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Bachelor Thesis

ASSESSING THE PREDICTIVE POWER OF CAR SALES ON LITHUANIA'S ECONOMIC FLUCTUATIONS

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Vilnius, 2024

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Bachelor Thesis

Quantitative Economics programme

Faculty of Economics and Business Administration

Supervisor – lecturer PhD Žymantas Budrys

Vilnius, 2024

Summary

The main goal of the thesis is to evaluate the predictive power of car sales on Lithuania's economic fluctuations. The research aims to determine if car sales can forecast vital economic indicators such as Gross domestic product (GDP), unemployment, inflation, and interest rates. The study uses data from 1998 to 2024, focusing on a post-Soviet economy that has undergone significant changes.

The literature review highlights the relationship between car sales and economic conditions, demonstrating that downturns in car sales often precede economic contractions. The methodology includes data from car registrations and various economic indicators. The Vector Autoregression (VAR) model was used to capture dynamic relationships among variables best. The results from Forecast Error Variance Decomposition (FEVD) and Mean Squared Forecast Error (MSFE) analyses confirm that car sales have significant predictive power for GDP and unemployment but less so for inflation and interest rates. Granger causality tests indicate that car sales can predict changes in unemployment, GDP, and consumer confidence, particularly before COVID-19. However, car sales do not significantly predict the Euribor 3-month rate.

The findings suggest that car sales are a valuable leading indicator of economic health, particularly for short-term forecasts. Policymakers and industry stakeholders can use car sales data to anticipate economic shifts and formulate strategic responses. This research contributes to a deeper understanding of the automotive market's role in economic forecasting and planning in Lithuania.

ASSESSING THE PREDICTIVE POWER OF CAR SALES ON LITHUANIA'S ECONOMIC FLUCTUATIONS

NOJUS ŠLIUOŽA

Bakalauro baigiamasis darbas

Kiekybinė ekonomika

Ekonomikos ir verslo administravimo fakultetas

Baigiamojo darbo vadovas - lektorius Dr. Žymantas Budrys

Vilnius, 2024

Santrauka

Pagrindinis šio baigiamojo darbo tikslas yra įvertinti automobilių pardavimų prognozavimo galimybes Lietuvos ekonomikos svyravimams. Tyrimo metu siekiama nustatyti, ar automobilių pardavimai gali prognozuoti pagrindinius ekonominius rodiklius, tokius kaip Bendras vidaus produktas (BVP), nedarbas, infliacija ir palūkanų normos. Šiame tyrime naudojami duomenis nuo 1998 iki 2024 metų, dėmesį skiriant posovietinei ekonomikai, kuri patyrė reikšmingų pokyčių.

Literatūros apžvalgoje išryškinamas ryšys tarp automobilių pardavimų ir ekonominių sąlygų, rodantis, kad automobilių pardavimų mažėjimas dažnai prognozuoja ekonomikos nuosmukius. Metodikoje naudojami automobilių registracijų ir įvairių ekonominių rodiklių duomenys. Ryšiui tarp kintamųjų fiksuoti buvo naudojamas vektorinės autoregresijos (VAR) modelis. Prognozės klaidos dispersijos dekompozicija (FEVD) ir vidutinės kvadratinės prognozės klaidos (MSFE) analizės rezultatai patvirtina, kad automobilių pardavimai turi reikšmingą prognozavimo galią BVP ir nedarbo atžvilgiu, tačiau mažiau infliacijos ir palūkanų normų atžvilgiu. Granger priežastingumo testai rodo, kad automobilių pardavimai gali prognozuoti nedarbo, BVP ir vartotojų pasitikėjimo pokyčius, ypač prieš COVID-19 laikotarpį, iki 2019 metų galo. Tačiau automobilių pardavimai neturi reikšmingos prognozavimo galios Euribor 3 mėnesių normai.

Išvados rodo, kad automobilių pardavimai yra vertingas ekonominės sveikatos rodiklis, ypač trumpalaikėms prognozėms. Politikos formuotojai ir pramonės dalyviai gali naudoti automobilių pardavimų duomenis, siekdami numatyti ekonominius pokyčius ir formuoti strateginius atsakus. Šis tyrimas prisideda prie gilesnio supratimo apie automobilių rinkos vaidmenį ekonomikos prognozavimui ir planavimimui Lietuvoje.

CONTENTS

INTRODUCTION

The automotive industry, a crucial component of modern economies, is a significant indicator of economic health. Understanding how car sales can predict broader economic fluctuations is paramount for policymakers, businesses, and economists. In Lithuania, the automotive market provides unique insights due to its distinct economic landscape and historical context. This study aims to explore the predictive power of car sales on Lithuania's economic fluctuations, with the potential to significantly influence economic forecasting and planning, particularly for policymakers.

The novelty of this research lies in its focus on Lithuania, a post-Soviet economy that has undergone significant transformations since gaining independence. The intricate relationship between car sales and economic indicators like GDP, unemployment, inflation, and interest rates can reveal unique insights into economic dynamics. These insights are critical for effective policy formulation and business strategy. This topic is related to academics and practitioners in the automotive industry and economic policy, making it a timely and valuable contribution to the field. Previous studies have demonstrated the importance of car sales as a leading indicator of economic health, further justifying this research focus (Smith et al., 2009).

The primary aim of this research is to evaluate the predictive power of car sales on Lithuania's economic fluctuations. This aim aligns with the underlying goal of understanding the interplay between automotive market trends and broader economic conditions. The specific objectives of the work include analysing the relationship between car sales and key economic indicators, over time applying Principal Component Analysis (PCA) to reduce multicollinearity among economic indicators and transforming them into principal components for more robust analysis. Employing a Vector Autoregression (VAR) model to capture the dynamic interdependencies among variables and assess the predictive power of car sales within this framework. Conducting Forecast Error Variance Decomposition (FEVD) to determine the proportion of forecast error variance attributable to shocks from each variable, including car sales. Comparing the Mean Squared Forecast Error (MSFE) of models with and without car sales, assessing the added predictive value of including car sales in economic forecasting models.

The bachelor thesis is structured to analyse the research question comprehensively. The introduction outlines the topic's relevance, the problem, the aim and objectives, and the methods used, providing an overview of the paper's structure. The literature review comprehensively examines existing research on the relationship between car sales and economic indicators, focusing on studies relevant to Lithuania and broader economic contexts. Additionally, our literature review dives into the past of the automobile sector in Lithuania. It explores potential changes in the future of the automobile industry, particularly how these changes could impact sales and predictability. The methodology section describes the data sources, transformation techniques, and the VAR model setup, including the rationale for choosing these methods. The empirical analysis section presents and discusses the empirical results, including the findings from the FEVD and MSFE comparisons. The discussion and implications section interprets the results, highlighting the implications for policymakers, industry stakeholders, and future research. Finally, the conclusion summarises the findings, contributions of the study, and suggestions for further research.

The primary challenge encountered during this research was handling the large and complex dataset of car sales and economic indicators. Ensuring the accuracy and reliability of data transformations, particularly in achieving stationarity and removing multicollinearity, required meticulous attention and iterative adjustments. Moreover, economic relationships' dynamic and complex nature presented significant challenges in modelling and interpreting the results, requiring robust statistical methods and meticulous analyses.

1. ANALYSIS OF SCIENTIFIC LITERATURE

1.1. Employment and Cyclical Economic Impact

The study by Smith et al. (2009) analyses the connection between car sales and economic performance. Their findings indicate that economic, demographic, and technological factors significantly influence automotive markets. For example, Smith et al. (2009) highlight that car sales typically decline by an average of 15-20% during economic downturns, reflecting reduced consumer confidence and spending power. This comprehensive analysis underscores how these factors collectively shape automotive demand and broader economic conditions.

Additionally, Samaddar et al. (2022) emphasise the impact of shifts in the automotive industry on the broader economy. Their research shows that a 10% increase in car sales can lead to a 1.5% increase in GDP, demonstrating the sector's significant contribution to economic growth. This relationship is further illustrated by data showing that automotive industry growth often precedes overall economic recovery by several quarters.

The profound connection between car sales and employment is also well-documented. The automotive industry directly employs millions worldwide and indirectly supports many more through related services such as sales, maintenance, and supply chains (Smith et al., 2009). For instance, in the United States, the automotive sector supports approximately 4.1 million jobs, highlighting its pivotal role in the economy.

The cyclical nature of the automotive industry is another crucial aspect detailed in economic analyses. Studies indicate that reduced automotive sales can lead to significant layoffs and economic contractions during economic downturns. For example, during the 2008 financial crisis, the automotive industry in the United States saw a sales drop of over 30%, resulting in the loss of nearly 350,000 jobs (U.S. Bureau of Labor Statistics, 2010). Conversely, recovery phases typically witness a surge in automotive sales, which can signal economic recovery. Data from the post-2008 recovery period shows that car sales increased by 25% from 2009 to 2012, corresponding with reduced unemployment rates and a revival in economic activity (Federal Reserve, 2013).

These recurring patterns underscore the automotive sector's role as a harbinger of economic health, making it a critical focus area for policymakers and economic strategists. By understanding these dynamics, policymakers can better stabilise and stimulate economies during various phases of the economic cycle (Samaddar et al., 2022).

1.2. Government Stimulus and Consumer Behaviour in the Automotive Market

In the article by Plache (2013), the resilience of the automotive sector amid rising unemployment rates is closely examined. Typically, unemployment is seen as a precursor to reduced consumer spending, particularly on large purchases such as vehicles. However, the trends analysed in the article suggest that this is not always the case, pointing to a more intricate connection between car sales and economic health than previously understood.

The analysis dives into the role of government stimulus measures, which have been instrumental in maintaining consumer purchasing power during economic slowdowns. These measures often include tax incentives and rebates targeted at new vehicle purchases. For example, during the 2009 financial crisis, the U.S. government introduced the Car Allowance Rebate System, which provided $3,500 to $4,500 for consumers trading in older vehicles for new, more fuel-efficient models. This program led to the sale of nearly 700,000 vehicles and was credited with boosting car sales by 1-2% during the recession period (Plache, 2013).

Moreover, the article explores shifts in consumer behaviour during periods of economic uncertainty. It notes that during such times, consumers often prioritise reliability and long-term value in their purchases to mitigate future financial risks. For instance, data from the 2008-2009 recession indicate that sales of new vehicles with better fuel efficiency and lower maintenance costs increased by approximately 15% as consumers sought to reduce potential future expenses (Plache, 2013).

The enduring strength of car sales despite high unemployment rates also highlights the effectiveness of financing options available to consumers. Automotive manufacturers and dealerships frequently offer special financing rates, such as reduced interest rates or extended payment terms, making new cars accessible for individuals who might otherwise be deterred by economic uncertainty. For example, during the 2008-2009 recession, many manufacturers offered 0% financing deals, which led to a 20% increase in sales financed through such programs (Plache, 2013). These financing options can ease the immediate financial burden of purchasing a new vehicle, making it a more viable option for consumers even during downturns.

Additionally, the analysis considers the psychological aspect of consumer behaviour, where purchasing a new car is seen as a practical investment and a morale booster during tough times. Buying a new car can provide a sense of normalcy and control, which is particularly appealing when economic conditions feel unstable and unpredictable. Surveys conducted during economic downturns show that 30% of consumers view new car purchases as achieving more excellent financial stability and reliability (Plache, 2013).

This nuanced understanding of the relationship between car sales and economic indicators like unemployment highlights the complex interplay between government policy, consumer behaviour, and financial mechanisms. It suggests that car sales are not merely a reflection of the economy's current state but also a response to anticipatory actions by consumers and policymakers. By examining these dynamics, the article provides valuable insights into how automotive sales can serve as a leading, complex indicator of economic health.

1.3. Long-term patterns

Enduring trends in automotive demand also shed light on structural changes in the economy and labour market. Demographic shifts, urbanisation, and evolving consumer preferences significantly influence vehicle demand. These trends not only affect manufacturing but also have consequences for the broader economy, influencing jobs in retail, after-market services, and infrastructure development associated with automotive needs. For instance, the increasing preference for electric vehicles can spur new industries and services centred around this technology, creating new employment opportunities and economic pathways (Gao et al., 2018; Smith et al., 2009).

The study by Gao et al. (2018) utilises the Consumer Confidence Index, steel production rates, the Consumer Price Index, and gasoline prices to predict sales trends, providing a sophisticated model that combines these elements with sales data from a prominent domestic automaker, Chery. The study highlights significant long-term relationships between the chosen economic indicators and car sales using Vector Auto-Regression (VAR) and Vector Error Correction Models (VECM). This methodological approach not only underscores the direct impact of economic health on automobile sales but also refines forecasting accuracy, which is crucial for automotive manufacturers and policymakers (Gao et al., 2018).

1.4. Predicting vehicle sales using various economic indicators

The study by Sivak (2013) highlights the robust correlation between GDP and vehicle sales. Through regression analysis, Sivak demonstrates that the logarithm of GDP serves as a reliable linear predictor for the logarithm of vehicle sales across a diverse group of countries. This relationship persisted from 2005 to 2011, marked by significant economic fluctuations. The analysis included a detailed examination of vehicle sales data and GDP from 48 countries. For instance, vehicle sales ranged from about 16,000 to 18.5 million annually, while GDP values spanned from approximately $23 billion to $11.7 trillion. The study found that an average of 1,869 vehicles were sold for every billion dollars of GDP. This ratio provides a precise quantitative measure of the relationship between economic output and automotive demand. These findings underscore the potential of GDP as a predictive tool for automotive markets, suggesting that increases in GDP are typically accompanied by proportional increases in vehicle sales, indicating a close connection between these two variables (Sivak, 2013).

The scientific paper by Lin (2015) explores how changes in various economic predictors like GDP, unemployment rate, crude oil prices, and others can influence auto sales. The study highlights the sensitivity of automobile sales to shifts in economic indicators, drawing parallels to the "boiled frog" analogy where significant economic conditions can have pronounced effects on auto sales. This sensitivity is exemplified by the noticeable drop in car sales during the 2008 financial crisis, underscoring the sector's role as an economic indicator. Also, the thesis employs various statistical models, including functional data analysis and regression, to quantify the impact of economic variables on car sales. It was found that the first derivatives of predictors are crucial for understanding the level of change in car sales. This approach allows for a nuanced understanding of how subtle shifts in economic conditions can affect automobile market dynamics (Lin, 2015).

Additionally, the study uses time series analysis to account for the autocorrelations often present in economic data, enhancing the predictive accuracy of the models used. Overall, Lin's (2015) thesis offers a detailed exploration of how car sales can be a leading indicator of economic health, influenced by various economic factors. The findings underscore the interconnectedness of the automobile industry with broader economic cycles, providing insights applicable not just to the U.S. but to other economies with similar market dynamics (Lin, 2015).

1.5. Car sales during an economic recession

In Lithuania, as in many countries, the automotive industry can be a benchmark for overall economic health due to its direct connection to consumer confidence and spending. This link was starkly demonstrated during the 2007-09 global financial crisis when a substantial downturn in car sales preceded and accompanied deeper economic troubles. Economist Dupor (2019) discusses this connection more deeply.

Car sales are susceptible to changes in consumer confidence. Consumers are less likely to make significant financial commitments when uncertain about the future - due to factors like job security, interest rates, or economic stability. Purchasing a car often requires substantial personal investment or financing, making it a strong consumer confidence indicator. During economic downturns, a decline in car sales can usually predict a broader economic slowdown, as observed in numerous global instances, including the 2007-09 recession (Dupor, 2019).

Moreover, car sales correlate closely with access to credit. Credit conditions typically tighten during economic contractions as lenders become more cautious, affecting consumers' ability to finance new car purchases. The decrease in car sales during such periods reflects a decline in consumer demand and a broader tightening of economic credit conditions. For instance, the 2007-09 recession saw a lending contraction that directly led to decreased auto sales, mirroring the broader economic contraction (Smith et al., 2009; Lin, 2015).

Furthermore, a downturn in car sales can lead to reductions in manufacturing output, affecting employment directly in automotive production and related industries, including parts suppliers and distribution networks. Government policies can also influence car sales through regulations and incentives. For example, tax incentives for lower-emission vehicles can drive sales of certain types of cars, while import tariffs or restrictions can decrease them. The interplay between government policy and car sales offers insights into how regulatory environments affect consumer behaviour and industry health, providing another layer of data for predicting economic shifts (Samaddar et al., 2022).

1.6. Post-Soviet car market recovery

When Lithuania was still part of the Soviet Union, the primary problem with its automobile industry was the massive demand for cars coupled with insufficient production to meet that demand. This issue was prevalent across all Soviet countries, as noted by Katsenelinboigen (1977). Consequently, only more privileged individuals could secure vehicles. The broader economic condition was characterised by a surplus of money but a shortage of products.

After gaining independence, Lithuania had to rapidly adapt its economic and industrial frameworks to fit into the global market system in the early years following independence. As Kvaraciejūtė (2011) noted, the government's approach to European Union directives and regulations, post-accession in 2004, played a crucial role in shaping the automotive industry's landscape. These changes impacted everything from environmental standards to trade agreements. Lithuania invested significantly in transport infrastructure after its acceptance into the European Union. For instance, in 2004, there was substantial financial support of 785 million LT (approximately 227.35 million Euros) from the European Union invested in road infrastructure. This investment improved roads within and between cities, prompting more people to switch from public transport to private automobiles.

1.7. Auto Sales Trends

The report by Manzi (2022) provides several significant insights regarding the relationship between automobile sales and economic variables. In 2022, the U.S. auto market experienced constraints primarily due to inventory shortages, which directly affected the number of vehicle sales. As Patrick Manzi highlighted, "There were more buyers than there were cars," indicating that demand exceeded supply, partially due to ongoing global supply chain disruptions and semiconductor shortages (Manzi, 2022).

Despite these challenges, the forecast for 2023 anticipates an improvement in sales figures (Manzi, 2022). This prediction assumes that the supply chain issues will begin to resolve, allowing manufacturers to meet the rising demand more effectively. This scenario suggests a direct correlation between manufacturing output (supply capacity) and sales volumes, underlining the sensitivity of the auto market to economic conditions and global industrial productivity. The automotive industry's health can thus be seen as a leading indicator of financial stability, where higher sales volumes often correspond with periods of economic growth and consumer spending resilience.

The insights from Manzi (2022) align with earlier research by Sivak (2013), which found a robust correlation between GDP and vehicle sales. This relationship indicates that economic output significantly influences automotive demand. Similarly, Lin (2015) explored how various economic predictors influence auto sales, such as GDP, unemployment rate, and crude oil prices. These studies collectively highlight the auto market's responsiveness to broader economic variables.

1.8. Supplementary sanctions are decelerating car sales

In Europe, pollution taxes on the registration of used cars have been in place since 1990, as Huitema (2022) mentioned. These taxes have been progressively increased and implemented in new ways in recent years. For example, in 2021, Lithuania introduced a pollution tax on the registration of used cars, significantly impacting consumer behaviour within the automotive market. This tax was part of a broader initiative to address environmental concerns and promote the use of less polluting vehicles. However, this policy shift had unintended consequences across the European countries on the dynamics of car ownership and sales patterns, as stated by Jacobsen et al. (2022).

The pollution tax imposed an additional financial burden on registering older, more polluting vehicles. This move aimed to discourage the purchase of older used cars, which typically have higher emissions than newer models. Although the tax aimed to achieve long-term environmental benefits, it initially led some consumers to retain their existing vehicles for more extended periods. By keeping their older cars, individuals could avoid the taxes associated with registering another used vehicle that might fail to meet newer emission standards. This strategy allowed them to accumulate more savings to eventually buy a newer car that would incur lower pollution taxes (Jacobsen et al., 2022).

As a result, car sales, particularly in the used car market, experienced some decline following the introduction of the tax. The decision by many to extend the life of their current vehicles rather than face the financial implications of the new tax also affected the average age of cars on Lithuanian roads. While the policy aimed to reduce pollution and encourage the use of modern vehicles with lower emissions, the immediate effect was stagnating the renewal of the national car fleet. Over time, however, the policy's effectiveness became evident as more consumers began transitioning to newer, less polluting vehicles, as confirmed by Jacobsen et al. (2022).

This situation is particularly relevant to our research on car sales as it highlights how environmental policies can directly influence market dynamics and consumer behaviour. Understanding the impact of such taxes helps to elucidate the broader trends and fluctuations in car sales. The initial decline in used car sales, followed by a gradual shift towards newer vehicles, underscores the complex interplay between policy measures and market responses. This case study demonstrates that while the immediate effects of environmental taxes might include a temporary slowdown in sales, the long-term benefits align with the goals of reducing pollution and modernising the vehicle fleet.

1.9. EU-wide ban on petrol and diesel cars

The impending EU-wide ban on the sale of new petrol and diesel cars, set to take effect by 2035, represents a significant turning point for the automotive industry and car sales trends in Europe, including Lithuania. This move is part of the European Union's ambitious goals to reduce greenhouse gas emissions and promote environmental sustainability (Wolde-Rufael, 2023; Wappelhorst et al., 2018). The ban is expected to drastically reshape the automotive market landscape, accelerating the shift towards electric vehicles (EVs) and other alternative fuel vehicles (Huitema, 2022; Wappelhorst et al., 2018).

In Lithuania, as in other EU countries, the transition away from petrol and diesel cars will likely lead to a surge in demand for electric and hybrid vehicles. This shift will necessitate significant changes in consumer behaviour, automotive manufacturing, and national infrastructure. For consumers, the shift will be influenced by the increasing availability of EVs, improvements in EV technology that lead to longer ranges and shorter charging times, and decreased costs due to economies of scale and technological advancements (Wappelhorst et al., 2018). The infrastructure in Lithuania will also need to evolve to support the increasing number of EVs on the road. This includes expanding charging networks within cities and nationwide to facilitate long-distance travel. Government policies will play a crucial role in this transition, as incentives for EV purchases and investments in charging infrastructure can help accelerate the shift away from petrol and diesel cars (Huitema, 2022).

Economically, the shift to EVs may initially disrupt car sales patterns. As consumers anticipate the upcoming ban, some may choose to hold off on purchasing new petrol or diesel vehicles, potentially causing a dip in car sales in the short term. However, as the deadline approaches and more consumers switch to EVs, a resurgence in car sales is likely driven by renewed consumer interest and confidence in the available EV options (Wappelhorst et al., 2018; Huitema, 2022).

The transition to electric vehicles (EVs) also presents a significant challenge for specific demographics, particularly those with lower incomes who rely on older petrol or diesel cars. As the market shifts towards newer, environmentally friendly technologies, the cost of purchasing an EV remains a significant barrier for many. Although the prices of electric vehicles are expected to decrease over time due to economies of scale and technological advancements, there is still a considerable upfront cost associated with acquiring EV car models (Huitema, 2022; Wappelhorst et al., 2018). This economic disparity raises concerns about the accessibility of clean transportation options. People who drive older vehicles often do so out of economic necessity rather than choice. Mandatory upgrades to cleaner vehicles may seem ominous if not financially impractical for these individuals. Without adequate financial support or incentives from the government, such as subsidies, tax breaks, or affordable financing options, the gap between those who can afford new EVs and those who cannot widen further. Furthermore, the infrastructure needed to support EVs, such as charging stations, may not be as readily available in poor or rural areas, adding another layer of complexity to the transition. Because of these possible problems, people in rural areas might be keener to keep driving cars with internal combustion engines and facing the consequences of possible high taxes rather than switching to EVs. Ensuring that the shift towards electric vehicles will change automobile sales patterns in the short run might also affect them over the extended duration (Wolde-Rufael, 2023; Huitema, 2022; Wappelhorst et al., 2018).

1.10. Emerging issues in new vehicle sales

In examining the predictive value of car sales on economic trends, an article by Lassa et al. (2023) provides compelling evidence that surges in vehicle purchases can act as a buoyant force against economic downturns. The article highlights that despite widespread concerns over an economic slowdown, the automotive sector experienced a significant uptick in sales. In 2023, forecasts by industry analysts were adjusted upward, predicting a total of 15 million new vehicle sales in the United States—an increase that substantially exceeded earlier projections. This resurgence in car sales is particularly notable as it contrasts with other economic indicators that suggest a looming recession. The robustness of the auto sales market serves as a counterpoint, indicating that consumer confidence and discretionary spending remain strong despite broader economic uncertainties. This phenomenon can be attributed to several pivotal factors for understanding economic resilience. First, the availability of financing options and low interest rates have made car purchases more accessible, thereby encouraging consumers to invest in new vehicles despite potential economic uncertainties. Additionally, the desire for personal mobility, especially in post-pandemic recovery, has driven a significant portion of these sales, indicating a shift in consumer priorities that directly impacts the automotive market (Lassa et al., 2023).

Following the analysis of the effects of car sales on the economy, a subsequent exploration into the hardships faced by younger consumers, particularly those from Generation Z and millennials, reveals another dimension of the automotive market's influence on economic indicators. According to a detailed report by White (2023), there has been a dramatic increase in auto loan negligence among these younger demographics. In 2022, drivers aged between 18 and 39 were responsible for nearly $20 billion in delinquent auto loans over 90 days past due. This troubling trend corresponds with a significant rise in total outstanding debt among individuals under 30, which surged by 37% since the onset of the pandemic, reaching a staggering $1.27 trillion by the end of 2022. These financial burdens are worsened by escalating insurance premiums and rising service and repair costs, further compounding car ownership expenses. Such economic pressures prompt young consumers to reconsider their transportation needs, potentially opting for alternative transportation methods or postponing car purchases. This shift in consumer behaviour due to financial constraints impacts car sales. It indicates economic health, mainly reflecting younger demographics' economic resilience or vulnerability within the broader economy (White, 2023).

1.11. Summary

The literature review comprehensively explores the intricate relationship between car sales and various economic indicators, highlighting the automotive industry's significant role in shaping and reflecting broader economic conditions. Studies by Smith et al. (2009) and Samaddar et al. (2022) reveal that economic, demographic, and technological factors collectively drive automotive demand, influencing broader economic conditions. The industry's cyclical nature means that downturns in car sales can trigger economic contractions and layoffs, while upturns can signal economic recovery (Smith et al., 2009; Samaddar et al., 2022). The resilience of car sales amid rising unemployment, as discussed by Plache (2013), suggests a more intricate connection between car sales and economic health than previously understood.

Long-term patterns and forecasting studies highlight enduring trends and structural changes in vehicle demand influenced by demographic shifts, urbanisation, and evolving consumer preferences. The study by Gao et al. (2018) on Chinese automobile sales forecasting demonstrates the use of advanced models like VAR and VECM to predict sales trends. Similarly, Sivak (2013) and Lin (2015) underscore the robust correlation between GDP and vehicle sales, showcasing the predictive potential of economic indicators for automotive markets. These insights are crucial for understanding how car sales can serve as a leading indicator of economic health across different regions.

Lithuania's transition from Soviet rule to an independent market economy involved significant changes in the automotive sector, with imported used cars from Western Europe helping to meet domestic demand (Katsenelinboigen, 1977; Kvaraciejūtė, 2011). The government's adherence to EU regulations and substantial investment in transport infrastructure post-EU accession further shaped the market. Recent studies also address the impact of pollution taxes and the shift towards electric vehicles (EVs) on consumer behaviour and market dynamics (Huitema, 2022; Jacobsen et al., 2022; Mohr et al., 2020).

The review concludes by examining the predictive value of car sales on economic trends, with evidence from Lassa et al. (2023) suggesting that surges in vehicle purchases can act as a buoyant force against economic downturns. It also highlights the financial challenges younger consumers face, which impact car sales and reflects broader economic resilience or vulnerability (White, 2023). This comprehensive analysis underscores the automotive industry's interconnectedness with broader economic cycles, providing valuable insights for policymakers and industry stakeholders.

2. RESEARCH METHODOLOGY

2.1. Car Sales data

For this study, I have harnessed a vast and meticulously structured dataset of car registrations sourced from the official “Regitra” page. This dataset, updated as of March 31, 2024, consists of over 4,497,200 individual entries, each representing a unique car registration within the dataset's period. Every registration in Lithuania is equal to the sale of a car the only exception being – gifting a car to another person. The dataset's structure, with rows corresponding to specific vehicle registrations and columns housing various attributes, allows for a comprehensive and robust analysis of automotive trends and their economic impacts over time.

2.2. Economic variables data

This research has compiled an extensive and comprehensive set of economic variables suitable to Lithuania's economy, covering January 1998 through January 2024. These variables encompass a range of frequencies and sources carefully selected to facilitate a comprehensive analysis of macroeconomic factors that may correlate with or be influenced by car sales trends in Lithuania. Variables of Interest:

1. GDP (Quarterly, 1998-01 to 2023-10): Lithuania's Gross Domestic Product (GDP) figures are a fundamental measure of the country's economic activity and overall health. This data was sourced from the Federal Reserve Economic Data (FRED) website, a trusted repository for economic data since 1991. Analysing GDP alongside car sales data can unveil how economic landscape shifts align with vehicle sales volume changes.
2. Inflation (Monthly, 1998-01 to 2024-01): Monthly inflation data seasonally adjusted is essential for gauging consumer purchasing power and the cost environment for goods and services, including automobiles. This data was sourced from Lithuania's government's official statistical portal.
3. Unemployment Rate (Monthly, 1998-01 to 2024-01): The unemployment rate is a crucial indicator of economic conditions influenced by consumer spending patterns, including automobile purchases. This data, already adjusted for seasonal variations, was sourced from Lithuania's government’s official statistical portal.
4. Euribor Rates (3-Month, 1999-01-01 to 2024-01): Euribor rates, precisely the 3-month rate, significantly influence borrowing costs. The analysis will explore how changes in car

sales may predict Euribor rates and borrowing behaviour fluctuations. This data, spanning from January 1999 to January 2024, was sourced from Bloomberg.

5. Consumer Confidence Index (Monthly, 2001-06-01 to 2024-01): The Consumer Confidence Index provides insights into consumer sentiment and expectations, which can influence purchasing decisions, including automobile related. The analysis will investigate how changes in car sales may forecast consumer confidence levels. This data, collected from a sample size of 1200 individuals over 16 years, was sourced from Bloomberg.
6. Industrial Production (Monthly, 1998-01 to 2024-01): Lithuania's industrial production figures are a critical measure of the country's manufacturing and production activities, reflecting its industrial sector's overall health and growth. This monthly data, spanning from January 1998 to January 2024, provides insights into fluctuations in industrial output. The relationship between the country's industrial performance and consumer demand for vehicles can be understood by analysing industrial production alongside car sales data. This data was sourced from the Federal Reserve Economic Data (FRED) website, a trusted repository for economic data since 1991.

2.3. Removing seasonality

In our analysis, I encountered the need to address seasonality specifically in car sales data, while other variables were already seasonally adjusted. Recognising this unique requirement, I applied tailored methods to ensure accurate and reliable analysis of car sales trends. This section focuses on the methods employed to handle seasonality in car sales data, highlighting seasonal dummies and Seasonal-Trend decomposition using Loess (STL). These techniques were instrumental in effectively capturing and adjusting for seasonal variations in car sales, thereby enhancing the validity and interpretability of our findings.

Seasonal dummies are a statistical technique for seasonal variations in time series data. This method involves creating a set of binary variables, also known as dummy variables, to represent each season or period within a year. By including these dummy variables in regression models, I can effectively control for seasonal effects and isolate the impact of other variables on the outcome of interest.

On the other hand, Seasonal-Trend decomposition using Loess (STL) is a more sophisticated technique that decomposes a time series into three components: seasonal, trend, and residual. The seasonal component represents the periodic fluctuations that occur at regular intervals, such as daily, monthly, or yearly patterns. The trend component captures the data's long-term direction or overall trend, while the residual component accounts for random variation or noise in the data that the seasonal and trend components cannot explain. Unlike traditional seasonal adjustment methods, STL offers greater flexibility and adaptability to handle irregular or non-linear seasonal patterns. It is beneficial for analysing complex time series data with multiple seasonal cycles or trends.

By combining seasonal dummies with the STL method, I effectively captured and adjusted for the seasonal variations in car sales data, thereby improving the accuracy and reliability of our analysis. These methods provided a robust framework for exploring the underlying trends and dynamics in the data, enabling us to make more informed decisions and predictions in the automotive industry.

2.4. Achieving data stationarity and removing trends

For all the time series derived from car sales data and key economic variables, achieving stationarity was crucial for ensuring reliable analysis. To accomplish this, I employed a common technique known as first-order differencing. This method involves computing the difference between consecutive observations in a time series, effectively removing any underlying trends and transforming the data into a stationary process. By eliminating trends and capturing only the changes between successive data points, first-order differencing helps stabilise the variance and make the series more amenable to statistical analysis, such as forecasting or regression modelling. This approach was applied consistently across all relevant time series to ensure comparability and facilitate meaningful interpretation of the data. With first-order differencing, I aimed to create a stationary time series that provided a stable foundation for investigating the relationships and dynamics within the data, ultimately enhancing the robustness and reliability of our analysis.

To confirm the stationarity of our data, I performed the Augmented Dickey-Fuller (ADF) test on each time series. The table below summarises the results of the ADF tests for key economic variables and car sales data.

Table 1

Stationarity check for all our economic variables and car sales

Variable	Test Statistic	Critical Value (5%)	p-value	Stationarity
Inflation	-5.9471	-2.87	< 0.001	Yes
Unemployment	-5.9343	-2.87	< 0.001	Yes
Euribor 3-month	-6.2565	-2.87	< 0.001	Yes
Car Sales	-16.4178	-2.87	< 0.001	Yes
Consumer Confidence	-11.1248	-2.87	< 0.001	Yes
Industrial Production	-14.4114	-2.87	< 0.001	Yes

These results indicate that all the time series became stationary after first-order differencing, as the test statistics were significantly lower than the critical values at the 1% significance level. This confirmed that the differenced series were suitable for further statistical analysis, enhancing the reliability of our findings.

2.5. Addressing non-linearity

A uniform approach of log transformation was employed to address the non-linearity present in the time series data derived from car sales and key economic variables. Log transformation mitigates non-linear relationships by compressing larger values while expanding smaller ones, resulting in a more symmetrical data distribution. Applying the natural logarithm function to each data point in the time series aimed to linearise the underlying relationships between variables. This transformation is particularly beneficial when dealing with variables that exhibit exponential growth or decay, as it helps render the relationships more linear and ensures that proportional changes are consistent across all levels of the data. By systematically applying log transformation to all-time series, the goal was to enhance the interpretability and reliability of the analysis by uncovering more transparent, discernible patterns and relationships within the data.

2.6. Linear regression model

Initiating the analysis, a linear regression model was constructed to examine the relationship between car sales and economic indicators, including unemployment rates, inflation levels, GDP figures, EURIBOR 3-month rates, and the consumer confidence index.

Scatter plots were meticulously crafted to visually represent the relationship between the logarithm of car sales and each economic variable. These visualisations provided an initial glimpse into the magnitude and direction of influence exerted by each economic indicator on the fluctuations in car sales. Following this preliminary exploration, I employed a plot of residuals versus fitted values, leveraging Weighted Least Squares (WLS), to evaluate the efficacy of our regression model. Unlike ordinary least squares (OLS), WLS assigns varying weights to observations based on their level of precision or reliability. This weighting scheme is particularly advantageous in scenarios where the variance of the errors is non-constant across different levels of the predictor variables. By incorporating these weights, WLS ensures that observations with more robust inferences contribute more to the estimation process, thereby mitigating the impact of outliers and heteroscedasticity on the regression results.

2.7. Correlation

An extensive analysis employing multiple methodologies was conducted to explore the correlation between car sales and economic variables. Initially, the regular correlation between car sales and each economic indicator was examined to discern any immediate associations. This straightforward approach provided a broad overview of the relationships between car sales and economic conditions, shedding light on potential drivers of automotive market dynamics.

In addition to regular correlation analysis, lagged and leading correlations between car sales and economic variables were investigated. This involved systematically shifting the time series of economic indicators forward and backwards by various lag periods (ranging from 1 to 12 months) relative to car sales data. By assessing correlations at different time lags, the analysis aimed to capture any delayed or anticipatory effects of car sales on economic variables, thereby unravelling the temporal dynamics of their relationship.

Furthermore, the correlation between month-to-month differences in car sales and economic variables was explored. This approach allowed a focus on the changes or fluctuations in both car sales and economic indicators from one month to the next, providing insights into the short-term dynamics and responsiveness of the automotive market to financial shifts. Analysing correlations based on month-to-month differences aimed to uncover more immediate and localised effects of economic conditions on car sales.

2.8. Granger Causality Test

The Granger causality test is a statistical method for assessing the causal relationship between two-time series variables. The test evaluates whether one variable, known as the "predictor," can predict future values of another variable, known as the "response," above and beyond its past values. In this analysis, the Granger causality test was applied to examine whether car sales could cause changes in other economic variables, providing insights into the directional influence between automotive market trends and broader economic conditions.

To determine the appropriate lag amount for the Granger causality test, several information criteria were employed, including the Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQ), Bayesian Information Criterion (BIC) and Final Prediction Error (FPE). These criteria assess the trade-off between model complexity and goodness-of-fit, helping to identify the lag length that strikes the optimal balance between capturing relevant information and avoiding overfitting. The AIC, HQ, BIC, and FPE criteria each provide different perspectives on model selection, considering factors such as model complexity, the number of parameters, and the amount of residual error.

Two tests were performed to establish the optimal lag lengths: one based on the BIC (Bayesian Information Criterion) and the other determined by the lag length most frequently identified by the AIC, HQ, and FPE criteria in cases where these criteria differed significantly from the BIC, the most distinct lag length was selected for comparative analysis.

Utilising the Granger causality test and lag length selection methods, an effort was made to unveil the causal relationships between car sales and economic variables. This endeavour aimed to provide valuable insights into the directional influence between automotive market trends and broader economic conditions, achieving a deeper understanding of the interplay between the automotive sector and the economy.

2.9. Vector Autoregression (VAR)

The Vector Autoregression (VAR) model is a powerful statistical technique that captures the dynamic relationships between multiple time series variables. It is beneficial for analysing economic data, where variables often influence each other over time. Our analysis employs the VAR model to examine the interdependencies between car sales and key financial indicators.

The VAR model is well-suited for our research for several reasons. Firstly, its multivariate nature allows us to analyse multiple time series simultaneously. This is crucial because car sales do not operate in isolation, various economic factors influence them. The VAR approach captures the complex interactions and feedback loops between car sales and the broader economy by including all relevant variables in the model. Another significant advantage of the VAR model is its ability to incorporate lagged values of the variables. Economic relationships often have delayed effects; for example, changes in interest rates may not immediately impact consumer borrowing and spending. Including lagged terms allows the VAR model to account for these delayed responses, providing a more accurate representation of the temporal dynamics between variables. This feature is particularly beneficial for our study, as it helps identify whether past values of economic indicators have predictive power over future car sales. The flexibility of the VAR model in handling multiple variables and incorporating structural changes makes it a robust tool for our research. By fitting a VAR model, it can systematically explore the dynamic relationships between car sales and economic indicators, identify key drivers, and understand the underlying mechanisms. This approach enhances the explanatory power of our analysis and improves our forecasts' accuracy.

2.10. Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a statistical technique that transforms a set of correlated variables into a smaller set of uncorrelated variables known as principal components. In our research, PCA was essential for several reasons.

Firstly, the economic indicators often exhibit multicollinearity, where variables are highly correlated. Multicollinearity can lead to unstable estimates in regression models, making it difficult to determine the individual effect of each variable. Applying Principal Component Analysis (PCA) reduces multicollinearity by transforming the original correlated variables into uncorrelated principal components. This transformation ensures that our VAR model estimates are more reliable and interpretable.

Secondly, PCA helps reduce noise by focusing on the principal components that capture the most significant patterns and variations in the data. This allows us to filter out the less essential variations, enhancing the model's performance. The principal components extracted through PCA serve as inputs to our VAR model, providing a more robust framework for analysing the dynamic relationships between car sales and economic indicators.

PCA was crucial in preprocessing the economic data, ensuring that our subsequent VAR analysis was accurate and reliable. This methodological step allowed us to effectively handle multicollinearity and focus on the data's most informative aspects, enhancing our analysis's predictive power.

2.11. Mean Squared Forecast Error (MSFE) and Diebold-Mariano Test

The Mean Squared Forecast Error (MSFE) is an essential metric in evaluating the accuracy of forecasting models. It measures the average squared difference between actual and forecasted values, quantitatively assessing a model's predictive performance. The Mean Squared Forecast Error (MSFE) compares the forecasting accuracy of VAR models that include car sales data versus those that do not. Specifically, the aim is to determine whether including car sales data leads to better forecasts of economic indicators such as unemployment.

The dataset is divided into two periods: an in-sample period for training the models and an out-of-sample period for testing their forecasting ability. This division ensures that the model's performance can be evaluated on unseen data, robustly assessing their predictive power.

Two VAR models are estimated: one that includes car sales data and one that excludes it. The forecasts generated by both models for the out-of-sample period allow for calculating the MSFE for each economic indicator. The MSFE is calculated for each variable by averaging the squared differences between the actual out-of-sample values and the forecasted values from both models. This calculation provides two sets of MSFE values: one for the model, including car sales, and one for the model, excluding car sales. By comparing these MSFE values, it can be determined whether including car sales data improves forecasting accuracy. Lower MSFE values indicate better predictive performance, suggesting that car sales data enhances the model's forecasts.

The Diebold-Mariano (DM) test is then applied to statistically compare the forecast accuracy of the two models. The DM test evaluates whether the differences in forecasting errors between the two models are statistically significant. This test involves comparing the forecast errors from the model, including car sales, with those from the model, excluding car sales, using a paired difference approach. The DM test is crucial for validating whether the observed differences in MSFE are not due to random chance. In our implementation, the DM test is conducted for each economic variable in the out-of-sample period. Forecast errors are calculated as the difference between actual and forecasted values for both models. The DM test is then performed on these errors to assess whether the model that includes car sales provides significantly better forecasts. This approach ensures a rigorous and statistically sound comparison of the models' forecasting performance.

Our analysis rigorously evaluates the predictive power of car sales data for economic forecasting using MSFE and the Diebold-Mariano test. These techniques help us determine whether incorporating car sales data into VAR models significantly improves their ability to predict vital economic indicators, thereby providing valuable insights into the role of car sales in economic forecasting and planning.

3. DATA ANALYSIS AND RESULTS

3.1. Introduction to Statistical Tests

The analyses presented were conducted using log-transformed, seasonally adjusted, and first-order differenced data. These preprocessing steps are essential to stabilise variance, remove seasonal effects, and ensure stationarity of the time series data, which are crucial assumptions for the validity of linear regression, correlation analyses, and Granger causality tests. These transformations enhance the accuracy and reliability of the results, providing a robust foundation for exploring the dynamic relationships between car sales and various economic indicators in Lithuania.

3.1.1 Rationale behind separate analysis for all variables till the COVID-19 period

Excluding the period during the COVID-19 pandemic in the analysis of economic variables is crucial due to its highly unpredictable and chaotic nature, which significantly disrupted traditional economic theories and relationships. The COVID-19 pandemic is considered a "black swan" event - a rare and unpredictable occurrence with severe consequences. During this period, various economic phenomena occurred that defied conventional expectations, making it difficult to draw reliable inferences based on historical data alone (Bratianu, 2020).

The pandemic led to extraordinary economic impacts, such as a sharp contraction in global GDP, significant disruptions in supply chains, and unprecedented levels of government intervention through fiscal and monetary policies. These factors created anomalies that are not representative of typical economic cycles and could skew the results of any predictive models if included. The complexity of the COVID-19 crisis, influenced by the health system crisis, governmental policies, and people's behaviour, underscores the necessity of excluding this period to maintain the integrity and reliability of economic analyses (Bratianu, 2020).

Focusing the analysis on the period before COVID-19 makes it possible to derive more stable and reliable relationships between economic variables without the distortion caused by the pandemic's unique conditions. This approach ensures that the models used are based on more predictable and typical economic environments, providing more valid insights into the relationships being studied.

3.2. Car Sales and Unemployment (1998/01-2024/01)

The correlation analysis shows a weak and not statistically significant relationship between car sales and unemployment, with a correlation coefficient of -0.035 and a p-value of 0.5376. This suggests that there is no linear relationship between the two variables. However, lagged and lead correlations indicated slightly firmer but weak negative correlations over various intervals. Specifically, the lagged correlations ranged from -0.007 to -0.079, while the lead correlations ranged from -0.003 to -0.109. These results suggest minor predictive relationships, though they remain weak overall.

Additionally, a positive coefficient of 0.0733 was found when examining the month-to-month differences, indicating a fragile positive relationship between car sales and unemployment growth rates. This implies that an increase in unemployment growth rates is weakly associated with increased car sales growth rates, though this relationship remains tenuous.

Granger causality tests revealed that past car sales values do not have statistically significant predictive power over unemployment with one lag (F-statistic of 1.5321, p-value of 0.2167) and seven lags (F-statistic of 1.6506, p-value of 0.1211).

3.2.1 Car Sales and Unemployment till COVID-19 (1998/01-2019/12)

The updated correlation between unemployment and the logarithm of car sales before the COVID-19 pandemic was -0.042, a slight increase in the strength of the negative correlation compared to the previous value of -0.035. This minimal change slightly strengthens the weak negative relationship.

Granger causality tests showed a significant result with one lag (F-statistic: 5.1935, p-value: 0.02349), indicating that past values of car sales provide significant predictive power over future unemployment values. This result suggests that car sales can help predict changes in unemployment one period ahead. However, at lag 5, the test did not show statistical significance (F-statistic: 1.7347, p-value: 0.1272), indicating that the predictive power of car sales on unemployment diminishes or becomes statistically insignificant when extending the analysis to include more past periods.

The significant result with one lag before the COVID-19 pandemic contrasts with the broader, long-term analysis where no significant predictive relationship was observed. This suggests that there may be short-term predictive value in car sales data for anticipating changes in the unemployment rate, which could be particularly useful for short-term economic forecasting and planning. This insight highlights the potential of car sales data as a tool for short-term economic forecasting, particularly in predicting unemployment fluctuations.

3.3. Car Sales vs Industrial Production (1998/01-2024/01)

Correlation analysis showed a weak and not statistically significant relationship between car sales and industrial production, with a correlation coefficient 0.035 (p-value = 0.5412). Lagged and lead correlations indicated slightly more robust but still weak relationships. Specifically, the lagged correlation was 0.121, suggesting minor changes in industrial production precede changes in car sales, though not significantly. The lead correlation was -0.017, indicating a fragile negative relationship, where minor changes in industrial production slightly follow changes in car sales. The month-to-month differences analysis resulted in a coefficient of 0.005, indicating a fragile positive relationship between car sales and industrial production growth rates. The analysis over intervals showed variations, with lagged correlations ranging from -0.017 to 0.121 and lead correlations from -0.066 to 0.106.

Granger causality tests revealed that past industrial production values do not have statistically significant predictive power over car sales with one lag (F-statistic of 0.8604, p-value of 0.3545). However, with three lags, the F-statistic of 2.123 and a p-value of 0.0977 indicate that the relationship is significant at the 10% level, suggesting some predictive power over car sales.

3.3.1 Car Sales and Industrial Production till COVID-19 (1998/01-2019/12)

The updated correlation between industrial production and the logarithm of car sales before the COVID-19 pandemic was 0.028, a slight decrease in the strength of the correlation compared to the previous value of 0.035. This minimal change suggests no significant direct relationship.

Granger causality tests showed a non-significant result with one lag (F-statistic: 0.8604, p-value: 0.3545), indicating that past industrial production values do not provide significant predictive power over future car sales. At lag 3, the test did show statistical significance at a 10% level (F-statistic: 2.123, p-value: 0.0977), suggesting that extending the analysis to include more past periods does reveal a predictive relationship.

The analysis reveals a weak relationship between car sales and industrial production, with no statistically significant correlation. Granger causality tests revealed that past car sales values do not have statistically significant predictive power over industrial production with a single lag. However, with more lags, the results indicate that the relationship is significant at the 10% level, suggesting some predictive power over car sales. This finding underscores the limited interaction between these two variables, suggesting that car sales have some predictive power for industrial production over longer lag periods.

3.4. Car Sales and Inflation (1998/01-2024/01)

Correlation analysis reveals a weak and not statistically significant relationship between inflation and car sales, with a correlation of 0.018 (p-value = 0.7517). Lagged and lead correlations indicated slightly stronger but still weak relationships. Specifically, the lagged correlation was 0.0924, suggesting a weak positive relationship when inflation is shifted one month earlier relative to car sales. The lead correlation was -0.0466, suggesting a weak negative relationship when inflation leads car sales by one month. The analysis over intervals showed variations, with lagged correlations ranging from -0.0466 to 0.0997 and lead correlations ranging from -0.0316 to 0.0924. Month-to-month differences in car sales and monthly inflation growth rates show a correlation of -0.0212, suggesting a negligible inverse relationship between car sales growth rates and inflation.

Granger causality tests with two lags show a near-significant result (F-statistic: 2.805, p-value: 0.0621), indicating a potential predictive power of past car sales on future inflation. While this result is not significant at the conventional 5% level, it does suggest a weaker causality at the 10% confidence level. At lag 12, the test is less significant (F-statistic: 1.473, p-value: 0.1338), suggesting that including more past data may provide worse predictive insight.

3.4.1 Car Sales and Inflation till COVID-19 (1998/01-2019/01)

Correlation analysis for the period until COVID-19 shows a slight decrease in the strength of the relationship to 0.016 from 0.018, indicating a continued very weak and statistically insignificant correlation.

Granger causality tests show no significant predictive power of car sales on inflation at lag 1 (F-statistic: 2.157, p-value: 0.1431). However, at lag 12, the causality test is significant (F-statistic: 2.2668, p-value: 0.0099), suggesting that on a longer time scale, past car sales values have some predictive power over future inflation rates.

These findings provide an in-depth view of car sales and inflation dynamics, highlighting the weak correlation between different time frames and suggesting that any predictive relationship is limited and context dependent. While the relationship between car sales and inflation remains weak, there is significant predictive power for bigger lag at the 5% level in the pre-COVID period and an indication of weaker causality at the 90% confidence level at lag 1.

3.5. Car Sales and Euribor 3-Month Rate (1999/01-2024/01)

Correlation analysis reveals a weak but positive correlation between Euribor rates and car sales (0.1), which is not statistically significant (p-value = 0.08281). The lagged and lead correlations indicated slightly more substantial but still weak relationships. Specifically, the lagged correlation with the Euribor rate lagged by one month relative to car sales is 0.0247, suggesting a minimal influence of past Euribor rates on current car sales. The lead correlation is 0.0121, indicating that future Euribor rates have minimal predictive power on current car sales. The month-to-month differences show a correlation of 0.1289, suggesting a weak positive relationship between car sales growth rates and Euribor rates. The analysis over intervals showed variations, with lagged correlations ranging from -0.0526 to 0.1028 and lead correlations ranging from -0.0489 to 0.1113.

Granger causality tests indicate no significant predictive relationship at lag 1 (F-statistic = 0.9587, p-value = 0.3283) or lag 3 (F-statistic = 2.053, p-value = 0.1066), reinforcing the conclusion that past car sales values do not predict future Euribor rates over these periods.

3.5.1 Car Sales and Euribor 3-Month Rate till COVID-19 (1999/01-2019/12)

Correlation analysis for the period leading up to COVID-19 shows a weak negative correlation (-0.004), suggesting virtually no linear dependence of car sales on Euribor rates.

Granger causality tests at lag 1 (F-statistic = 2.31, p-value = 0.1298) and lag 12 (F-statistic = 1.243, p-value = 0.2553) show no significant results, indicating that past car sales values do not predict Euribor rate changes even before the pandemic.

These findings suggest that interest rates are not strongly influenced by nor predictive by car sales.

3.6. Car Sales and Consumer Confidence Index (2001/06-2024/01)

Correlation analysis reveals a weak and negative correlation (-0.117) between the Consumer Confidence Index and car sales, which is not statistically significant (p-value = 0.0554). Lagged and lead correlations indicated slightly stronger but still weak relationships. Specifically, the lagged correlation with consumer confidence lagged by one month relative to car sales is 0.131, indicating a weak positive relationship. The lead correlation is -0.160, showing a weak negative relationship, suggesting that higher future consumer confidence is associated with slightly lower current car sales. The month-to-month differences show a correlation of -0.0899, indicating a weak inverse relationship between the growth rates of these two variables. The analysis over intervals showed variations, with lagged correlations ranging from -0.0243 to 0.1295 and lead correlations ranging from -0.0563 to 0.3433.

Granger causality tests reveal a significant predictive relationship at lag 1 (F-statistic: 26.63, p-value: 0), indicating that changes in the Consumer Confidence Index predict car sales at this lag. At lag 12, the causality test also shows a significant result (F-statistic: 4.841, p-value: 0.0000004), suggesting that past values of the Consumer Confidence Index can predict future car sales even over a more extended period.

3.6.1 Car Sales and Consumer Confidence Index Period till COVID-19 (2001/06-2019/12)

During the period leading up to COVID-19, the correlation between the Consumer Confidence Index and car sales shifted to a very weak negative correlation (-0.069), suggesting almost no linear dependence of car sales on the Consumer Confidence Index.

Granger causality tests at lag 1 (F-statistic: 0.2318, p-value: 0.6307) and lag 12 (F-statistic: 0.4791, p-value: 0.9252) show no significant results, indicating that long-term car sales do not predict changes in the Consumer Confidence Index even before the pandemic.

Granger causality analysis for the entire period indicates a strong causality of car sales on the Consumer Confidence Index, from the shortest lag of 1 month to as long as 12 months, suggesting a robust relationship with 99% confidence. This strong relationship observed for the entire period contrasts with the non-significant Granger causality results for the pre-COVID period, indicating that the dynamics between car sales and consumer confidence changed significantly due to the pandemic and larger sample.

3.7. Car Sales and GDP (1998/01-2023/10)

To ensure a consistent and meaningful analysis, car sales data initially recorded every month were aggregated into quarterly figures. This transformation involved summing the car sales every four months to convert them into quarterly sales, aligning with the quarterly GDP data for a more accurate comparison and correlation analysis.

The correlation coefficient between GDP and car sales is weakly positive (0.063), indicating a slight association where car sales increase with GDP. This correlation is not statistically significant (p-value = 0.52968), suggesting the relationship may not be robust across different contexts. Lagged and lead correlations indicated variations. Specifically, lagged GDP negatively correlates with car sales (-0.15999), suggesting that previous GDP values might inversely affect current car sales, though this observation is not typical. Leading GDP also displays a weak negative correlation (-0.03581), suggesting a minimal influence of future GDP on current car sales. The month-to-month differences analysis yielded a correlation of -0.0487, indicating a slight inverse relationship. This suggests that increases in GDP growth are marginally associated with decreases in car sales growth, although the relationship is weak and likely influenced by other factors. The analysis over intervals showed variations, with lagged correlations ranging from -0.1708 to 0.0534 and lead correlations ranging from -0.1719 to 0.1385.

Granger causality tests indicate a statistically significant relationship (F-statistic: 4.1236, p-value: 0.04497), suggesting that past car sales have some predictive power over future GDP movements. However, at lag 2, the test shows no significant predictive relationship (F-statistic: 2.7503, p-value: 0.06895), indicating that extending the lag does not maintain same strength predictive power observed at lag 1. This implies that while car sales may provide valuable insights into short-term GDP fluctuations, their predictive power weakens when considering a slightly more extended timeframe.

3.7.1 Car Sales and GDP till COVID-19 (1998/01-2023/10)

During the period leading up to the COVID-19 pandemic, the correlation between GDP and car sales was slightly more robust than in the entire period analysed but still weakly positive (0.086). This indicates a minimal change in the relationship due to economic conditions before the pandemic.

At lag 1, the Granger causality test is insignificant (F-statistic = 2.3713, p-value = 0.1274), suggesting no short-term predictive power of car sales on GDP movements. At lag 4, the test also shows no significant results (F-statistic = 1.8952, p-value = 0.1202), indicating that extending the analysis to include more past periods does not reveal any predictive relationship.

The analysis suggests that the relationship between car sales and GDP is generally weak and not statistically robust. Granger causality results indicate that car sales do not consistently predict GDP movements, and this observation holds across different periods and economic conditions. This analysis highlights the limited interaction between car sales and broader economic performance measured by GDP. While there is some indication of a predictive relationship at certain lags, it is not strong enough to be considered reliable at a weaker 10% confidence level. However, there is a significant predictive relationship at the 5% level at lag 1, suggesting that car sales may have some short-term predictive power over GDP movements, although this effect does not persist across different timeframes.

3.8. Granger causality tests with differently adjusted data

The results from Granger causality tests between car sales and various economic variables have been performed and discussed. Now, transforming data using three different methods yields varied results worth analysing.

- Logarithmic Transformation, Seasonal Adjustment, and First-Order Differencing
- Logarithmic Transformation and First-Order Differencing
- Seasonal Adjustment, First-Order Differencing, and then Logarithmic Transformation

For each of these transformation methods, four tests were performed:

- Two tests using the entire period of available data.
- Two tests using data up to December 2019 (pre-COVID-19 period).

Within these four tests, two different lag lengths were used:

- One lag length was determined by the Bayesian Information Criterion (BIC).
- The other lag length was chosen based on the frequency of its appearance across the other three tests: Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQIC), and Final Prediction Error (FPE). If all these tests provided different lags, the recommended lag from one of the three criteria showing a different perspective from the BIC determined lag was picked.

Table 2

Granger causality tests on economic variables by car sales with different data transformation methods

Variable	Logarithmic transformation, seasonal adjustment, and First-order differencing	Logarithmic transformation and First-order differencing	Seasonal adjustment, First-order differencing and after that logarithmic transformation
Unemployment (BIC)	-	-	-
Unemployment with longer lag	-	-	Granger causes
Unemployment Till Covid-19 (BIC)	Granger causes	Granger causes	-
Unemployment Till Covid-19 with longer lag	-	-	-
Inflation (BIC)	-	-	-
Inflation with longer lag	-	-	-
Inflation Till Covid-19 (BIC)	-	-	-
Inflation Till Covid-19 with longer lag	Granger causes	Granger causes	-
Euribor 3 month (BIC)	-	-	-
Euribor 3 month with longer lag	-	-	-
Euribor 3 month Till Covid-19 (BIC)	-	-	-
Euribor 3 month Till Covid-19 with longer lag	-	-	-
Consumer Confidence Index (BIC)	Granger causes	-	Granger causes
Consumer Confidence Index with longer lag	Granger causes	Granger causes	Granger causes
Consumer Confidence Index Till Covid-19 (BIC)	-	-	-
Consumer Confidence Index Till Covid-19 with longer lag	-	-	-
GDP (BIC)	Granger causes	-	Granger causes
GDP with longer lag	-	Granger causes	Granger causes
GDP Till Covid-19 (BIC)	-	-	-
GDP Till Covid-19 with longer lag	-	-	-
Industrial Production (BIC)	-	-	-
Industrial Production with longer lag	Granger causes	-	-
Industrial Production Till Covid-19 (BIC)	-	-	-
Industrial Production Till Covid-19 with longer lag	-	-	-

Note: Table presents the results of Granger causality tests, indicating whether car sales Granger-cause each economic indicator (denoted by a "Granger causes") or vice versa(denoted by a "-").

The results indicate a mixed relationship between car sales and unemployment. Generally, unemployment does not appear to be Granger-caused by car sales based on initial tests with the BIC criterion and longer lag tests. However, there are notable exceptions. Specifically, when considering the period until COVID-19 and applying the BIC criterion, unemployment is Granger-caused by car sales. Overall, car sales seem to have some predictive power towards unemployment, especially with shorter lag periods.

The relationship between car sales and inflation remains relatively consistent across different lags and transformation methods, indicating no Granger causality. However, there are notable exceptions. Specifically, when considering the period until COVID-19 and applying the longer lag criterion, inflation is Granger-caused by car sales. Car sales seem to have some predictive power towards inflation, especially with longer lag periods.

There is no indication that car sales Granger caused the Euribor 3-month rate across all lags and transformation methods. This suggests that car sales do not have predictive power over short-term interest rates.

The Consumer Confidence Index consistently seems to be Granger-caused, with shorter and longer lags. by car sales when considering the whole period. Interestingly, when focusing on the period until COVID-19, the relationship between car sales and consumer confidence diminishes. This suggests that the predictive power of car sales on consumer confidence is strongly linked with the COVID-19 period and longer sample period. The strong connection during the pandemic period leaves interesting insight for future investigation.

When considering the whole period, GDP consistently seems to be Granger-caused by car sales across shorter and longer lags. Interestingly, when focusing on the period until COVID-19, the relationship between car sales and GDP completely diminishes. This indicates the same results as the Consumer Confidence Index displayed with car sales. This pattern suggests that the predictive power of car sales on both GDP and the Consumer Confidence Index is strongly influenced by the economic conditions during and after the COVID-19 pandemic. It may imply that the pandemic introduced new dynamics or heightened the sensitivity of these economic indicators to car sales, highlighting the need for further investigation into how significant events like the pandemic alter economic relationships.

Industrial production shows very limited predictive power from car sales. For the longer lag, industrial production is Granger-caused by car sales only under logarithmic transformation, seasonal adjustment, and first differencing. This indicates that, under certain data transformations, car sales can predict industrial production, but this relationship is not robust across other lags and conditions, resulting in really limited predictive power.

The analysis reveals varied relationships between car sales and different economic indicators. Car sales demonstrate some predictive power over unemployment, especially with shorter lags, and inflation, particularly with longer lags until COVID-19. However, car sales do not exhibit predictive power over the Euribor 3-month rate. The Consumer Confidence Index and GDP both show strong Granger causality from car sales across the entire period, but this relationship weakens significantly when focusing on the pre-COVID-19 period. Industrial production shows very limited predictive power from car sales, indicating that the relationship is not robust. These findings suggest that the economic impact of car sales varies from strong Granger causality to non-existent across different indicators and is significantly influenced by the period under consideration, particularly highlighting the effects of the COVID-19 pandemic.

3.9. Vector Autoregression (VAR) Model

In our analysis, the Vector Autoregression (VAR) model explores the dynamic interrelationships between car sales and various economic indicators, including unemployment, inflation, the 3-month Euribor rate, the consumer confidence index, and industrial production. The goal of including car sales as a central variable is to determine its predictive power concerning the broader economic environment.

Monthly data for each variable was collected to set up the VAR model. This data was processed to ensure stationarity, a critical assumption for VAR models, achieved through differencing and logarithmic transformation. Principal Component Analysis (PCA) was then applied to reduce the dimensionality and multicollinearity among the economic indicators, allowing the extraction of principal components that capture most of the variance in the data. The VAR model used these principal components and car sales data as endogenous variables. This approach maintains the essential information from the original indicators while simplifying the model structure, enabling a robust investigation of the causal relationships, and forecast effects of car sales on economic conditions.

3.9.1 Principal Component Analysis (PCA) Overview

PCA is a statistical technique that transforms a set of correlated variables into a set of uncorrelated variables called principal components. Each principal component is a linear combination of the original variables, where the first principal component captures the maximum variance in the data, the second principal component captures the maximum variance orthogonal to the first, and so on.

The principal components are ordered by the amount of variance they explain in the data. This technique allows us to reduce the dimensionality of the data while preserving as much variability as possible.

The table below shows the loadings of each economic indicator on the first five principal components (PC1, PC2, PC3, PC4, and PC5). These loadings indicate each indicator's contribution to the respective principal component.

Table 3

Economic variable contributions to principal components

Indicator	PC1	PC2	PC3	PC4	PC5
Inflation	0.0361	-0.2138	0.5501	0.7360	-0.1101
Unemployment	-0.0596	0.6380	0.1147	-0.1932	-0.2420
Euribor 3 month	-0.0997	-0.5495	-0.0424	-0.3133	0.4195
Consumer conf.	0.0089	-0.4380	-0.1257	-0.1976	-0.8557
Industrial prod.	0.0191	0.0569	-0.8132	0.5176	0.0030
time	-0.4936	-0.0234	-0.0008	-0.0231	0.0750
break_dummy_1	-0.4785	0.1710	0.0604	0.0452	-0.0496
break_dummy_2	-0.5110	0.0142	-0.0372	0.0206	-0.1138
break_dummy_3	-0.5010	-0.1424	-0.0177	0.1131	0.0118

The dummy variables (break_dummy_1, break_dummy_2, break_dummy_3) represent structural breaks in the time series data. These structural breaks are points where the series' behaviour changes significantly, possibly due to external shocks, policy changes, or other significant events. Including these dummy variables in the PCA allows us to account for these breaks and ensure that the principal components accurately reflect the underlying patterns in the data.

These dummy variables help capture the shifts in the time series data and prevent the PCA from being biased by these structural changes.

The "time" variable in the table represents the chronological order of the observations in the dataset. It is included in the PCA to account for trends or patterns that evolve over time. By incorporating the "time" variable, the PCA can capture temporal dynamics and long-term trends that might influence the economic indicators.

In the PCA table, the loading for the "time" variable under each principal component indicates how much of the variance in the data is attributed to the passage of time for that principal component. For example:

- PC1 (time loading: -0.4936): This high loading suggests that PC1 captures a significant trend over time. It means that changes in the time variable substantially influence the first principal component, indicating long-term trends or shifts in the data.
- PC2, PC3, PC4, PC5 (time loadings: -0.0234, -0.0008, -0.0231, 0.0750): These lower loadings suggest that time has a less significant influence on these principal components than PC1.

Including "time" in the PCA ensured that any temporal patterns affecting the economic indicators were considered, providing a more comprehensive understanding of the underlying dynamics in the dataset.

3.9.2 Discussion of Principal Components

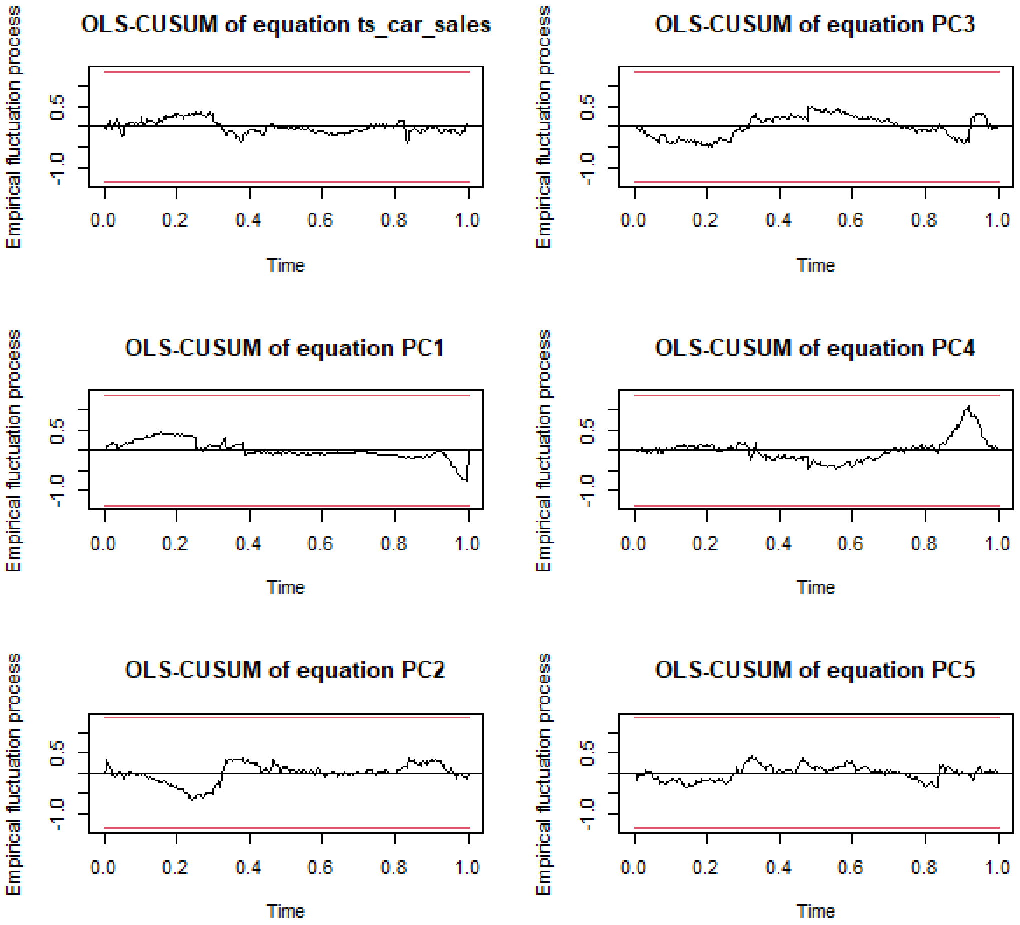
- PC1: The first principal component (PC1) is most significantly influenced by the time variable (-0.4936), break_dummy_2 (-0.5110), and break_dummy_3 (-0.5010). This suggests that PC1 captures a trend and significant structural breaks within the dataset over time.
- PC2: The second principal component (PC2) is heavily influenced by unemployment (0.6380) and ts_euribor3 (-0.5495). This indicates that PC2 captures the dynamics between unemployment and interest rates.
- PC3: The third principal component (PC3) is primarily driven by inflation (0.5501) and industrial production (-0.8132), suggesting it captures the relationship between inflation and industrial production.
- PC4: The fourth principal component (PC4) shows significant loadings on inflation (0.7360) and industrial production (0.5176), indicating it also captures trends related to these economic indicators.
- PC5: The fifth principal component (PC5) has a high loading on consumer confidence (-0.8557) and euribor3 (0.4195), suggesting it captures the relationship between consumer confidence and interest rates.

These principal components help set up a valid model and simplify our analysis by focusing on the main patterns and relationships within the economic data. This facilitates a clearer understanding of how car sales interact with broader economic indicators.

3.9.3 Assessing the stability of VAR

Figure 1

The OLS-CUSUM (Cumulative Sum of Ordinary Least Squares) graphs for PCA stability

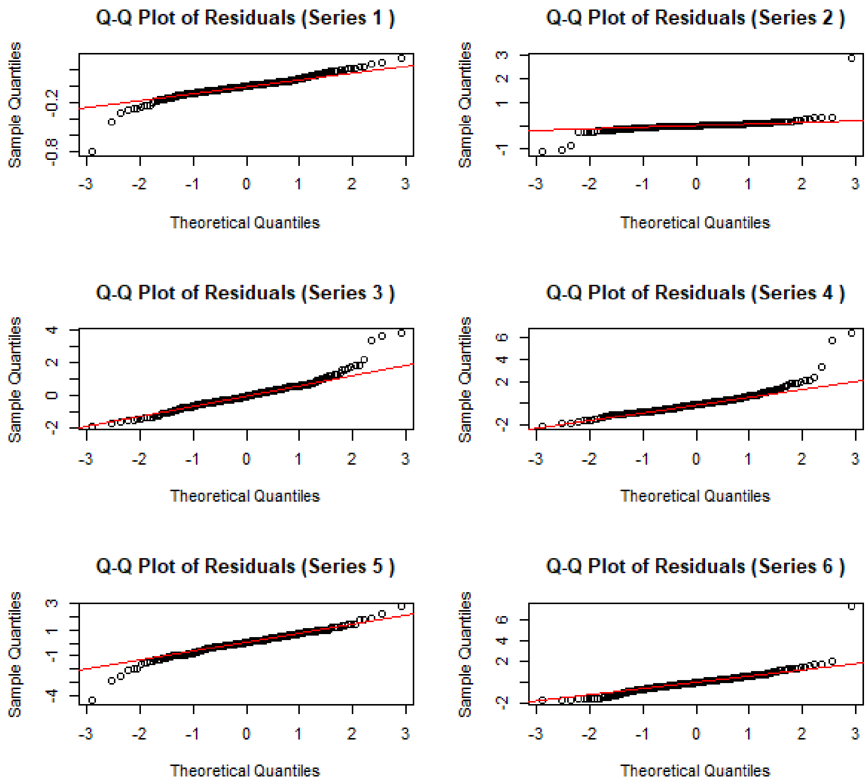


The OLS-CUSUM (Cumulative Sum of Ordinary Least Squares) graph provides a diagnostic tool to assess the stability of the estimated coefficients in time series models by plotting the cumulative sum of recursive residuals over time. The red lines represent the critical bounds, typically set at a 5% significance level. If the CUSUM line remains within these bounds, it indicates stability; if it crosses the bounds, it suggests instability.

The CUSUM plot for car sales (ts_car_sales) shows the cumulative sum of residuals remaining within the critical bounds throughout the sample period, indicating a stable model with no significant structural changes. Similarly, the CUSUM lines for PC2, PC3, and PC5 stay within the bounds with minor fluctuations, suggesting that these models are stable. However, the plots for P1 and PC4 show potential instability towards the end of the period, with the CUSUM lines approaching the critical bounds, indicating possible structural changes or instability in these models. Overall, bounds are not crossed in either graph, providing information that the model is stable.

Figure 2

Q-Q Plots of Residuals for Principal Component Analysis (PCA) Model



The Q-Q plots of the residuals for each series in our VAR model indicate how well the residuals adhere to a normal distribution. In these plots, the residuals are compared against the theoretical quantiles of a normal distribution. Ideally, the points should lie along the red line if the residuals are normally distributed.

From the plots, it is evident that most residuals adhere closely to the normal distribution line, particularly in the central range of the data. However, there are deviations at the tails, suggesting potential issues with normality. Specifically, the residuals for Series 2, Series 4, and Series 6 show more pronounced deviations in the upper quantiles, indicating that these series might have heavier tails or are subject to outliers. Outliers were removed; therefore, only the possibility of heavier tails remains.

Despite these deviations, the overall adherence to the normal line suggests that the residuals are reasonably normally distributed. This is an essential assumption for many statistical tests and can enhance the reliability of our VAR model's estimations and forecasts.

Several techniques were employed to address and remove non-normality from the residuals in the analysis. Outliers in the car sales time series were identified and removed, as they could skew the residual distribution. Following this, linear interpolation imputed missing values to ensure a continuous dataset. With the cleaned and interpolated data, the VAR model was refitted to enhance the normality of residuals. A robust regression model was also applied to account for any remaining non-normality. Recognising the potential for heteroskedasticity, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models were implemented. These models specifically targeted the variance of residuals, further improving their distribution and addressing issues related to non-normality. Despite these efforts, complete removal of non-normality in the residuals was not achieved.

3.9.4 Forecast Error Variance Decomposition (FEVD)

Forecast Error Variance Decomposition (FEVD) analysis was conducted to assess the predictive power of car sales on Lithuania's economic fluctuations. The FEVD allows us to determine the proportion of each variable's forecast error variance attributable to shocks from each variable in the model, including the principal components derived from our initial economic indicators.

The results of the FEVD are summarised as follows:

- Cross-Influences: Over time, car sales' influence on the principal components increases, highlighting their role in affecting broader economic variables encapsulated by these principal components.

Economic Insights from Principal Components:

- PC1 (Unemployment, Inflation, GDP): The FEVD analysis shows that car sales gradually contribute to the forecast error variance of PC1. Changes in car sales have a meaningful impact on unemployment, inflation, and GDP over time. Specifically, increased car sales can signal or result in lower unemployment and higher GDP, reflecting economic growth and potentially impacting inflation rates due to increased consumer spending.
- PC2 (Euribor 3-month rate, Unemployment): The analysis indicates that car sales influence PC2 notably. Fluctuations in car sales can lead to changes in interest rates and employment conditions. For instance, a rise in car sales may lead to higher interest rates as economic activity increases and may correlate with improved employment conditions.
- PC3 (Consumer Confidence, Industrial Production): Car sales' increasing contribution to the forecast error variance of PC3 indicates that consumer sentiment and industrial activities are sensitive to changes in car sales. This suggests that a boost in car sales can enhance consumer confidence and drive industrial production, as more car sales typically reflect higher consumer confidence and necessitate increased industrial output.
- PC4 (Industrial Production, Inflation): The FEVD analysis reveals that car sales significantly influence PC4, indicating that changes in car sales can affect industrial

activity and price levels. Increased car sales can stimulate industrial production and potentially lead to higher inflation due to greater demand and economic activity.

- PC5 (GDP, Euribor 3-month rate): Car sales' impact on PC5 highlights the interplay between automotive market dynamics, economic output, and interest rates. Rising car sales can contribute to higher GDP and may influence interest rates, reflecting the overall economic conditions and monetary policy adjustments.

The findings from the FEVD analysis underscore the predictive power of car sales on Lithuania's economic fluctuations. Car sales significantly impact key economic indicators such as unemployment, inflation, GDP, interest rates, consumer confidence, and industrial production. By understanding these contributions, policymakers and industry stakeholders can identify which economic factors are influenced by car sales and adjust their strategies accordingly to stabilise or boost the economy. This comprehensive understanding can help develop policies that leverage car sales as a predictive economic planning and forecasting tool.

3.9.5 Mean Squared Forecast Error (MSFE) Analysis

Mean Squared Forecast Error (MSFE) is a measure used to evaluate the accuracy of a forecasting model. It calculates the average squared differences between the actual observed values and the values predicted by the model. Lower MSFE values indicate better predictive accuracy of the model.

The table below summarises the MSFE for models with and without car sales, along with the differences:

Table 4

Comparison of MSFE with and without Car Sales

	With car sales	Without car sales	Difference
PC1	**0.937406**	**0.936684**	**-0.00072**
PC2	**1.338658**	**1.346555**	**0.007897**
PC3	2.220461	2.219977	-0.000484
PC4	2.537773	2.536867	-0.000906
PC5	2.441084	2.440487	-0.000597

Interpretation:

- PC1: Including car sales results in a slight increase in MSFE (-0.00072), indicating a negligible decrease in forecast accuracy. PC1 mainly consists of GDP and inflation.
- PC2: Including car sales results in a slight decrease in MSFE (0.007897), indicating a slight improvement in forecast accuracy. PC2 mainly consists of unemployment and the Euribor 3-month rate.
- PC3: Including car sales results in an almost negligible increase in MSFE (-0.000484), indicating an almost negligible decrease in forecast accuracy. PC3 mainly consists of inflation and consumer confidence.
- PC4: Including car sales results in a slight increase in MSFE (-0.000906), indicating a negligible decrease in forecast accuracy. PC4 mainly consists of industrial production and consumer confidence.
- PC5: Including car sales results in a slight increase in MSFE (-0.000597), indicating a negligible decrease in forecast accuracy. PC5 mainly consists of GDP and Euribor 3-month rate.

3.9.6 Diebold-Mariano Test Results

The Diebold-Mariano (DM) test compares the forecast accuracy of two models. The test results are as follows:

- PC1:
  - DM Test: DM = 3.8335, p-value = 0.0003321
  - Interpretation: The two models significantly differ in forecast accuracy, favouring the model without car sales.

- PC2:
  - DM Test: DM = -4.524, p-value = 3.367e-05
  - Interpretation: The two models significantly differ in forecast accuracy, favouring the model with car sales.

- PC3:
  - DM Test: DM = 0.80966, p-value = 0.4217
  - Interpretation: The two models have no significant difference in forecast accuracy.

- PC4:

- DM Test: DM = 0.85323, p-value = 0.3973
- Interpretation: There is no significant difference in forecast accuracy between the two models.

- PC5:
  - DM Test: DM = 0.41665, p-value = 0.6786
  - Interpretation: The two models have no significant difference in forecast accuracy.

3.9.7 VAR test summary

- MSFE and DM Test Results: Including car sales slightly, but significantly improves the forecast accuracy for PC2, mainly because of unemployment and the Euribor 3-month rate. However, other principal components, including car sales, either have a negligible effect or slightly worsen the forecast accuracy. The Diebold-Mariano test results support these findings, showing significant improvement only for PC2.
- Economic Interpretation: The inclusion of car sales data improves the model's ability to predict economic fluctuations related to unemployment and short-term interest rates. However, other economic indicators like GDP, inflation, consumer confidence, and industrial production, including car sales, do not significantly enhance the model's predictive power. This indicates that car sales data is particularly relevant for forecasting variables closely linked to consumer financial conditions and borrowing costs.

CONCLUSIONS

The analysis conducted in this study demonstrates that car sales have significant predictive power for several key economic indicators in Lithuania. Integrating car sales data into economic models revealed meaningful insights into future economic conditions, explicitly influencing unemployment rates, inflation, GDP, interest rates, consumer confidence, and industrial production. This indicates that car sales can serve as a valuable leading indicator for broader economic trends.

The Granger causality tests provided significant insights into the temporal dynamics between car sales and various economic indicators. The results indicated that car sales Granger cause changes in several critical indicators, particularly in the context of unemployment, inflation, gross domestic product (GDP), and consumer confidence. Significant Granger causality was found for unemployment, especially during COVID-19. Similarly, inflation showed significant Granger causality in this period, reinforcing the predictive power of car sales on these variables. The consumer confidence index demonstrated a robust predictive relationship, showing significant Granger causality across almost all tested scenarios, underscoring its strong connection with car sales. In most tests, car sales also caused GDP when considering the entire period. However, the results changed for the period till COVID-19, the same as for the consumer confidence index, indicating that GDP was not Granger caused by car sales, highlighting the impact of the chaotic COVID-19 period. This shift suggests that including the COVID-19 period in the analysis alters the dynamics, making GDP and consumer confidence index appear as Granger caused by car sales when considering the entire timeframe. In contrast, no significant Granger causality was found between car sales and the Euribor 3-month rate, reflecting the nuanced and selective nature of car sales' predictive power on different economic indicators.

Principal Component Analysis (PCA) was essential in reducing multicollinearity among the economic indicators, resulting in a more accurate analysis. The principal components derived from PCA captured the main variance in the economic data, allowing for a clearer understanding of the underlying dynamics. This transformation effectively represented the combined effects of multiple economic indicators, making the subsequent VAR modelling more efficient and interpretable.

The VAR model, incorporating both car sales and principal components, effectively captured the dynamic interrelationships among the variables. Various diagnostic tests confirmed the model's stability and reliability, validating its suitability. The Forecast Error Variance Decomposition (FEVD) analysis highlighted the significant role of car sales in influencing the forecast error variance of principal components, particularly those associated with unemployment, inflation, consumer confidence, and industrial production. The Mean Squared Forecast Error (MSFE) analysis showed that including car sales in the model improved the forecast accuracy for PC2, mainly consisting of unemployment and the Euribor 3-month rate. The Diebold-Mariano test confirmed a significant improvement in forecasting accuracy for PC2 by including car sales data. However, other principal components, including car sales, had either a negligible effect or a slight negative impact on forecast accuracy.

These findings from the VAR analysis and Granger causality tests underscore car sales data's value in economic forecasting. The VAR model's ability to capture dynamic interdependencies and the Granger causality test's capability to identify predictive relationships provide a comprehensive understanding of how car sales influence economic variables. This combined approach enhances the explanatory power of our analysis and improves the accuracy of economic forecasts, offering valuable insights for policymakers and economic analysts.

Based on these findings, policymakers and economic analysts should incorporate car sales data into their forecasting models to enhance the accuracy of unemployment and short-term interest rate predictions. This integration can provide early indicators of economic shifts, aiding in proactive policy formulation.

Stakeholders should closely monitor vital economic indicators represented by PC2, such as unemployment and short-term interest rates, due to the significant predictive power of car sales on these variables. Understanding their interaction with car sales can provide valuable insights for economic planning and policy adjustments. While car sales showed significant predictive power for specific economic indicators, future research should explore additional variables that might enhance the forecast accuracy of other principal components. This could involve incorporating more macroeconomic and industry-specific data. Also, a more thorough examination of the COVID-19 period impact on economic variables should shed more light on relationships between economic variables and car sales.

Update the models regularly with new data and validate their performance to ensure the continued accuracy and relevance of economic forecasts. This practice will help capture evolving economic dynamics and maintain forecasts' reliability. These recommendations are based on the comprehensive analysis conducted in this study, which provides actionable insights for leveraging car sales data in economic forecasting.

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ANNEX

Figure A.1

Car sales and unemployment values

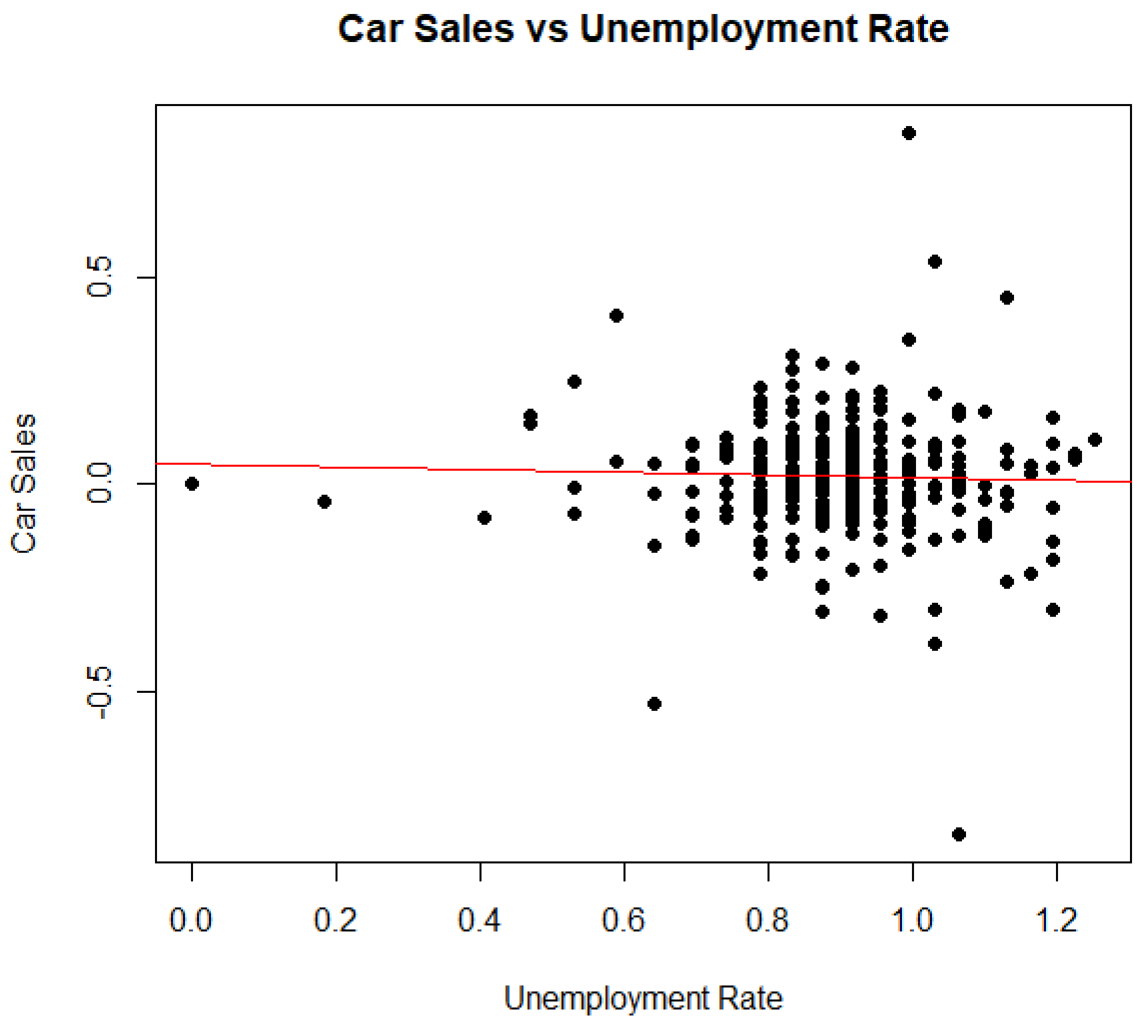

Figure A.2

Car sales and unemployment Normal Q-Q plot

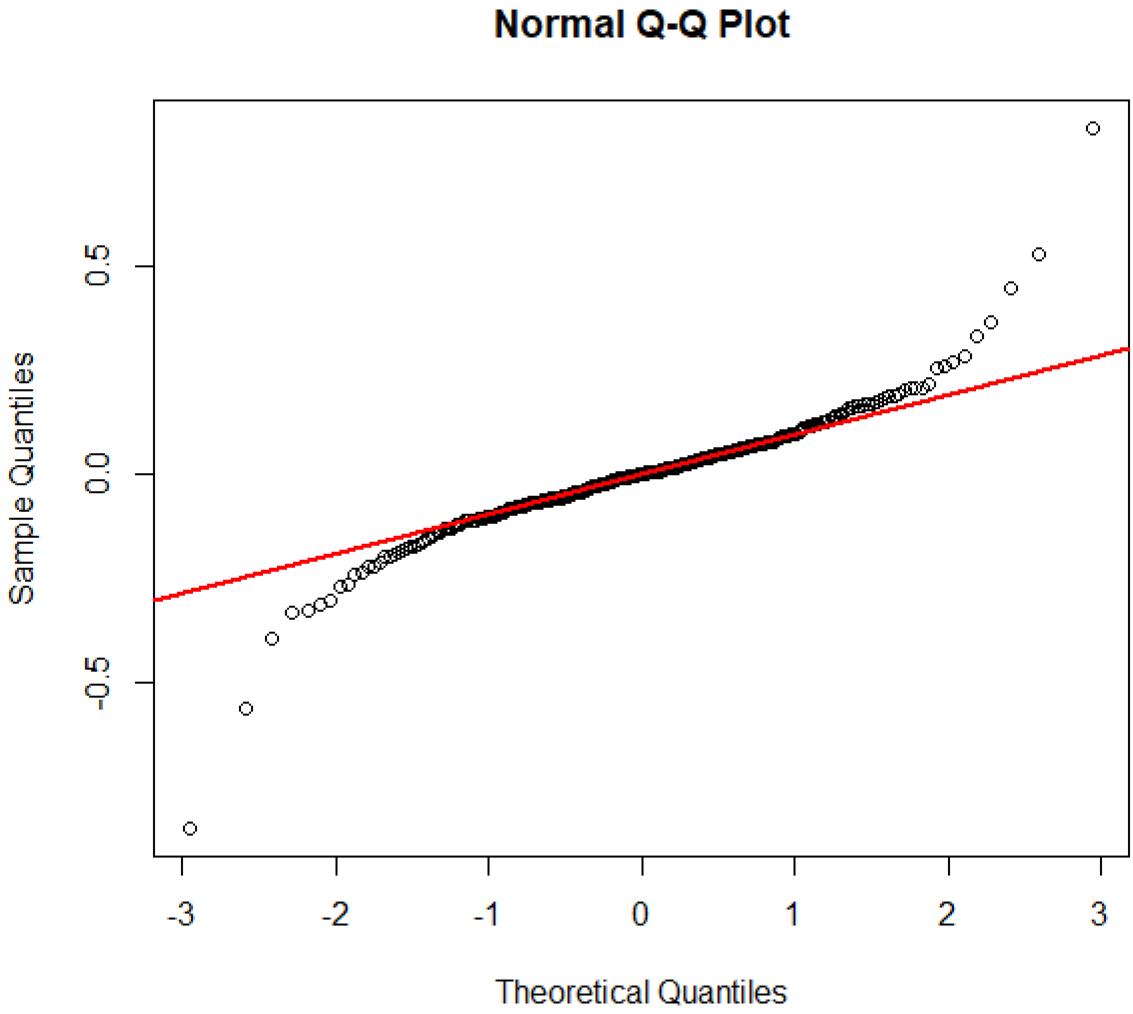

Figure A.3

Car sales and unemployment Kernel density plot of residuals

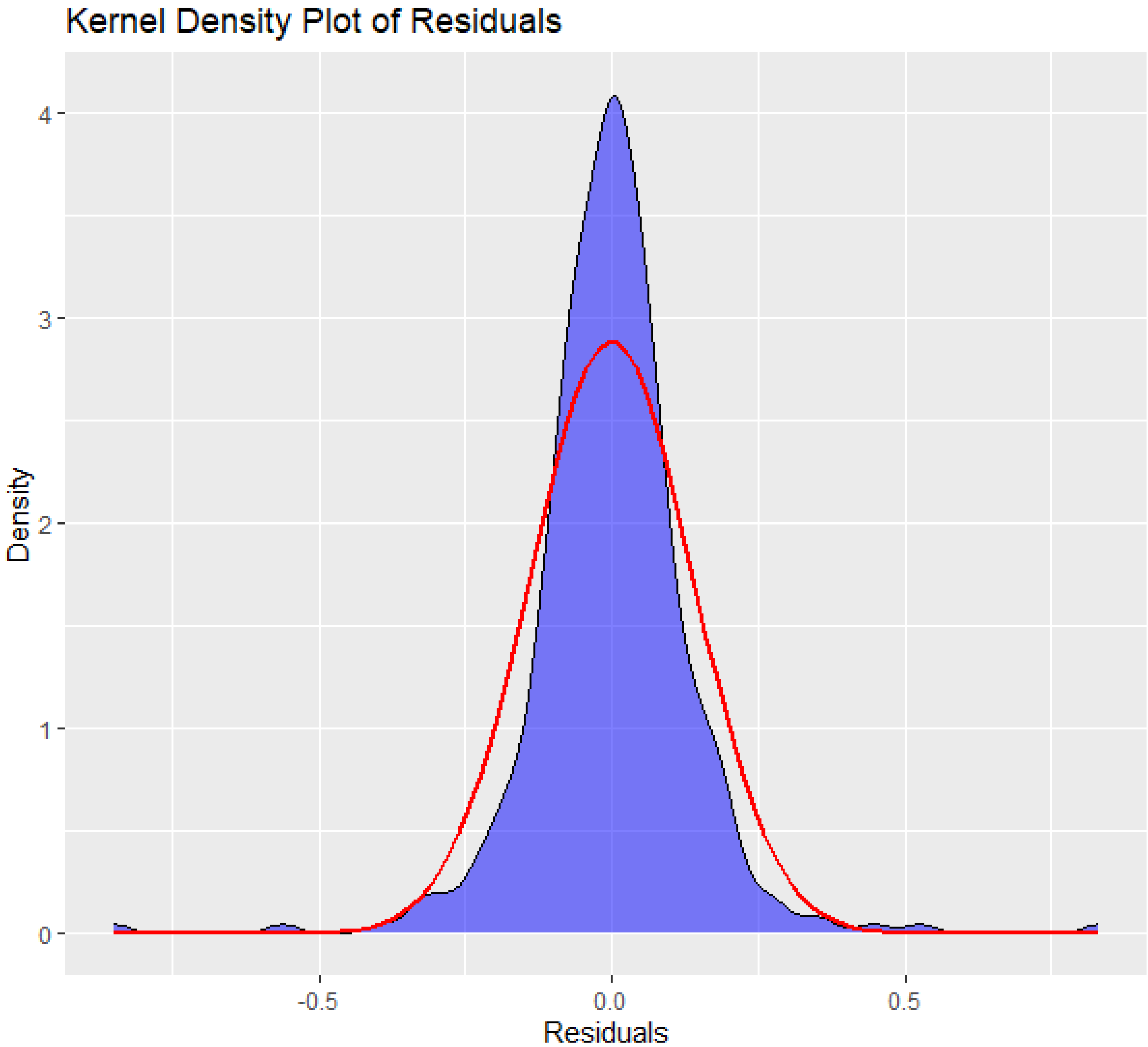

Figure A.4

Car sales and industrial production values

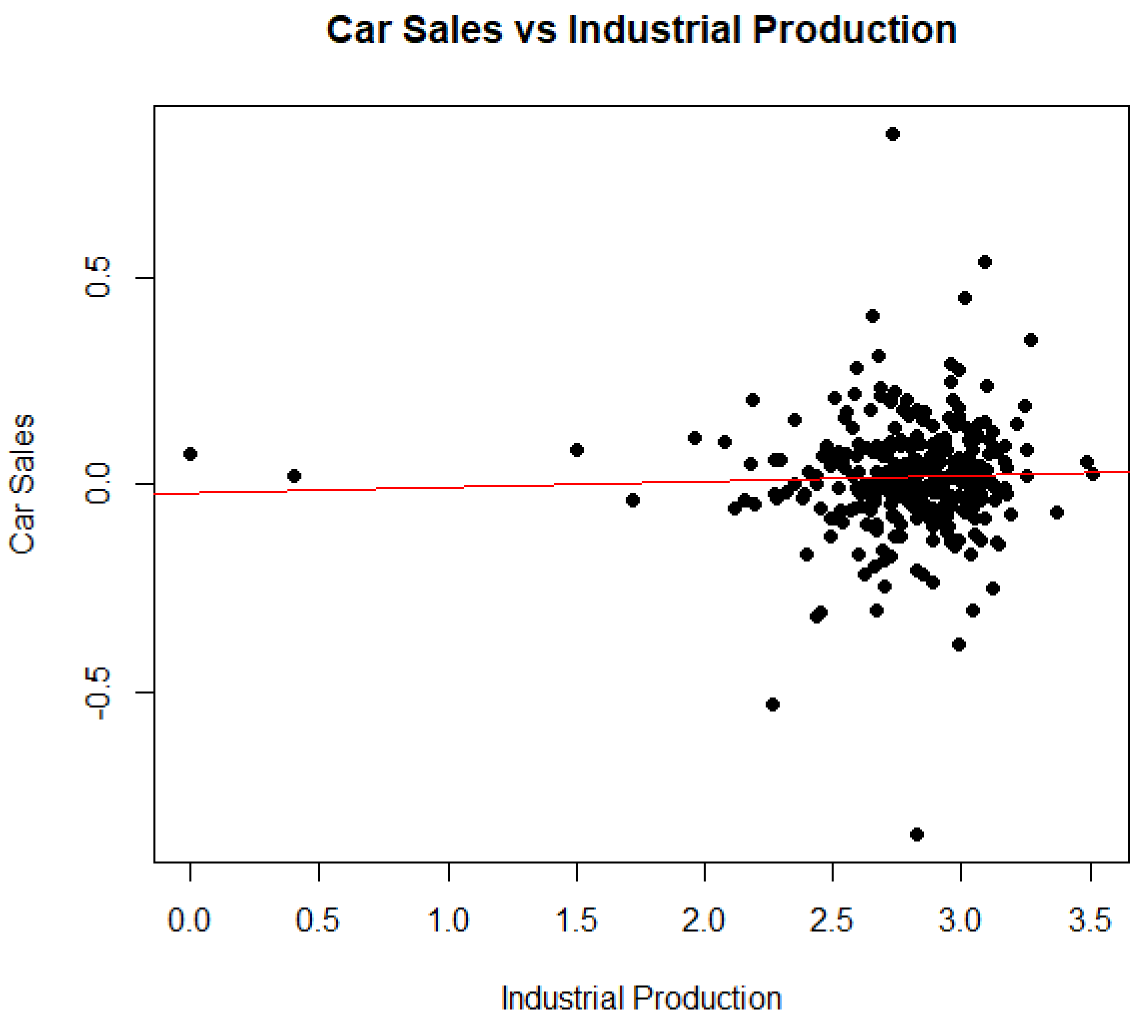

Figure A.5

Car sales and industrial production Normal Q-Q plot

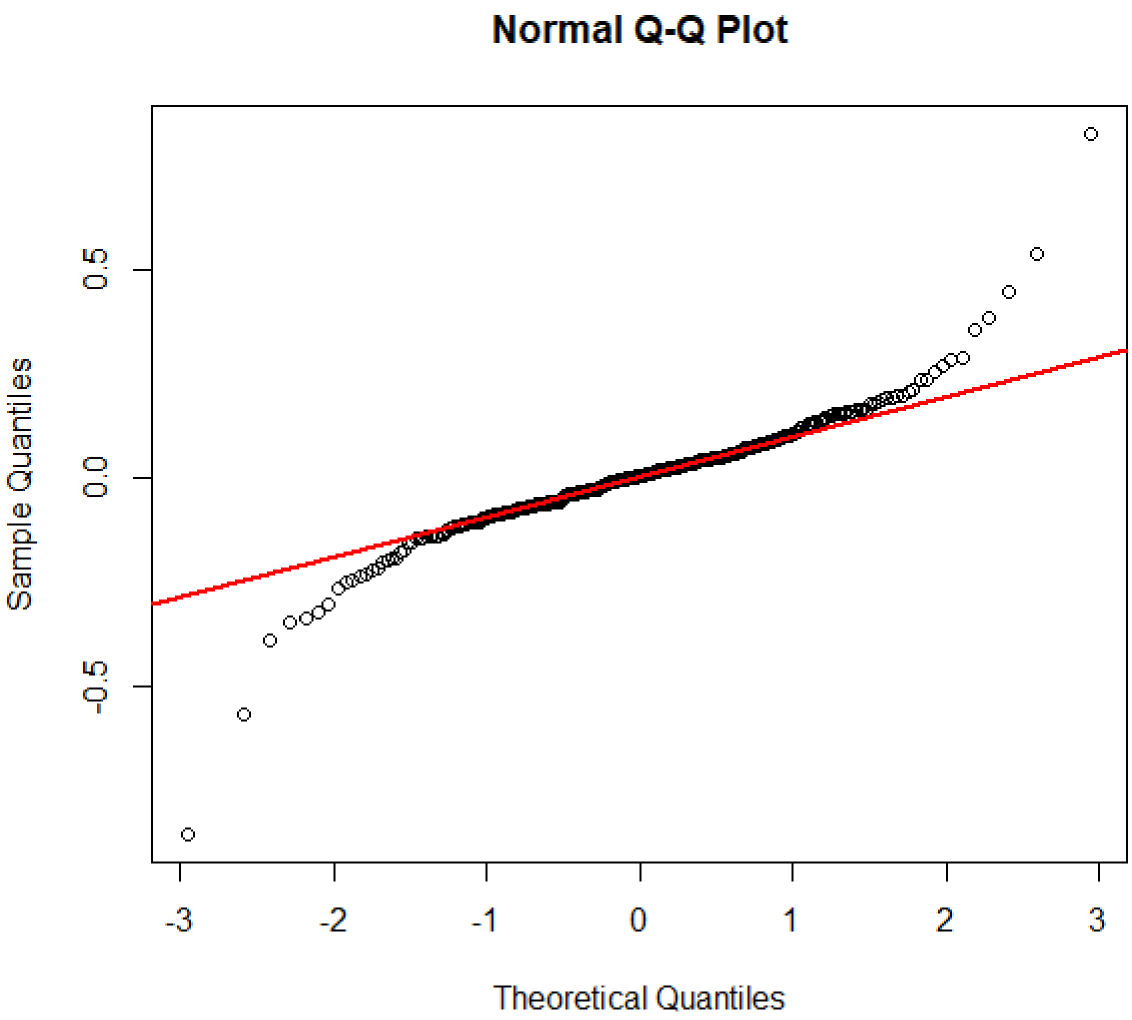

Figure A.6

Car sales and industrial production Kernel density plot of residuals

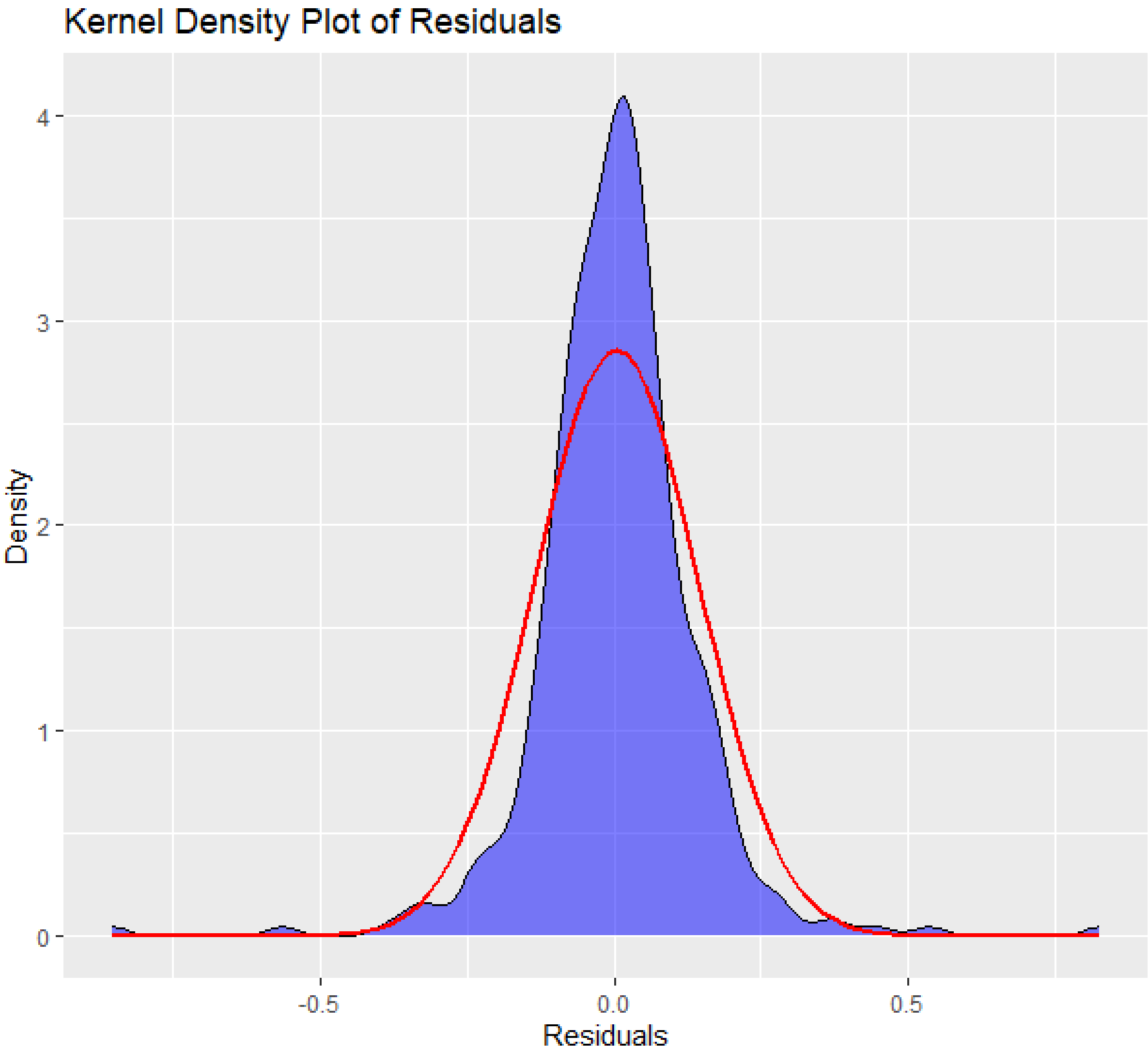

Figure A.7

Car sales and inflation rate values

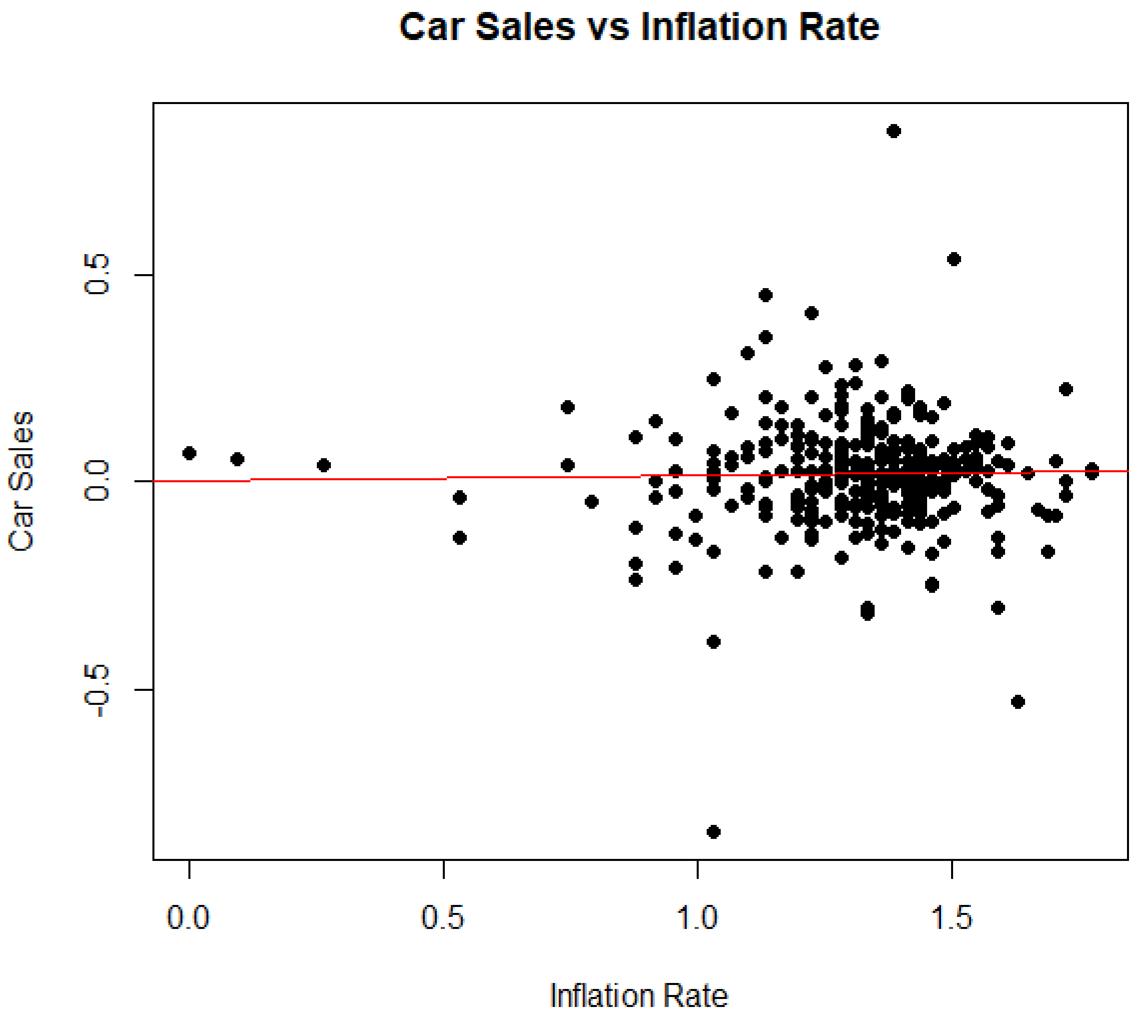

Figure A.8

Car sales and inflation rate Normal Q-Q plot

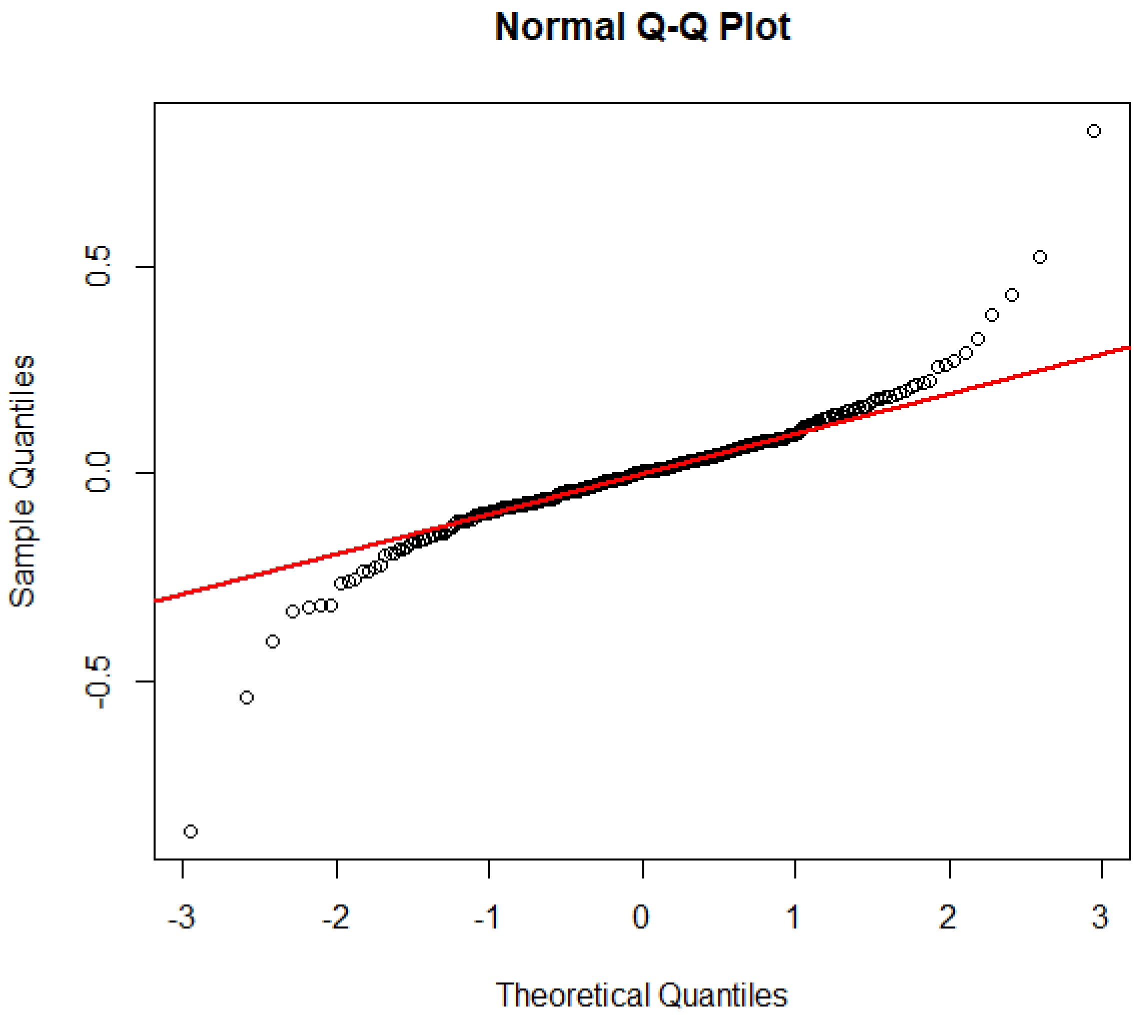

Figure A.9

Car sales and inflation rate Kerner density plot of residuals

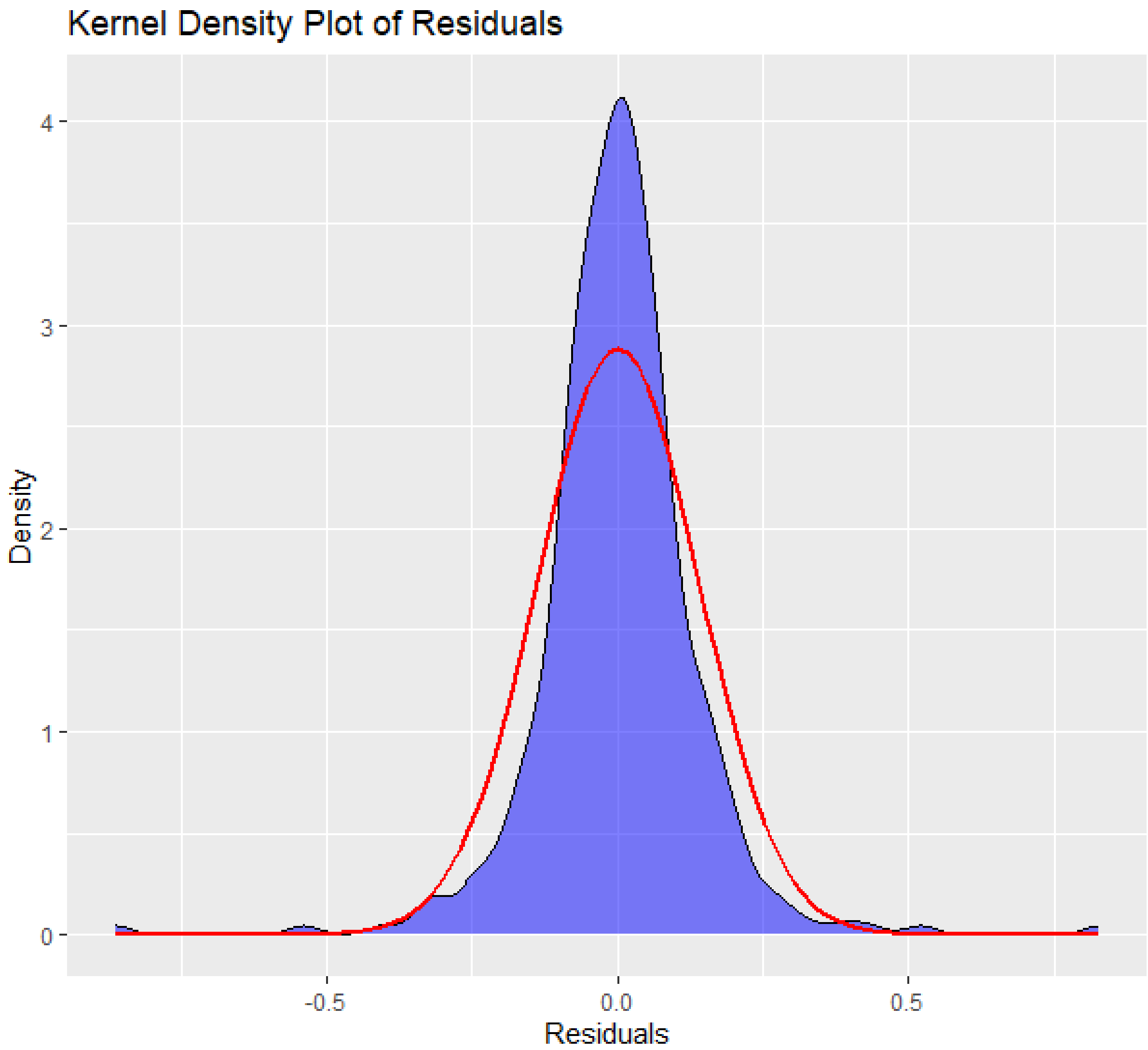

Figure A.10

Car sales and Euribor 3-month rate values

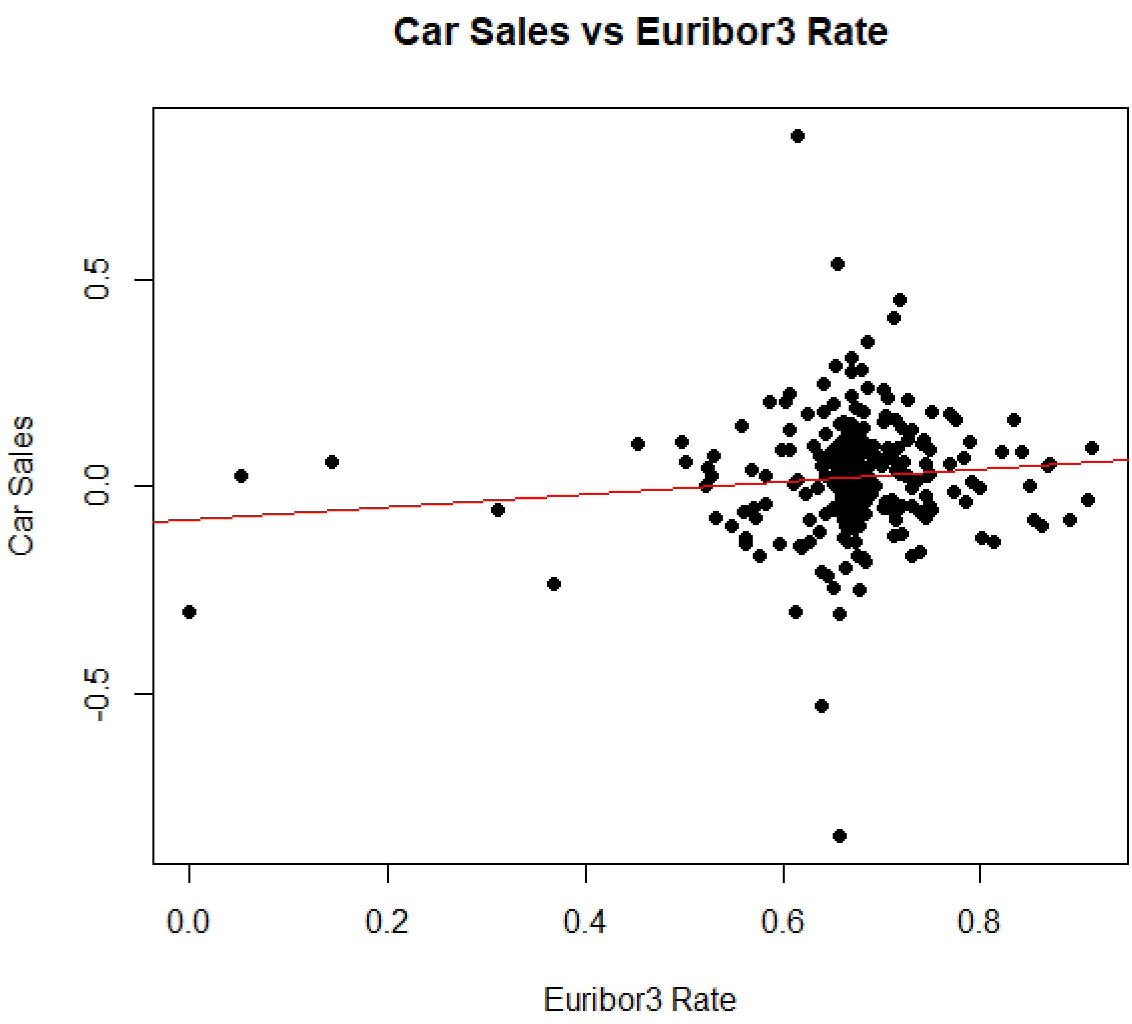

Figure A.11

Car sales and Euribor 3-month rate Normal Q-Q plot

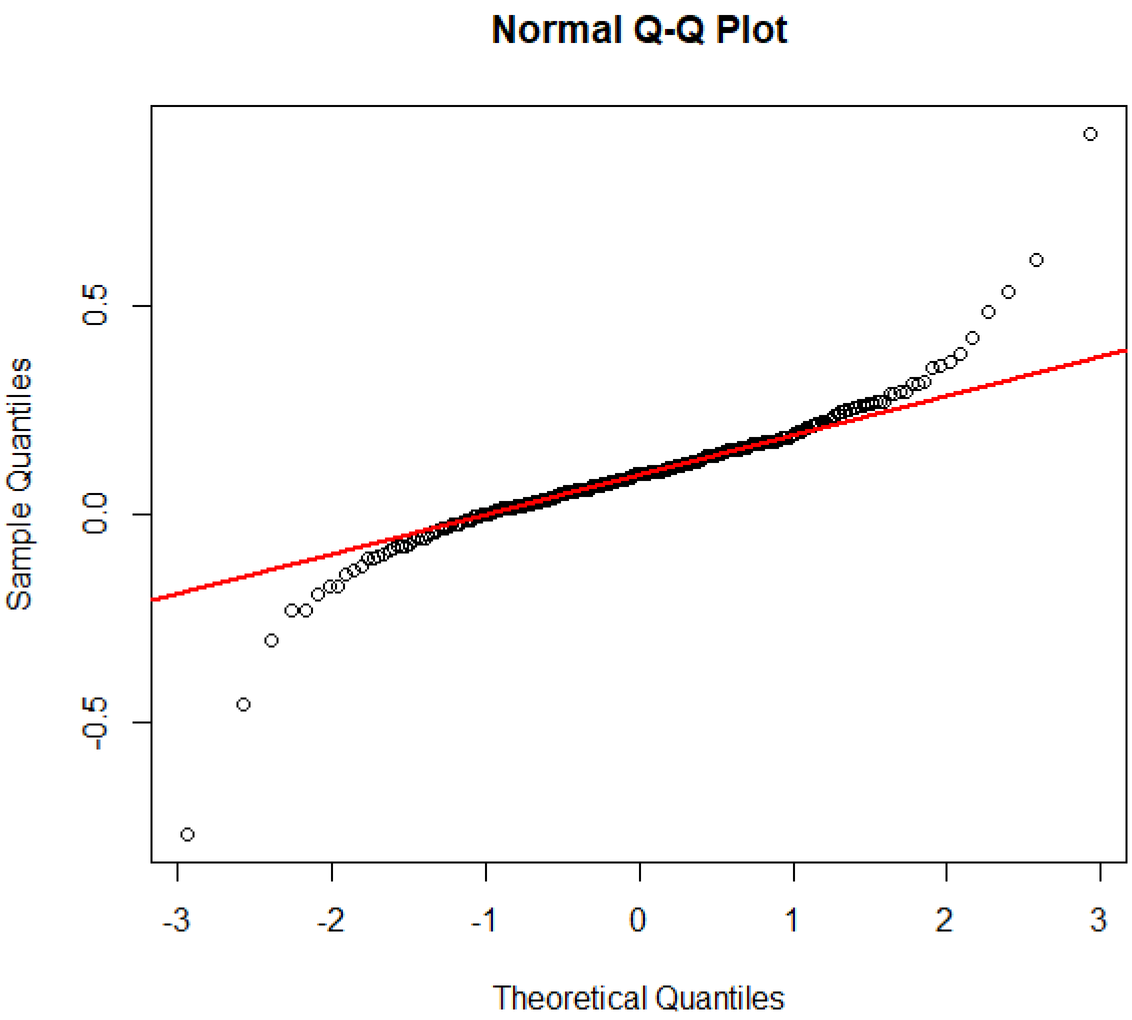

Figure A.12

Car sales and Euribor 3-month rate Kernel density plot of residuals

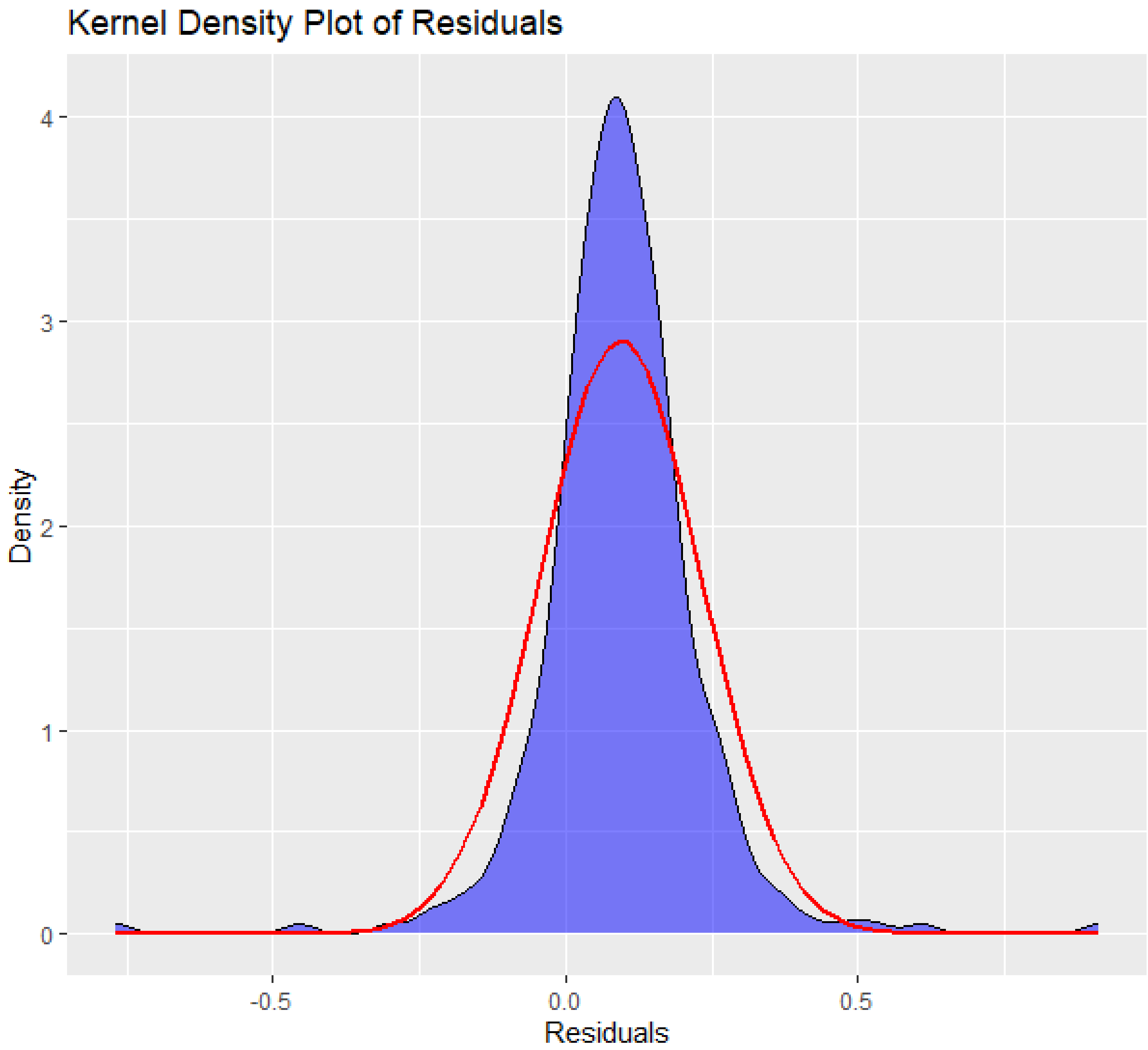

Figure A.13

Car sales and consumer confidence index values

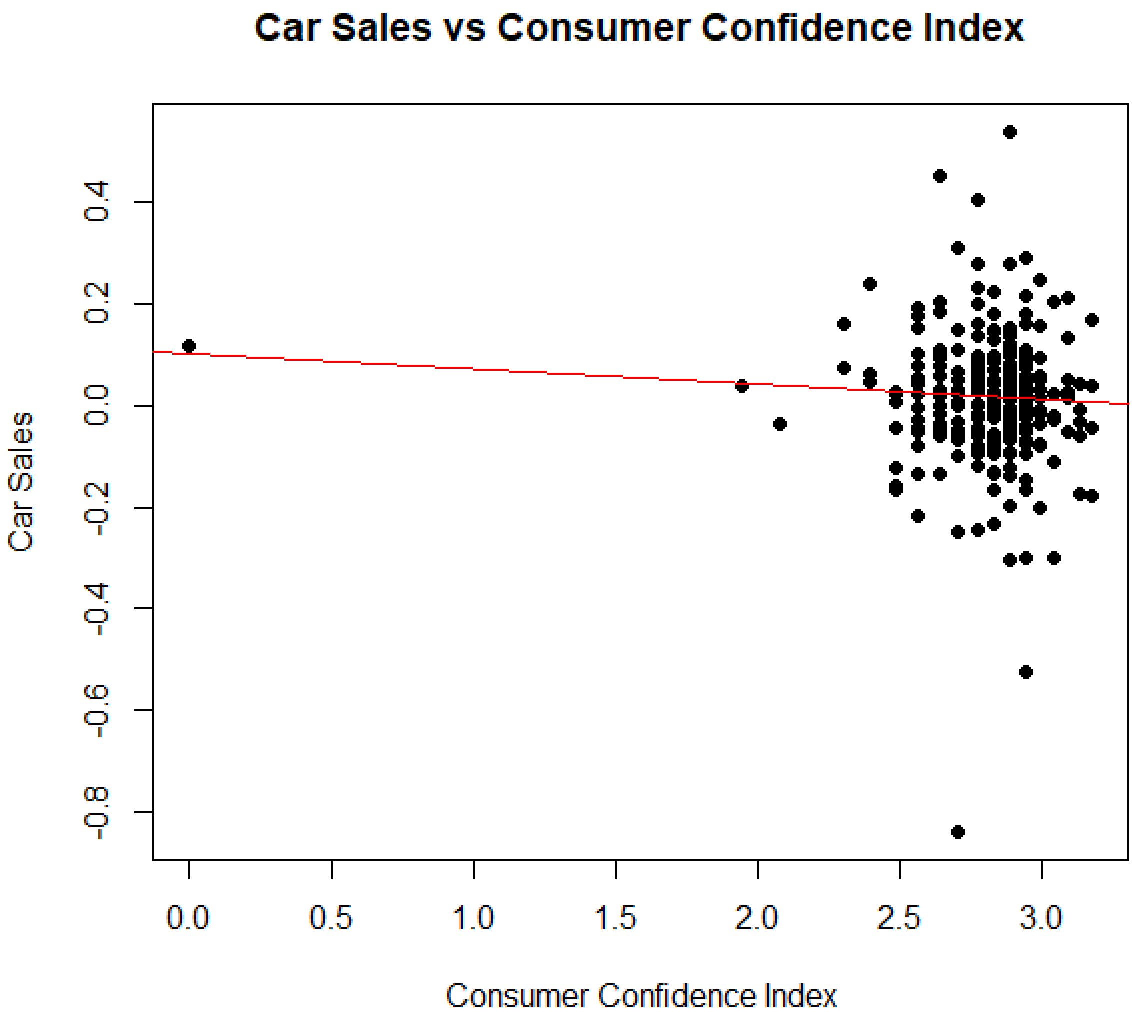

Figure A.14

Car sales and consumer confidence index Normal Q-Q plot

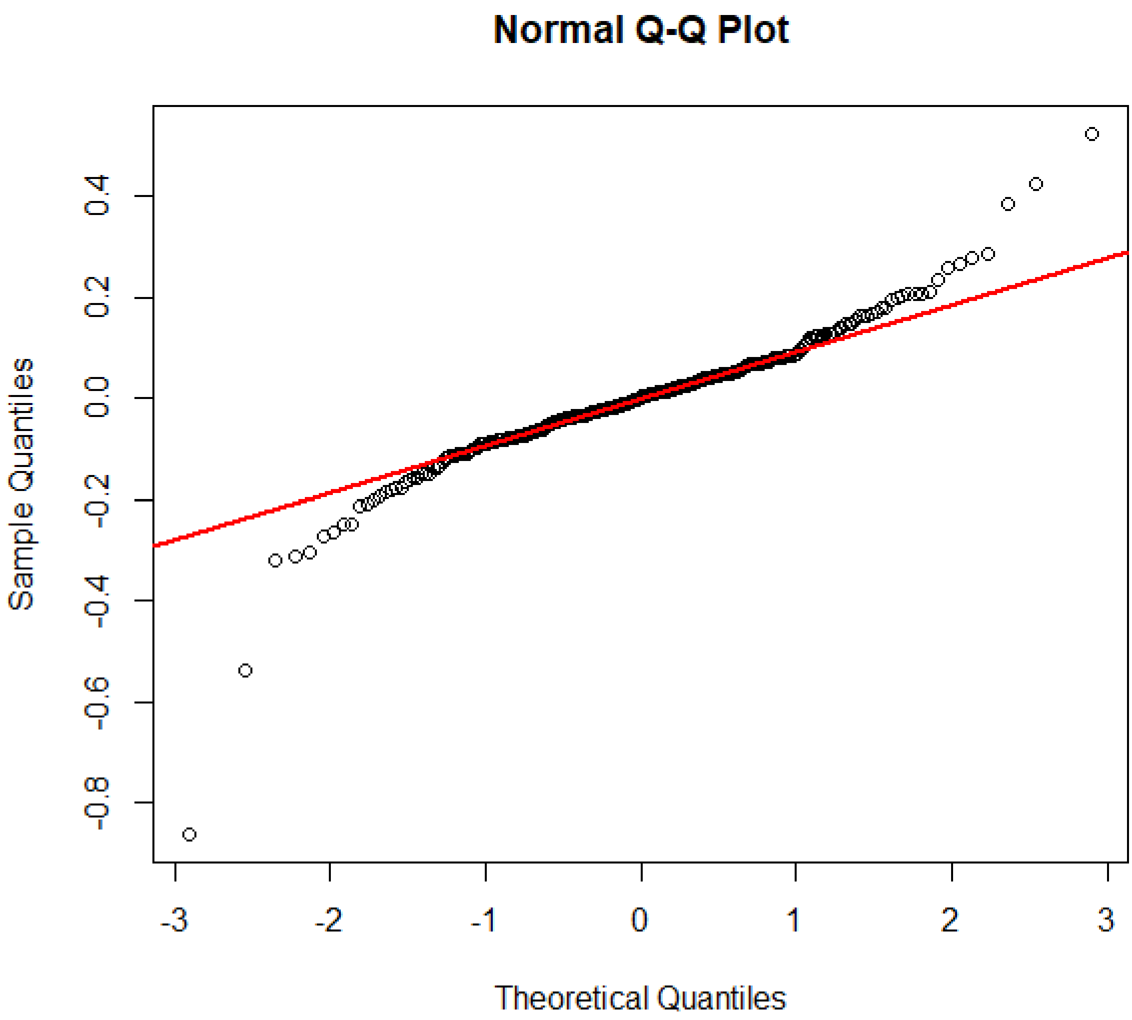

Figure A.15

Car sales and consumer confidence index Kernel density plot of residuals

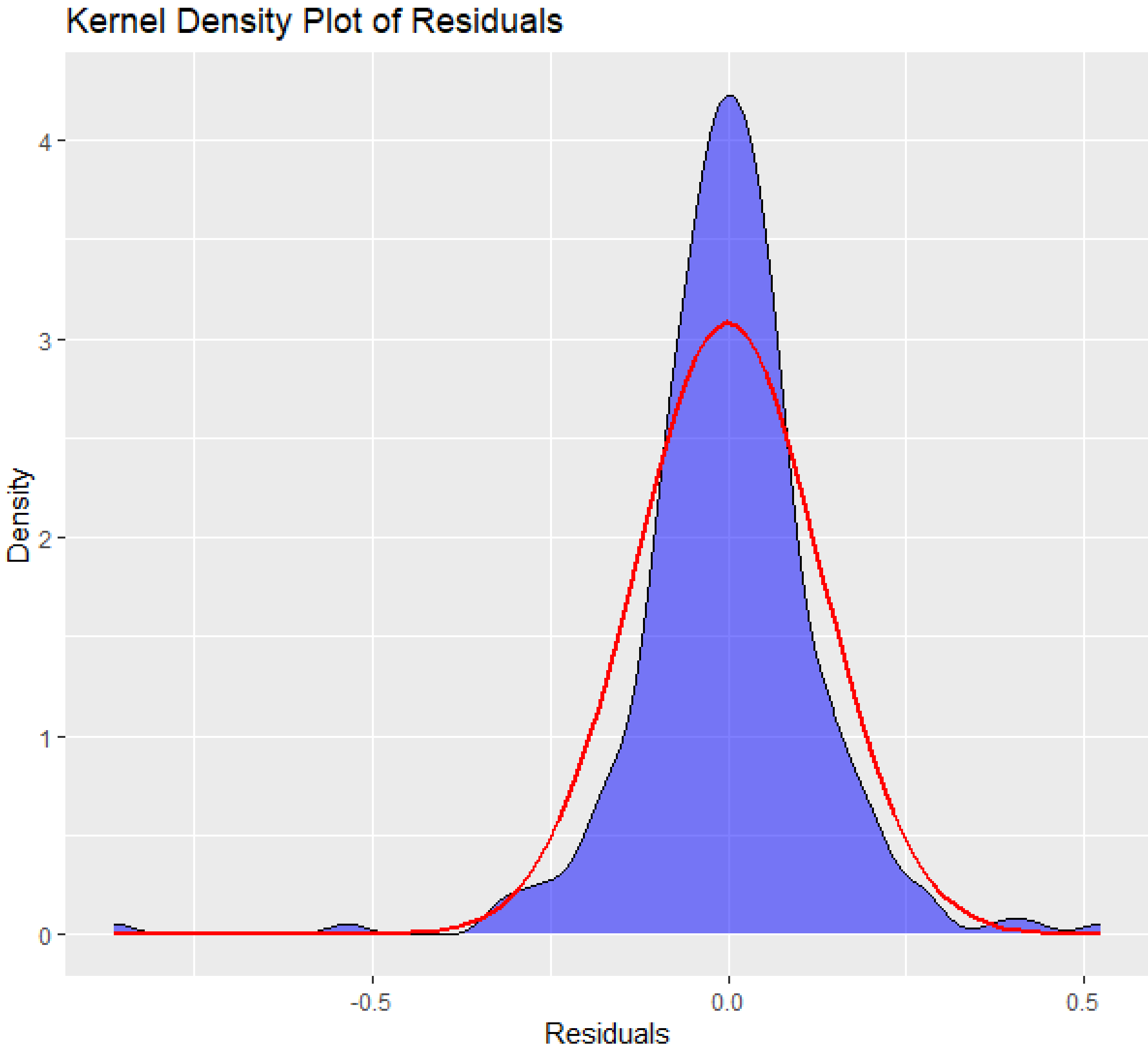

Figure A.16

Car sales and Gross domestic product (GDP) values

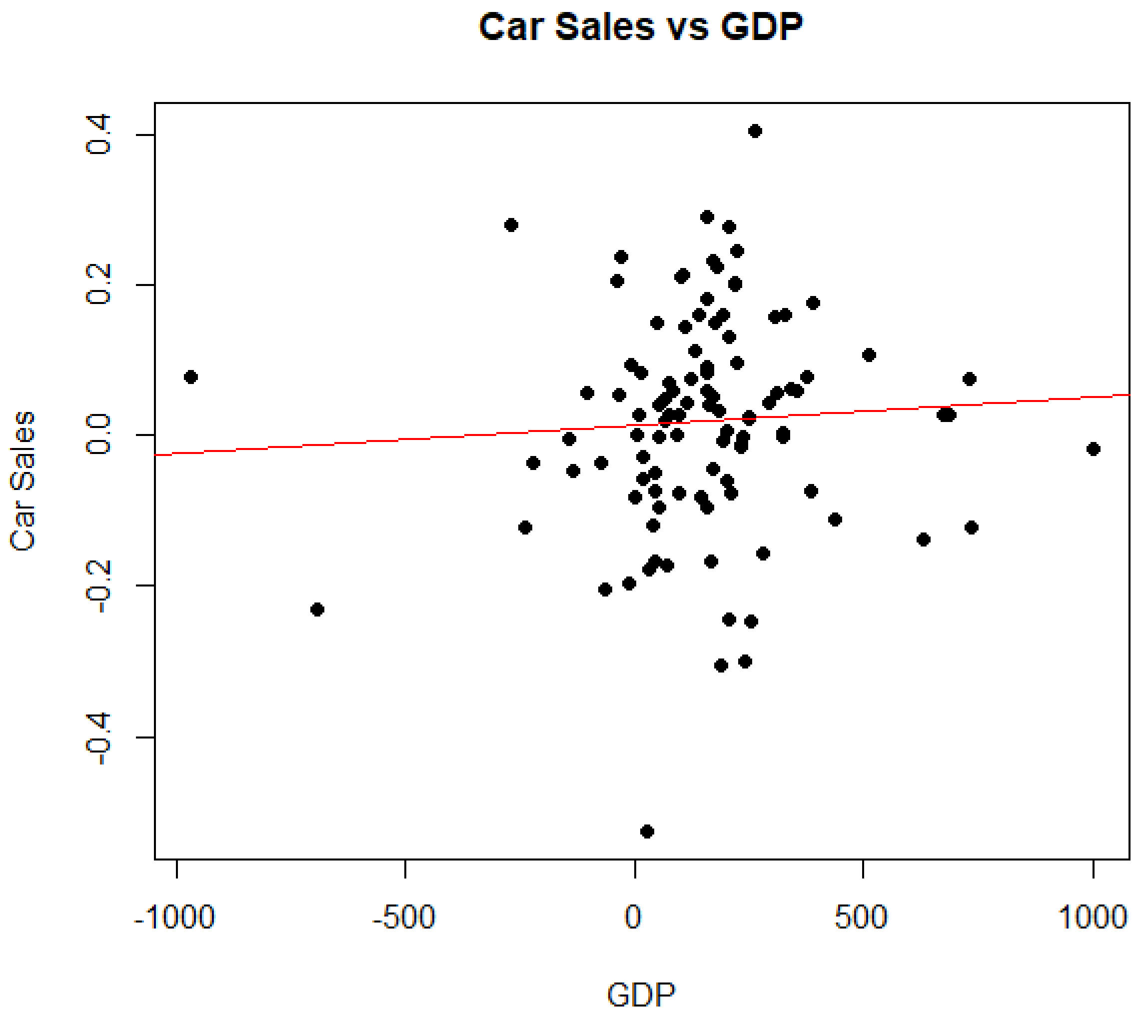

Figure A.17

Car sales and Gross domestic product (GDP) Normal Q-Q plot

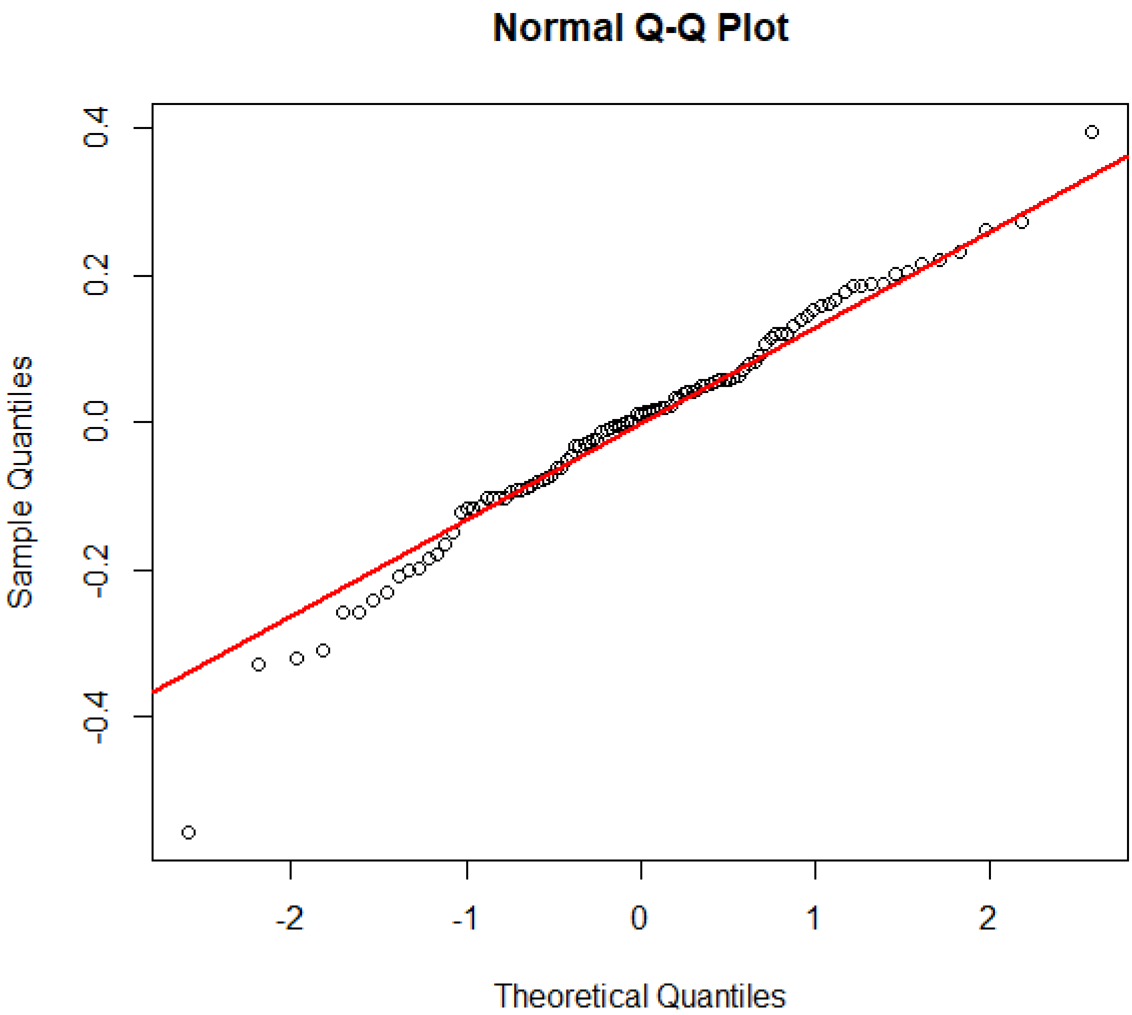

Figure A.18

Car sales and Gross domestic product (GDP) Kernel density plot of residuals