.25%	0.68	Yes	No	No	No

Table 4.6: Model Summary (Reg_Vehicle)

EV	Forecast Evaluation		Significance	Residual Diagnostic		
	MAPE	R2	Jointly	Serial Correlation	Heteroscedasticity	Normality
Model with exogenous variable	45.36%	0.91	Yes	No	Yes	No

Table 4.7: Model Summary (EV dataset)

Out of all our models, the model with removed outliers is the overall better performer. It indicates the highest forecast accuracy, having a MAPE of 9.25%. The R-squared value of 0.68 shows that the model explains a good portion of the variance in the vehicle registrations.

The model also shows no issues regarding serial correlation. This is an important diagnostic for the forecasting as it indicates independent residuals over time. Removing the outliers also resulted in no heteroscedasticity, implying constant variance of the residuals. This model, like most of the other models, suffers from non-normality in residuals. This could affect the validity of some statistical tests.

The other models show several weaknesses. The full model including outliers have a good R-squared value of 0.78 but it suffers from both non-normality and heteroscedasticity.
The model split before break show a more mixed performance. As the model uses more stable data, it does not suffer from heteroscedasticity and has normally distributed residuals. MAPE is also quite good, sitting at 10.15%. A lower R-squared of 0.48 shows it explains less of the variance in vehicle registrations compared to the full model and the model without outliers.

The model split after break performs poorly with a negative R-squared, showing it does not explain the variance in vehicle registrations. It has a decent MAPE at 11.92%, but it suffers from heteroscedasticity and non-normality just like the full model. This can be explained by both the models containing the volatile data present later in the time series.

Finally, the model using EV as target variable and interest rate as an exogenous variable shows that despite having the highest R-squared of all the models at 0.91, also have a very high MAPE of 45.36%. This suggests that the model is not very accurate in forecasting. It faces the same issues as many others, heteroscedasticity, and non-normality of residuals, further undermining the robustness of the models predictions.

4.7 Discussion and Recommendations for Research

4.7.1 Discussion

Our analysis of the electric vehicle registration data offers significant insights into the dynamics of vehicle adoption, which can be directly related to the findings from various studies discussed in the literature review.

Given the relatively short dataset for electric vehicles registrations, which is marked by high volatility and an upscaling period reflective of the government's ambition to achieve 100% newly registered zero-emission vehicles by 2025, and considering significant subsidiaries to incentivize consumers, electric vehicle registration data has not yet gotten the time to stabilize. Within this context, we set the interest rate as an exogenous variable and observe that the interest rate has a negative coefficient, suggesting a potential decrease in electric vehicle registrations as interest rates rise. This aligns with the theory that higher financing costs could deter purchases (Moore & Walkes, 2009), though the impact of this coefficient is not statistically significant, indicating it might not strongly or reliably influence electric vehicle registrations. In contrast, the Brent oil price shows a positive and significant coefficient, suggesting that increases in oil prices correlate with an increase in electric vehicle registrations, which is the opposite of what we observe in Tishler (1982) and consistent with the finding of Berthelsen and Arteaga (2016) . This could be interpreted as consumers turning to electric vehicles as a cost-effective alternative amid rising oil prices. Conversely, the electricity price exhibits a negative and significant coefficient, indicating a decline in electric vehicle registrations as electricity prices increase, which matches expectations considering the direct impact of electricity pricing on the operating costs of electric vehicles. This logic is found to be the same in the other studies under the literature review above.

The model before the break in 2010-06-31 can be seen as a model less impacted by electric vehicle registrations, as the proportion of electric vehicles in the market was quite low. Fossil fuel vehicles were predominant, with only 3 347 electric vehicles being registered at the time. The significant negative brent price coefficient would mean a decrease in vehicle registrations when oil prices rise which is in line with the findings of Tishler (1982).
The positive significant interest rate coefficients would imply rising interest rates cause increased vehicle imports. This is not consistent with the findings of Moore and Walkes (2009). We believe the increased interest rate will make financing more expensive is likely due to issues with structural breaks in the data.

For the model after the break we find that the oil price coefficient is significant and positive, where an increase in oil price increases vehicle registrations. They have a strong long term relationship which is expected and in line with theory as the model after the break sees the massive increase of electric vehicles in the market, turning consumers away from fossil-fueled vehicles when oil prices rise. However, after the break we actually now see a negative and significant interest rate coefficient, indicating that vehicle registrations decrease with higher interest rates.

The model without outliers removes the extreme values towards the end of our time series, where there was an increase of 39 000 vehicle registrations in December 2022 following regulations that introduced VAT for electric cars that cost over 500 000 kr. This caused a massive increase in imports before the regulation took effect. We attempted to reduce the volatility by removing the extreme values around this time period, because we saw that both the full model and the model after break suffered from heteroscedasticity. The outlier removal process proved to be a success where it resulted in a model outperforming the others thanks to the more stable time series. The model only had a significant negative long-term relationship with interest rate, showing a decrease in vehicle registrations as interest rates rise. This is consistent with the findings of Moore and Walkes (2009).

4.7.2 Recommendation for Further Research

While our employment of VAR and VECM provided valuable insights in both short- and long-term dynamics, the use of other alternative models could handle certain data differently and more effectively. Autoregressive Conditional Heteroscedasticity(ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models could be considered, especially since we have changing volatility in our data, known as heteroscedasticity. The ARCH model works by capturing the time-varying nature of volatility through modeling the variance of the current error term as a function of past error terms (Engle, 1982). GARCH adds to this, incorporating past variances to the model (Bollerslev, T. (1990). These models could have proven useful as several of our models suffer from heteroscedasticity likely due to policy changes.

The Autoregressive Distributed Lag (ARDL) model could prove useful as well. Described by Pesaran & Shin (1995), one of its main strengths is handling mixed stationarity in a set of variables. It can estimate short- and long-term dynamics without having to test for co-integration or unit roots. This could be a good alternative, as some of our variables show mixed results from ADF and KPSS, but show stationarity after differentiation.

As mentioned previously, Moore and Walkes (2009) presents a study analysis of the factors influencing the import demand for motor cars in Barbados over the period 1994 to 2008. They use several variables in their study that also could be interesting in our own analysis. Key findings from the article states that car price has a significant negative influence on car imports, as well as real GDP significantly influence car imports positively. We think it would be interesting to see if these variables would significantly influence the car registrations in Norway as well.

5 Conclusion

This thesis set out to investigate the interactions between vehicle registrations in Norway and various economic indicators, specifically electricity prices, Brent spot prices, and interest rates. The primary research question focused on understanding the relationships between these economic factors and vehicle registrations, particularly in light of the increases in electricity prices and the substantial uptake of electric vehicles.

We reject H_0 in our hypothesis, as we can conclude there is at least one long-term relationship between the variables. In fact, we have discovered that in some models, there exist up to two long-term relationships. The best performing model according to our analysis is the model without outliers, as this yields the best forecasting accuracy, through a model that exhibits more robust residual diagnostics and has a strong positive long-term relationship between vehicle registrations and interest rate.

While not performing well in terms of forecasting, the model capturing electric vehicle registrations and also therefore the volatile periods in our data, had expected long-term relationships in a negative impact from increased electricity price and a positive impact from increased oil price.

6 Appendix

6.1 Full Model

Stationarity Test Results (Before Differencing Reg_Vehicle Dataset):

	Series	Test	Test Statistic	p-value
0	Reg_Vehicle	ADF	-1.542569	0.512358
1	Reg_Vehicle	KPSS	2.078319	0.010000
2	NOK/Mwh	ADF	-3.870441	0.002263
3	NOK/Mwh	KPSS	0.680501	0.015318
4	Brent_Price	ADF	-1.097042	0.716250
5	Brent_Price	KPSS	1.534967	0.010000
6	Interest_Rate	ADF	-2.175691	0.215186
7	Interest_Rate	KPSS	1.593717	0.010000

Stationarity Test Results (After Differencing Reg_Vehicle Dataset):

	Series	Test	Test Statistic	p-value
0	Reg_Vehicle	ADF	-5.886130	2.998676e-07
1	Reg_Vehicle	KPSS	0.032707	1.000000e-01
2	NOK/Mwh	ADF	-5.480255	2.292822e-06
3	NOK/Mwh	KPSS	0.053702	1.000000e-01
4	Brent_Price	ADF	-6.589615	7.169206e-09
5	Brent_Price	KPSS	0.067589	1.000000e-01
6	Interest_Rate	ADF	-5.395664	3.458958e-06
7	Interest_Rate	KPSS	0.205274	1.000000e-01

Table 6.1.1: Stationarity tests & differencing normal dataset

VAR Order Selection (* highlights the minimums)

	AIC	BIC	FPE	HQIC
0	31.29	31.34	3.880e+13	31.31
1	30.33	30.59	1.483e+13	30.43
2	29.27	29.75*	5.157e+12	29.46
3	29.21	29.90	4.867e+12	29.49
4	29.12	30.02	4.418e+12	29.48
5	28.94	30.05	3.718e+12	29.39
6	28.84	30.16	3.364e+12	29.37*
7	28.86	30.39	3.416e+12	29.47
8	28.86	30.60	3.423e+12	29.56
9	28.86	30.82	3.453e+12	29.65
10	28.87	31.04	3.489e+12	29.74
11	28.75	31.13	3.097e+12	29.70
12	28.71*	31.30	2.988e+12*	29.75

Table 6.1.2: VAR Order Selection

```
Granger Causality Test:
                                  Test Statistic      p-value                          Conclusion
Reg_Vehicle    NOK/Mwh                  6.403709  5.353600e-11              Reject H0: (significant).
               Brent_Price              2.470356  3.522915e-03              Reject H0: (significant).
               Interest_Rate            1.550591  1.008170e-01  Fail to Reject H0: (not significant).
NOK/Mwh        Reg_Vehicle              6.495524  3.435722e-11              Reject H0: (significant).
               Brent_Price              5.924834  5.374485e-10              Reject H0: (significant).
               Interest_Rate            0.888098  5.588425e-01  Fail to Reject H0: (not significant).
Brent_Price    Reg_Vehicle              2.366928  5.316870e-03              Reject H0: (significant).
               NOK/Mwh                  1.952916  2.557894e-02              Reject H0: (significant).
               Interest_Rate            0.477383  9.285172e-01  Fail to Reject H0: (not significant).
Interest_Rate  Reg_Vehicle              0.918347  5.277256e-01  Fail to Reject H0: (not significant).
               NOK/Mwh                  1.132291  3.296453e-01  Fail to Reject H0: (not significant).
               Brent_Price              1.783125  4.665099e-02              Reject H0: (significant).
```

Table 6.1.3: Granger Causality Test all variables

Reg_vehicle	Cointegration Relation						
		coef	std err	z	P>|z|	[0.025	0.975]
Full model	beta.1	1	0	0	0	1	1
	beta.2	9.27E-18	0	0	0	9.27E-18	9.27E-18
	beta.3	-1.45E-16	0	0	0	-1.45E-16	-1.45E-16
	beta.4	984.907	126.007	7.816	0	737.937	1231.877
	const	-1.33E+04	24.184	-549.045	0	-1.33E+04	-1.32E+04

Table 6.1.4: Cointegration Relation

6.2 Before and after splitting the dataset

```
ADF and KPSS Results for 2000-2010/06 Dataset:
               ADF Test Statistic  ADF p-value  KPSS Test Statistic  KPSS p-value
Reg_Vehicle             -2.588185     0.095464             0.808414          0.01
NOK/Mwh                 -4.237708     0.000568             0.882461          0.01
Brent_Price             -1.678316     0.442318             1.432850          0.01
Interest_Rate           -2.014614     0.280202             0.815249          0.01
```

```
ADF and KPSS Results for 2010/06-2023 Dataset:
               ADF Test Statistic  ADF p-value  KPSS Test Statistic  KPSS p-value
Reg_Vehicle             -2.576920     0.097862             0.434059      0.062474
NOK/Mwh                 -3.303829     0.014708             0.629348      0.019968
Brent_Price             -1.290686     0.633422             0.424665      0.066524
Interest_Rate           -0.687331     0.850004             0.345192      0.100000
```

Table 6.2.1: ADF and KPSS results both splits

Reg_vehicle	Cointegration Relation						
		coef	std err	z	P>|z|	[0.025	0.975]
Before Break	beta.1	1	0	0	0	1	1
	beta.2	2.95E-16	0	0	0	2.95E-16	2.95E-16
	beta.3	-4.6858	1.43	-3.278	0.001	-7.488	-1.884
	beta.4	203.9832	0.142	1433.677	0	203.704	204.262
	const	-8115.5463	79.098	-102.602	0	-8270.575	-7960.518

Table 6.2.2: Cointegration Relation (Before Break)

Reg_vehicle	Cointegration Relation						
		coef	std err	z	P>|z|	[0.025	0.975]
After Break	beta.1	1	0	0	0	1	1
	beta.2	0.4656	1.332	0.35	0.727	-2.145	3.076
	beta.3	11.8817	3.904	3.043	0.002	4.23	19.533
	beta.4	-1725.2197	687.249	-2.51	0.012	-3072.203	-378.237
	const	-17400	1504.518	-11.566	0	-20300	-14500

Table 6.2.3: Cointegration Relation (After Break)

6.3 Outliers Removed

VAR Order Selection (* highlights the minimums)

	AIC	BIC	FPE	HQIC
0	28.65	28.71	2.782e+12	28.68
1	28.24	28.54*	1.846e+12	28.36
2	28.14	28.67	1.661e+12	28.35
3	28.04	28.80	1.502e+12	28.35*
4	27.98	28.99	1.425e+12	28.39
5	27.92	29.16	1.338e+12	28.42
6	27.76	29.24	1.142e+12	28.36
7	27.66*	29.37	1.036e+12*	28.35

Table 6.3.1: VAR Order Selection (Without Outliers)

Reg_vehicle	Cointegration Relation						
		coef	std err	z	P>|z|	[0.025	0.975]
Without outliers	beta.1	1	0	0	0	1	1
	beta.2	-5.57E-16	0	0	0	-5.57E-16	-5.57E-16
	beta.3	-0.1981	2.897	-0.068	0.945	-5.876	5.48
	beta.4	1464.5805	0.159	9205.365	0	1464.269	1464.892
	const	-13720	227.521	-60.298	0	-14200	-13300

Table 6.3.2: Cointegration Relation (Without Outliers)

6.4 EV dataset

```
 VAR Order Selection (* highlights the minimums)
==================================================
       AIC         BIC         FPE         HQIC
--------------------------------------------------
0        31.73       31.82   6.037e+13       31.77
1        30.82       31.24   2.417e+13       30.99
2        29.68      30.44*   7.737e+12       29.99
3        29.52       30.63   6.641e+12       29.97
4        29.23       30.67   4.964e+12       29.81
5        29.02       30.80   4.053e+12       29.75
6        28.72       30.84   3.007e+12      29.58*
7        28.67       31.13   2.893e+12       29.67
8        28.53       31.33   2.546e+12       29.67
9        28.39       31.53   2.251e+12       29.66
10       28.31       31.79   2.116e+12       29.72
11       28.12       31.94   1.799e+12       29.67
12       28.18       32.33   1.961e+12       29.86
13       28.04       32.53   1.773e+12       29.87
14      27.88*       32.71  1.578e+12*       29.84
15       27.90       33.08   1.699e+12       30.00
--------------------------------------------------
```

Table 6.4.1: VAR Order Selection (EV Dataset)

EV Data	Cointegration Relation						
		coef	std err	z	P>|z|	[0.025	0.975]
EV with exogenous variable	beta.1	1	0	0	0	1	1
	beta.2	26.3511	5.701	4.622	0	15.177	37.526
	beta.3	-19.3797	4.557	-4.252	0	-28.312	-10.447

Table 6.4.2: Cointegration Relation (With Exogenous Variable)

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