University of Padova

Department of Mathematics "Tullio Levi-Civita"

Master Thesis in Data Science

From Fossil Fuels to Electric: Modelling Battery Electric Vehicle Adoption with Innovation Diffusion and Machine Learning Models

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Academic Year

2024-2025

To my beloved family...

"The journey of a thousand miles begins with one step."
— Lao Tzu

Abstract

The transition from internal combustion engine (ICE) vehicles to battery electric vehicles (BEVs) is revolutionising the automotive sector at its core, and Norway is taking the lead. Inspired by pioneering government initiatives, rapid technological progress, and growing environmental awareness, BEV uptake has been gaining a spurt of interest. However, understanding the drivers behind this transition remains crucial for good policy making and strategic business planning.

This thesis examines the trends of BEV adoption and predicts future market penetration based on empirical facts and cutting-edge forecasting methods. Drawing on large vehicle registration data, the study also identifies the determinants of adoption and evaluates the effectiveness of policy interventions in influencing market results. Through an investigation of various alternative forecasting methods, the study aims to improve the accuracy of adoption prediction as well as to improve understanding of the ongoing transition to BEVs from ICE vehicles.

The findings highlight the key role of government subsidies in stimulating BEV adoption and demonstrate the asymmetric pace of decline in ICE registration. The findings offer valuable advice to policymakers, automotive manufacturers, and energy companies, guiding evidence-based policy measures toward a smoother and faster shift to electric mobility.

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Listing of acronyms

ARIMA	Autoregressive Integrated Moving Average
ARMAX	Autoregressive Moving Average with Exogenous Variables
BEV	Battery Electric Vehicle
BM	Bass Model
DL	Deep Learning
EDA	Exploratory Data Analysis
GBM	Generalized Bass Model
GBM1e	Generalized Bass Model with an Exponential Shock
GBM1e1r	Generalized Bass Model with One Exponential and One Rectangular Shock
GBM1r	Generalized Bass Model with a Rectangular Shock
GBM2e	Generalized Bass Model with Two Exponential Shocks
GBM3e	Generalized Bass Model with Three Exponential Shocks
ICE	Internal Combustion Engine
IEA	International Energy Agency
LightGBM	Light Gradient Boosting Machine
LOESS	Locally Estimated Scatterplot Smoothing
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
NA	Not Available / Missing Value

NLS . . . . Nonlinear Least Squares

NTP . . . . National Transport Plan

OFV . . . . Opplysningsrådet for Veitrafikken

OLS . . . . Ordinary Least Squares

DTSM . . . . Decomposable Time Series Forecasting Model

RF . . . . Random Forest

RMSE . . . . Root Mean Squared Error

RNN . . . . Recurrent Neural Network

SARMAX . . . . . Seasonal ARMAX

SVV . . . . Statens Vegvesen (Norwegian Public Roads Administration)

UCRCD . . . . Unbalanced Competition and Regime Change Diachronic Model

XGBoost . . . . Extreme Gradient Boosting

$\tilde{R}^2$ . . . . Partial Coefficient of Determination

R^2 . . . . Coefficient of Determination

1
Introduction

1.1 Introduction

The transition from Internal Combustion Engine (ICE) vehicles to Battery Electric Vehicles (BEVs) is one of the most significant shifts in the automotive industry. Norway has been at the forefront of this transition, and BEVs comprise the majority of new vehicle registrations. This shift is driven by a combination of government incentives, advancements in battery technology, and increased consumer awareness of sustainability. However, understanding the dynamics of BEV adoption is crucial for policymakers, automakers, and energy providers to optimise infrastructure and incentives. This thesis aims to analyse the trends in the adoption of BEVs and project the future penetration of the market using empirical analysis and machine learning models.

The study of innovation diffusion modelling and forecasting focusses on describing and predicting how new technologies spread within a social system. These models have been widely used in disciplines such as marketing, technology forecasting, and social sciences, drawing theoretical insights from epidemiology, physics, and non-linear regression approaches [1]. One of the foundational works in this field is Rogers' diffusion of innovations [2], which outlines the key elements that shape the adoption of innovations, including the attributes of technology, different segments of adopters, and external factors such as policy interventions. Battery Electric Vehicle (BEV) adoption follows a diffusion process similar to the spread of ideas, behaviours, or even contagious diseases within a population. Early adopters play a crucial role in this process by increasing awareness, influencing social perceptions, and accelerating acceptance through communication, visibility, and network effects [3, 4].

Mathematical models initially designed for epidemiological and biological systems have been adapted to analyse technological adoption and market expansion. The Bass Model (1969) and its subsequent extensions, such as the Generalized Bass Model (GBM) and the UCRCD model, establish a structured approach to modelling adoption curves and predicting market penetration trends [1]. These models have been extensively applied in marketing and innovation diffusion research, providing a deeper understanding of how innovators, early adopters, and mainstream consumers interact in the adoption process. More recently, network-based diffusion models have offered a refined perspective on adoption behaviour, particularly in diverse populations and intricate socio-technical ecosystems [5, 6].

With the rise of machine learning (ML) techniques, alternative approaches to forecasting technology adoption have gained prominence. ML models leverage large-scale datasets to capture complex temporal dependencies and external influences on adoption trends [7]. By comparing innovation diffusion models with machine learning-based forecasting, this thesis aims to provide a comprehensive analysis of BEV adoption dynamics in Norway.

This research will be based on Norwegian vehicle registration data compiled from Statens vegvesen (SVV) [8] and hosted by Digitaliseringsdirektoratet, supplemented with additional sources such as OFV.no. The thesis will analyse historical adoption trends, compare the predictive performance of diffusion models, predict the future with machine learning techniques, and interpret the findings to derive policy insights to promote sustainable mobility.

1.2 Research Questions

This study seeks to address the following key research questions:

- What are the main factors driving the adoption of BEV in Norway?
- How does the growth trajectory of BEV adoption compare to the decline of ICE vehicles?
- To what extent can innovation diffusion models (e.g., Bass Model, Generalized Bass Model, UCRCD) accurately predict BEV adoption patterns?
- How do machine learning models perform in forecasting BEV adoption?
- What policy recommendations can be derived from the findings to further accelerate the adoption of BEV?

1.3 Research Objectives

The primary objectives of this thesis are as follows:

- Analyse historical trends in the adoption of BEVs and assess their relationship with the decline in ICE vehicle registrations.
- Examine the impact of key policy interventions, including subsidies, tax incentives, and infrastructure investments, on BEV adoption trends.

- Implement and evaluate innovation diffusion models to understand the BEV and ICE diffusion process.

- Apply machine learning techniques to predict future BEV adoption and ICE decline and compare their performance.

1.4 Methodology Overview

To achieve these objectives, a combination of diffusion models, time series forecasting techniques, and machine learning approaches will be employed:

- **Exploratory Data Analysis (EDA):** Conduct a thorough analysis of BEV registration data to identify trends, seasonality, and anomalies using time series decomposition and visualisation techniques.

- **Innovation Diffusion Modelling:** Apply diffusion models, including the Bass Model (BM), the Generalised Bass Model (GBM), and the UCRCD Model, to estimate key adoption parameters such as the innovation coefficient (p) and imitation coefficient (q), thereby characterising the adoption dynamics of BEVs.

- **Forecasting and Predictive Modelling:** Implement and compare a range of forecasting approaches to predict BEV adoption and ICE decline. These include statistical time series models such as ARIMA, Facebook Prophet, as well as machine learning methods like XGBoost, LightGBM Random Forest, and LSTM. Assess and benchmark their predictive performance against diffusion models.

- **Policy Impact Assessment:** Investigate the effect of government incentives, tax reforms, and infrastructure policies on BEV adoption trends, integrating these factors into both forecasting and diffusion analyses.

In this research, new vehicle registrations are used as a proxy for new vehicle sales, as they closely reflect market adoption patterns and are commonly employed in the literature.

2

Theoretical Background

2.1 Innovation Diffusion Models

Innovation diffusion models provide a mathematical framework for understanding how new technologies, products, or ideas spread within a population over time. These models are widely used in various fields, including marketing, technology forecasting, economics, epidemiology, and social sciences, to analyse and predict the adoption dynamics of innovations. By capturing the rate of adoption and the influence of different adopter categories, these models help researchers and policymakers design strategies to accelerate or manage innovation diffusion.

Diffusion processes typically follow an S-shaped curve: initial adoption by a small group of early adopters is followed by rapid growth as the innovation spreads to the majority, and finally levels off as the market becomes saturated. This pattern, first explored by Rogers (1962) in his *Diffusion of Innovations* theory [2], highlights factors such as communication channels, social influence, external incentives, and product characteristics.

The Bass Diffusion Model (BM) [3] formalises this process by introducing two key forces: the **innovation effect** (p), representing external influences such as advertising and policies, and the **imitation effect** (q), capturing social influence as adoption grows.

Over time, several extensions and modifications of the Bass Model have been developed to better capture real-world adoption behaviours. These include the Generalized Bass Model (GBM), which incorporates marketing variables such as pricing and promotional efforts, and the UCRCD Model, which accounts for competition and market saturation effects.[1] The main objective of this research is to apply three models of diffusion of innovation to analyse the adoption of BEV and the decline of ICE in Norway.

2.2 Univariate Diffusion Models

2.2.1 The Bass Model (BM)

The Bass Model (BM) characterises the life cycle of a product by capturing its key phases: launch, growth, maturity, and decline. Originally developed in the field of marketing [3], its purpose is to model the adoption of a new product over time, driven by the purchasing behaviour of a population of potential adopters.

The BM suggests that adoption decisions are driven by two forces: external influence, known as the innovation effect (p), which includes media communication, advertising, and government incentives; and internal influence, known as the imitation effect (q), arising from word-of-mouth and peer interactions. These forces give rise to two types of adopters: innovators, who adopt due to external stimuli, and imitators, who adopt through social influence.

The model is formulated as:

$$\frac{dy(t)}{dt} = (p + qy(t))(1 - y(t)), \tag{2.1}$$

where $y(t)$ is the proportion of adopters at time t, p is the coefficient of innovation, and q is the coefficient of imitation.

The closed-form solution for cumulative adoption is given by:

$$y(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}}. \tag{2.2}$$

The Bass Model (BM) offers high interpretability, allowing for a clear distinction between early adopters and imitators. The model assumes that external conditions remain constant over time, which limits its capacity to capture dynamic real-world scenarios where incentives, regulations, and market conditions evolve. While the parameters p and q directly correspond to behavioural mechanisms of innovation and imitation, the BM exhibits limited flexibility as it assumes a fixed market potential and does not account for external shocks, seasonality, or policy changes.

2.2.2 The Generalized Bass Model (GBM)

The Bass Model (BM) has been criticised for its inability to incorporate marketing mix variables such as pricing and promotions [9, 10]. The Generalized Bass Model (GBM), developed by Bass et al. (1994) [11], addresses these limitations by introducing an intervention function $x(t)$ to capture external influences. The GBM retains the fundamental diffusion structure of the BM while integrating dynamic factors such as pricing and advertising effects.

$$z'(t) = \left(p + q\frac{z(t)}{m}\right)(m - z(t))x(t). \tag{2.3}$$

The GBM reduces to the BM when $x(t) = 1$; varying $x(t)$ allows diffusion to accelerate ($x(t) > 1$) or decelerate ($0 < x(t) < 1$), thereby capturing the impact of external interventions on adoption dynamics. Bass et al. (1994) [11] demonstrated that the GBM preserves the internal parameters m, p, and q, modifying only the timing of adoption to enable the evaluation of marketing mix strategies.

Shock Functions in the GBM

Guseo, Dalla Valle, and Guidolin [12] extended the GBM by introducing two types of external shocks: *exponential* and *rectangular* shocks, enabling more flexible modelling of adoption dynamics.

The exponential shock models rapid, transient perturbations such as marketing campaigns or economic crises. It is defined as:

$$x(t) = 1 + c_1 e^{b_1(t-a_1)} I_{\{t \geq a_1\}}, \tag{2.4}$$

where a_1 is the shock's start time, b_1 the memory decay rate (typically negative), and c_1 the shock's intensity.

The rectangular shock captures sustained interventions, such as policy measures, over a fixed time window:

$$x(t) = 1 + c_1 I_{\{a_1 \leq t \leq b_1\}}. \tag{2.5}$$

Here, a_1 and b_1 define the duration, and c_1 indicates the intensity.

In addition, multiple shocks can be combined, for example:

$$x(t) = 1 + c_1 e^{b_1(t-a_1)} I_{\{t \geq a_1\}} + c_2 I_{\{a_2 \leq t \leq b_2\}},$$

to model complex external influences.

By integrating shocks, the GBM significantly increases the flexibility of the model, allowing the adoption curve to adjust dynamically in response to policy changes, marketing campaigns, or unexpected market events. Despite its added complexity, the GBM maintains an interpretable structure by maintaining p and q. This framework is particularly suited to modelling the adoption of BEVs in Norway, where policy incentives have played a critical role.

2.3 Multivariate Diffusion Models

2.3.1 Unbalanced Competition and Regime Change Diachronic Model (UCRCD Model)

The UCRCD Model was introduced by Guseo and Mortarino in 2007 [13] to model the competitive diffusion of two products, incorporating a regime change where the market structure shifts over time. The model captures both monopoly and competition phases and the cross-influence between competing products.

The system of differential equations is:

$$z_1'(t) = m\{[p_{1a} + q_{1a}\frac{z(t)}{m}](1 - \mathbb{I}_{t>c_2}) + [p_{1c} + (q_{1c} + \delta)\frac{z_1(t)}{m} + q_{1c}\frac{z_2(t)}{m}]\mathbb{I}_{t>c_2}\}[1 - \frac{z(t)}{m}]$$

$$z_2'(t) = m[p_2 + (q_2 - \gamma)\frac{z_1(t)}{m} + q_2\frac{z_2(t)}{m}][1 - \frac{z(t)}{m}]\mathbb{I}_{t>c_2}$$

where m shifts from m_a (monopoly phase) to m_c (competition phase) at $t = c_2$.

Adoption is modelled through two imitation effects: imitation within the product (self-reinforcing growth) and imitation between the products (competitive pressure from rival products) [14]. The model accommodates asymmetric competition, meaning that incumbents and entrants can have differing competitive advantages. Despite increased mathematical complexity, UCRCD retains interpretability by clearly separating adoption dynamics before and after competition emerges. It is particularly suited to modelling the transition from ICE vehicles to BEVs.

Statistical Inference for Diffusion Models

Accurate estimation of diffusion model parameters depends on data availability. While non-cumulative data improve parameter estimation, they limit forecasting capabilities [15]. Ordinary Least Squares (OLS) methods often underestimate market potential and may yield negative coefficients, making them unsuitable for diffusion models [16, 17, 18, 19]. Non-linear least squares (NLS) is therefore preferred [15].

The nonlinear regression model is defined as [20]:

$$w(t) = \eta(\beta, t) + \varepsilon(t), \tag{2.6}$$

where $w(t)$ is the observed response, $\eta(\beta, t)$ the deterministic component, and $\varepsilon(t)$ the residual.

Model comparisons employ the partial correlation coefficient $\tilde{R}^2$ [21]:

$$\tilde{R}^2 = \frac{R^2_{m_2} - R^2_{m_1}}{1 - R^2_{m_1}}, \tag{2.7}$$

where $R^2_{m_1}$ and $R^2_{m_2}$ are the coefficients of determination for the baseline and extended models, respectively[1].

In this thesis, all three models are applied to analyse and forecast the adoption of BEVs in Norway. The BM provides a baseline, the GBM captures policy effects, and the UCRCD Model explains the transition from ICE vehicles to BEVs.

Linear Interpolation

Linear interpolation is a widely used technique in time-series analysis for estimating missing values between known data points. It assumes that changes between consecutive points follow a linear pattern, allowing the estimation of intermediate values using a straight-line approximation [20].

Given two known points, (x_1, y_1) and (x_2, y_2), the interpolated value y at any point x within this range is calculated as:

$$y = y_1 + \frac{(y_2 - y_1)}{(x_2 - x_1)}(x - x_1). \tag{2.8}$$

This method ensures a smooth transition between data points while preserving the overall trend of the data set. It is particularly effective in time series datasets where values change gradually over time [22].

2.4 Statistical, Machine Learning and Deep Learning Models

In addition to innovation diffusion models, statistical, machine learning (ML), and deep learning (DL) approaches offer powerful data-driven methods for forecasting technology adoption. These models can capture complex, non-linear relationships and interactions within the data that are difficult to model with classical statistical frameworks. In recent years, ML and DL have been increasingly applied in innovation diffusion research to enhance predictive performance and adapt to dynamic market environments.

2.4.1 ARIMA, ARMAX, and SARMAX Models

Autoregressive Integrated Moving Average (ARIMA) models are a classical approach for time-series forecasting. ARIMA combines three components: autoregression (AR), differencing (I), and moving average (MA). It is represented as:

$$y_t = c + \varphi_1 y_{t-1} + \cdots + \varphi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t, \tag{2.9}$$

where p, d, and q represent the orders of autoregression, differencing, and moving average components, respectively. The ARIMA model assumes stationarity and is effective for linear time series data [23].

ARMAX (Autoregressive Moving Average with Exogenous Variables) extends ARIMA by incorporating exogenous regressors (X) to improve forecasting accuracy. The model equation becomes:

$$y_t = c + \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{k=1}^{r} \beta_k x_{k,t} + \varepsilon_t, \tag{2.10}$$

where $x_{k,t}$ are exogenous variables [24].

SARMAX (Seasonal ARMAX) further generalises ARMAX by including seasonal effects. It is well-suited for time series data with seasonal trends and exogenous influences. SARMAX models are particularly useful in energy consumption, retail demand, and transportation forecasting [25].

One of the primary advantages of ARIMA-based models is their high interpretability. Each parameter has a clear statistical meaning, allowing users to diagnose the model's structure and understand the contribution of each component; autoregressive terms reflect past dependencies, moving averages account for error propagation, and exogenous inputs in ARMAX and SARMAX introduce external influences transparently.

These models are also flexible when the data exhibit well-defined linear trends and seasonal patterns. ARMAX accommodates external variables such as policy interventions or macroeconomic indicators, while SARMAX captures recurring seasonal behaviours. However, they may struggle to model complex non-linear dynamics, structural breaks, or interactions across multiple variables. In such cases, machine learning methods such as XGBoost or deep learning approaches like LSTM may offer superior adaptability, although at the expense of interpretability.

2.4.2 Prophet Model

Prophet is a time series forecasting model developed by Sean J. Taylor and Benjamin Letham at Facebook in 2017 to make forecasting accessible to analysts and businesses[26]. It was designed to handle irregular time series data characterised by multiple seasonalities, missing observations, and abrupt changes in trends. Prophet combines ideas from decomposable time series models with curve fitting techniques, allowing flexible and interpretable forecasting.

The model decomposes a time series into four components:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon(t), \tag{2.11}$$

where $g(t)$ represents the trend function, $s(t)$ models seasonal effects using Fourier series, $h(t)$ captures holiday or special event effects, and $\varepsilon(t)$ is the random error term.

The trend component $g(t)$ allows for both linear and logistic growth, with change points incorporated to capture shifts in the growth rate. Seasonality $s(t)$ is modelled as a sum of periodic functions, typically through a Fourier series expansion to capture yearly, weekly, or daily patterns. The holiday effect $h(t)$ models temporary deviations associated with known events, while $\varepsilon(t)$ captures unexplained variability in the data.

Prophet is highly interpretable, as it provides a clear decomposition of the forecast into trend, seasonality, and holiday components. It also offers significant flexibility, allowing users to handle missing data, specify custom seasonalities and holidays, and automatically detect change points in the trend.

2.4.3 Random Forest Model

Random Forest is an ensemble learning method introduced by Leo Breiman in 2001 [27] to improve the predictive performance of decision trees. The model constructs a multitude of decision trees during training, each built on a random subset of the data and features. The final prediction is obtained by aggregating the predictions of the individual trees, typically through averaging for regression tasks or majority voting for classification tasks.

Formally, if $f_1(x), f_2(x), \ldots, f_B(x)$ represent the predictions from B different trees, the Random Forest prediction $\hat{f}(x)$ is given by:

$$\hat{f}(x) = \frac{1}{B} \sum_{b=1}^{B} f_b(x). \tag{2.12}$$

By averaging across multiple trees, Random Forest reduces variance and improves generalisation, while maintaining relatively low bias.

Random Forest models offer moderate interpretability through feature importance measures, although they lack the transparency of individual decision trees. They provide good flexibility for regression and classification tasks but may be less effective than boosting methods, such as XGBoost, in capturing complex feature interactions.

2.4.4 Extreme Gradient Boosting (XGBoost)

XGBoost is a scalable and efficient gradient boosting framework developed by Tianqi Chen in 2016[28] . Designed to deliver high predictive performance with fast execution, XGBoost has gained widespread popularity in both academic research and industry applications. The algorithm builds an ensemble of decision trees sequentially, where each new tree is trained to correct the residual errors of the previous trees using gradient descent methods.

Formally, XGBoost optimises a regularised objective function defined as:

$$\mathcal{L}(\varphi) = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i\right) + \sum_{k=1}^{K} \Omega(f_k), \tag{2.13}$$

where $l(y_i, \hat{y}_i)$ denotes a differentiable loss function that measures the difference between the true value y_i and the predicted value $\hat{y}_i$, and $\Omega(f_k)$ is a regularisation term penalising model complexity. Here, n is the number of observations, and K is the number of trees.

The regularisation term $\Omega(f)$ is typically specified as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \|w\|^2, \tag{2.14}$$

where T is the number of leaves in the tree, w are the leaf weights, and γ and λ are regularisation parameters controlling the model's complexity and smoothness.

XGBoost offers high flexibility, capable of capturing complex non-linear relationships and interactions between variables. However, it is generally less interpretable than traditional statistical models. Interpretability can be enhanced through feature importance measures, partial dependence plots, and SHAP (SHapley Additive exPlanations) values, which provide insights into the contribution of each feature to the model's predictions.

2.4.5 Light Gradient Boosting Machine (LightGBM)

LightGBM is a highly efficient gradient boosting framework developed by Microsoft Research [29]. It is based on decision tree algorithms and is designed to be distributed and fast, with particular emphasis on scalability and performance on large datasets.

Unlike traditional gradient boosting implementations that grow trees level-wise, LightGBM employs a leaf-wise growth strategy. In this approach, the algorithm selects the leaf with the highest loss to grow, leading to deeper and potentially more accurate trees. This growth policy allows LightGBM to achieve lower loss than level-wise methods given the same number of splits.

The LightGBM model optimises the following regularised objective function:

$$\mathcal{L}(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k), \tag{2.15}$$

where $l(y_i, \hat{y}_i)$ is a differentiable loss function (e.g., squared error), and $\Omega(f_k) = \gamma T + \frac{1}{2}\lambda\|w\|^2$ is a regularisation term that penalises model complexity via the number of leaves T and leaf weights w.

LightGBM incorporates several innovations:

- **Histogram-based decision tree learning**, which discretises continuous features into bins to reduce memory usage and accelerate computation.
- **Gradient-based One-Side Sampling (GOSS)**, which prioritises instances with large gradients to focus on hard-to-predict cases.
- **Exclusive Feature Bundling (EFB)**, which bundles mutually exclusive features to reduce dimensionality without significant information loss.

From a forecasting perspective, LightGBM offers high flexibility and performance, especially when used with extensive feature engineering. It handles non-linear relationships, interactions, and variable importance effectively. However, like other tree-based methods, it lacks native support for extrapolation and may struggle to forecast beyond the range of training data without careful recursive strategies.

Interpretability is supported via built-in feature importance metrics and tools such as SHAP values. This makes LightGBM a powerful and interpretable model for structured time series forecasting tasks when proper lagged, seasonal, and exogenous features are incorporated.

2.4.6 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks were introduced by Hochreiter and Schmidhuber in 1997 [30] to address the limitations of traditional recurrent neural networks (RNNs) in learning long-term dependencies. LSTMs are a type of deep learning model specifically designed for sequential data, making them particularly effective for time series forecasting, natural language processing, and other tasks involving temporal patterns.

An LSTM unit consists of a cell state c_t and three gates that regulate information flow: the input gate i_t, the forget gate f_t, and the output gate o_t. The core equations governing an LSTM cell are:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f), \tag{2.16}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \tag{2.17}$$

$$\tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c), \tag{2.18}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t, \tag{2.19}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o), \tag{2.20}$$

$$h_t = o_t \odot \tanh(c_t), \tag{2.21}$$

where x_t is the input at time t, h_t is the hidden state, σ denotes the sigmoid activation function, tanh is the hyperbolic tangent function, and $\odot$ represents element-wise multiplication. The matrices W and vectors b are the model parameters learned during training.

LSTMs are highly flexible, capable of modelling complex, non-linear, and long-range dependencies in sequential data. However, they are less interpretable than traditional models, as the learned internal representations (such as cell states and gates) are difficult to directly relate to input features. Techniques such as attention mechanisms and input saliency maps can improve interpretability but are not inherently part of the standard LSTM architecture.

The statistical and machine learning models outlined were applied to analyse and forecast the adoption of BEVs in Norway. The subsequent sections detail the results obtained from these modelling approaches.

3
Dataset Preprocessing & Preparation

The accuracy and reliability of the forecasting models are highly dependent on the quality of the data and the effectiveness of the pre-processing steps. Raw datasets frequently contain missing values, inconsistencies, or structural issues that must be addressed before analysis can be conducted.

The dataset used in this study comprises monthly vehicle registration records in Norway, classified by fuel type and whether the vehicles are new or used. To ensure that the dataset was suitable for time series analysis, several pre-processing steps were undertaken, including handling missing values, standardising the time formats, renaming variables, and interpolating missing data points.

This chapter outlines the dataset's source, structure, and pre-processing steps implemented to prepare the dataset for further analysis and forecasting.

3.1 Dataset Source & Description

Data Source

The dataset used in this research has been compiled from Statens vegvesen (SVV) [8], hosted by Digitaliseringsdirektoratet [31], and supplemented with data from OFV (Opplysningsrådet for Veitrafikken) [32]. These sources are among Norway's most authoritative providers of vehicle registration statistics, ensuring a high level of reliability for analysing trends in BEV adoption.

Data Content and Coverage

The dataset covers the period from 1990 to the present and includes records of new and used vehicle registrations, categorised by engine type. This extensive historical coverage enables the analysis of long-term trends, shifts in consumer preferences, and the impact of policies on BEV adoption.

Key Variables

The dataset includes multiple variables related to vehicle registration numbers, categorised by fuel type and usage status (new vs. used). Below is a summary of the most relevant variables used in this research:

- **YYYYMM**: Represents the year and month of vehicle registration in a compact format (e.g., 202201 for January 2022).
- **Date**: A reformatted date variable used for time-series analysis.
- **BEV_New**: Number of new Battery Electric Vehicles (BEVs) registered in a given month.
- **BEV_Used**: Number of used BEVs registered.
- **Petrol_New**: Number of new petrol vehicle registrations.
- **Petrol_Only_Used**: Number of used petrol vehicle registrations.
- **Diesel_New**: Number of new diesel vehicle registrations.
- **Diesel_Only_Used**: Number of used diesel vehicle registrations.
- **Non_plugin_hybrid_New**: Number of new non-plug-in hybrid registrations.
- **Non_plugin_hybrid_Used**: Number of used non-plug-in hybrid registrations.
- **Plugin_hybrid_New**: Number of new plug-in hybrid registrations.
- **Plugin_hybrid_Used**: Number of used plug-in hybrid registrations.
- **Total_New**: Total number of new vehicle registrations across all fuel types.

These variables provide crucial insights on the evolution of BEV adoption and its competition with ICE vehicles.

This thesis focusses primarily on the new vehicle registration data for different fuel types, as it better reflects consumer preferences, market trends, and the impact of policy interventions on BEV adoption.

3.2 Data Preprocessing & Cleaning

Before performing any statistical or forecasting analysis, several preprocessing steps were performed to enhance the usability and integrity of the dataset. These steps included standardising the date format to enable accurate time-series analysis and renaming columns to improve clarity and readability. Missing and zero values were addressed to avoid distortions in the analysis, and data points from earlier years, characterised by excessive missing values, were excluded due to their unreliability. In addition, interpolation techniques were applied to impute missing values and ensure a smoother trend representation throughout the dataset.

Converting Time Format

The original dataset recorded time information in the **YYYYMM** format, which is not directly compatible with time-series analysis tools. To resolve this, the year and month values were extracted and the data was reformatted into a standardised **YYYY-MM-DD** format. The first day of each month was assigned as a placeholder to maintain consistency across all records.

This transformation facilitates seamless chronological ordering, enhances compatibility with time-series analysis tools, and enables accurate visualisation and forecasting.

Renaming Columns for Clarity

The dataset originally contained column names that were lengthy and difficult to interpret. To improve clarity and consistency, these names were standardised and reformatted to align with the common terminology used in vehicle market analysis.

For instance, the column *'BEV..New'* was renamed to *'BEV_New'*, while *'PetrolOnly..New'* was simplified to *'Petrol_New'*. This refinement significantly improved the readability and accessibility of the dataset for further analysis.

Handling Missing Values & Zero Values

Upon initial inspection, some months contained zero values for certain vehicle registrations. These zero values did not necessarily indicate a complete absence of registrations, but were instead assumed to represent missing data points.

To prevent these zero values from distorting the analysis, they were replaced with **NA (Not Available)**, ensuring that the dataset accurately reflected actual vehicle registration trends.

In addition, missing values were identified in key registration columns and marked for further processing.

Removing Early Years with Excessive Missing Data

The dataset includes records from 1990 onwards; however, the earlier years contained significant amounts of missing or inconsistent data. As incomplete data can distort trend analysis, a systematic approach was applied to identify the first month where all relevant columns contained valid values.

To enhance the reliability of the dataset, all data points prior to this threshold were removed.

Interpolating Missing Data

After addressing missing values, gaps remained in some registration records. To create a continuous and reliable time-series dataset, linear interpolation was applied to estimate missing values based on historical trends.

Interpolation is a widely used technique in time-series analysis that approximates missing values using neighbouring months. This method ensures a smooth progression of vehicle registrations while preserving the natural trends of the dataset.

3.3 Exploratory Data Analysis (EDA)

Following pre-processing of the dataset, a comprehensive exploratory data analysis (EDA) was conducted to uncover key insights. This included examining historical trends in battery electric vehicle (BEV) adoption, identifying seasonal patterns and significant market shifts, and detecting anomalies in vehicle registration data. Furthermore, the analysis explored the impact of policy incentives, taxation changes, and other external factors on BEV sales. Understanding these patterns provides a critical foundation for subsequent diffusion modelling and predictive analysis.

Vehicle Registration Trends

To analyse long-term trends, vehicle registration data was plotted over time. Figure 3.1 shows the monthly registrations of new BEVs compared to internal combustion engine (ICE) vehicles (petrol and diesel).

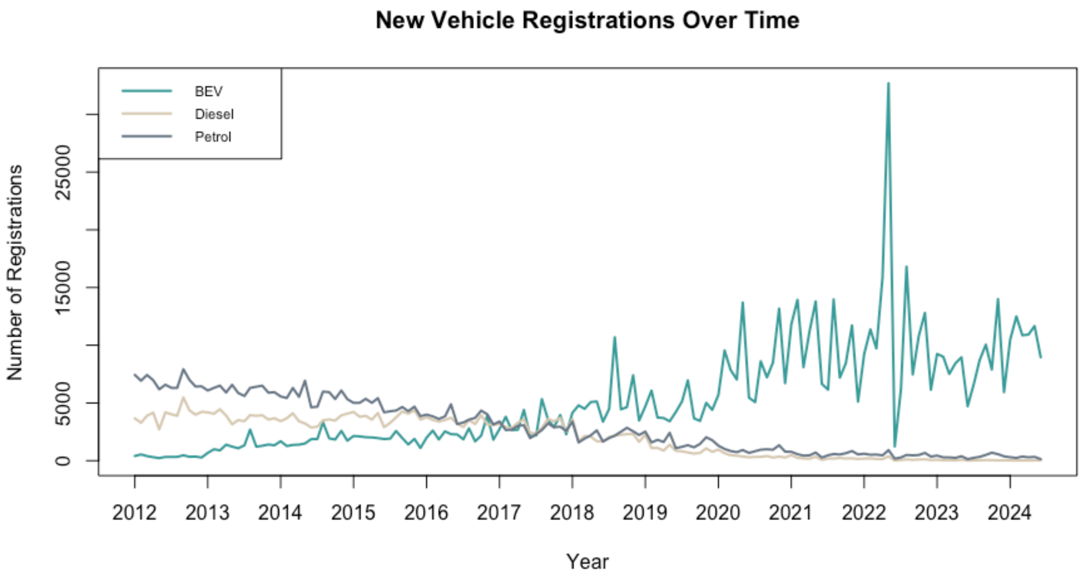

Figure 3.1: New Vehicle Registrations Over Time

The registration of BEVs has experienced accelerated growth since the mid-2010s, surpassing the registrations of petrol and diesel vehicles. This surge can be attributed to Norway's proactive policies on electric vehicles, substantial financial incentives, and continued improvements in the charging infrastructure [33, 34]. In contrast, ICE vehicle registrations, including petrol and diesel models, have steadily declined, particularly after 2018. This trend is largely driven by stricter emission regulations, raised taxes on fossil fuel vehicles, and increasing preference for sustainable transport options [35]. A significant spike in BEV registrations in late 2022 aligns with the expiration of government incentives, as consumers rushed to purchase electric vehicles before impending tax hikes [36]. These trends collectively highlight the effectiveness of policy interventions in accelerating the adoption of electric vehicles while simultaneously phasing out traditional fuel vehicles.

BEV Market Share

To measure the adoption of BEVs, its market share was calculated as the proportion of new BEV registrations compared to the total number of new vehicle registrations. Figure 3.2 shows the steady increase in the share of the BEV market over time, highlighting the growing dominance of electric vehicles on the Norwegian market.

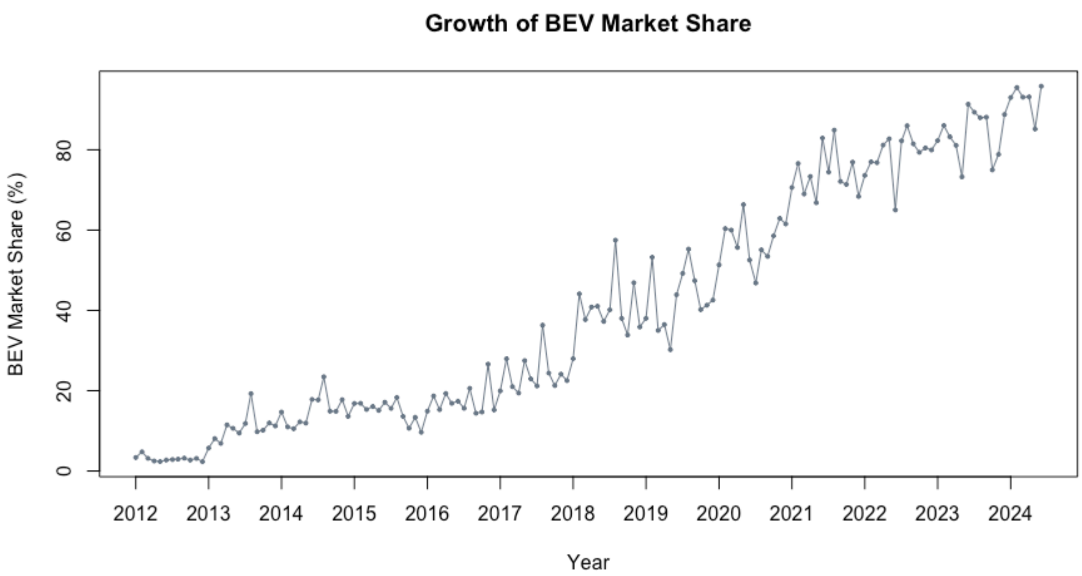

Figure 3.2: Growth of BEV Market Share

By 2024, the market share of Battery Electric Vehicles (BEVs) in Norway had steadily increased, exceeding 80% of total vehicle sales [37, 38]. This transition has been largely driven by government policies, including zero-emission vehicle (ZEV) mandates, tax reductions, and exemptions from toll road charges, all of which have incentivised consumers to adopt electric vehicles [33, 34].

Correlation Analysis: BEV vs. ICE Decline

To investigate the relationship between BEV registrations and the decline in ICE vehicle registrations, the Pearson correlation coefficient was calculated.

Comparison	Correlation Coefficient
BEV vs. Petrol	-0.75
BEV vs. Diesel	-0.72

Table 3.1: Pearson Correlation Between BEV Growth and ICE Decline

The Pearson correlation coefficient (r) quantifies the strength and direction of a linear relationship between two variables and is defined as:

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2}\sqrt{\sum(y_i - \bar{y})^2}} \tag{3.1}$$

where x_i and y_i are individual data points, and $\bar{x}$ and $\bar{y}$ denote their respective means. [39]

The Pearson correlation coefficient ranges from -1 to 1, where $r = 1$ indicates a perfect positive correlation (both variables increase together), $r = -1$ denotes a perfect negative correlation (one variable increases while the other decreases), and $r = 0$ signifies no linear correlation between the variables.

In this analysis, Pearson correlation tests were conducted between BEV registrations and petrol vehicle registrations, as well as between BEV registrations and diesel vehicle registrations. The results are summarised in Table 3.1.

The correlation results indicate a strong negative relationship between BEV registrations and ICE vehicle sales.

The correlation between BEV and petrol registrations ($r = -0.75$) suggests a direct market substitution effect, where petrol vehicle buyers are increasingly switching to BEVs.

Similarly, the correlation between BEV and diesel registrations ($r = -0.72$) indicates that diesel vehicles also experience a substantial decline in response to the growth of BEV.

The extremely low values of r confirm that these relationships are statistically significant, strengthening the shift from ICE vehicles to BEVs in the Norwegian automotive market.

These findings align with previous research highlighting the impact of Norway's EV incentives, taxation policies, and regulatory measures in accelerating the transition away from petrol and diesel vehicles [33, 34].

Growth Rate Analysis

To better understand adoption trends, the growth rates of BEV, petrol and diesel were analysed using a rolling average of 6 months to smooth out short-term fluctuations.

Smoothed growth rates for BEV, petrol and diesel registrations highlight key trends in Norway's transition to electric mobility. Since 2020, BEV registrations have surged, with a particularly sharp increase in 2023. This spike coincided with the introduction of a purchase tax on all vehicles based on weight, CO, and nitrogen oxides (NO_x) emissions, whereas electric vehicles had previously been exempt from the weight-based tax [33]. The market dynamics during this period were further influenced by government incentives, evolving taxation policies, and the

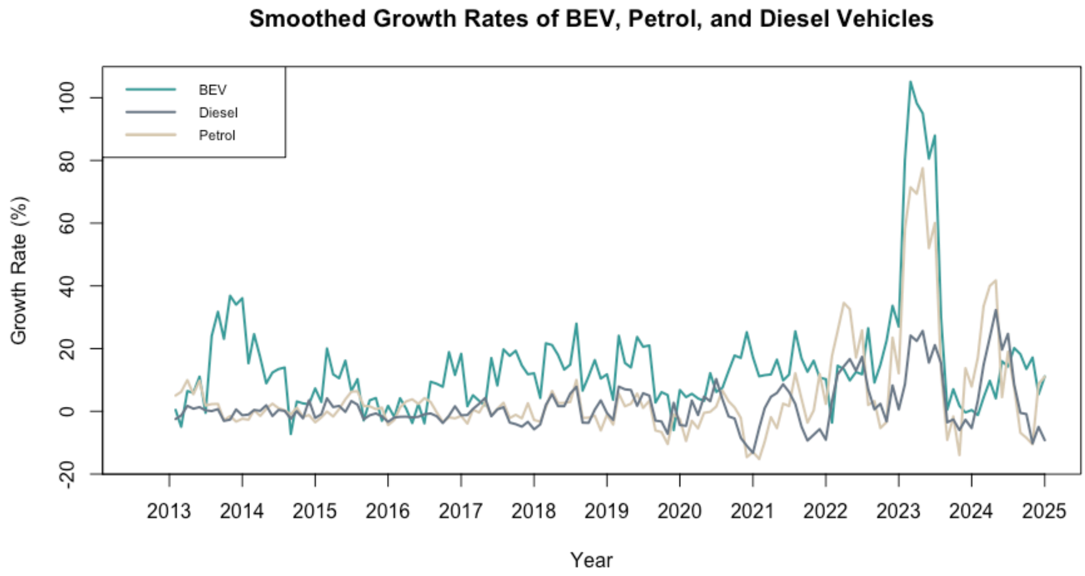

Figure 3.3: Smoothed Growth Rates of BEV, Petrol, and Diesel

launch of popular electric models such as the Tesla Model Y, all of which contributed to the accelerated adoption of BEVs [36, 40].

In contrast, registrations for petrol and diesel vehicles have shown a consistent decline, further strengthening the shift away from ICE vehicles to BEVs [37]. This trend reflects the tightening of emissions regulations, rising taxation on fossil fuel cars, and an overall consumer preference for sustainable mobility solutions.

Moreover, fluctuations in BEV growth rates closely align with major policy adjustments, underscoring the strong influence of financial incentives such as tax exemptions, subsidies, and toll reductions [33, 35]. Periods of rapid adoption of BEV often precede reductions in subsidies, as consumers seek to maximise benefits before regulatory changes take effect.

In general, the data underscore the pivotal role of policy interventions in accelerating the adoption of BEVs while highlighting the steady decline in the demand for fossil fuel vehicles in response to evolving regulatory and economic pressures.

Time Series Decomposition and Anomaly Detection

To gain deeper insights into the underlying patterns of BEV registrations, a Seasonal-Trend decomposition using LOESS (STL decomposition) was applied. This method separates the time series into three key components:

- **Trend Component:** Captures the long-term progression of BEV adoption, filtering out short-term fluctuations.

- **Seasonal Component:** Identifies recurring patterns in sales, often linked to consumer behaviour and market cycles.
- **Residual Component:** Represents irregular variations, including anomalies caused by external shocks.

The trend component indicates a sustained increase in the adoption of BEVs, confirming that the transition towards electric vehicles is a long-term structural change rather than a transient market phenomenon. The seasonal component highlights a pattern of higher sales towards the end of each year, which is likely influenced by consumers purchasing in advance of regulatory or incentive changes. The residual component reveals unexpected deviations, pointing to anomalies that may be linked to external policy changes or economic conditions.

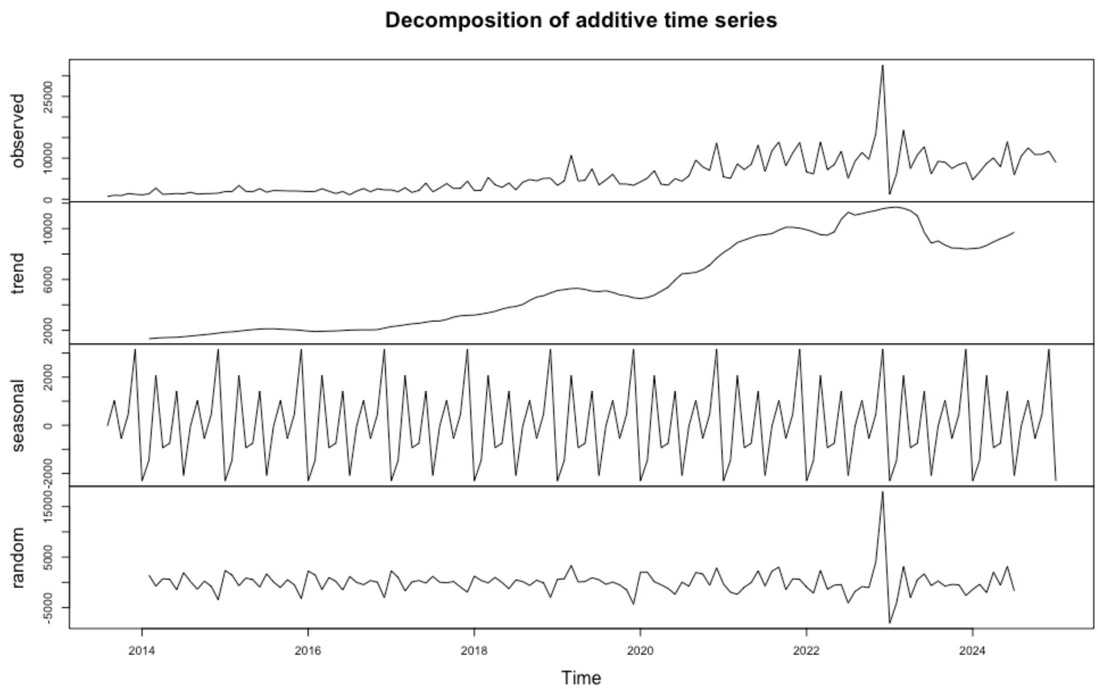

Figure 3.4: Decomposition of BEV Registration Time Series

Anomaly Detection in BEV Registrations

To detect unusual fluctuations in BEV sales, an anomaly detection method based on Z-scores was applied. The Z-score measures how far a data point deviates from the mean in terms of standard deviations and is defined as:

$$Z = \frac{x - \mu}{\sigma} \tag{3.2}$$

where x is the observed value, μ is the mean and σ is the standard deviation. A high absolute Z-score indicates that the data point differs significantly from the expected trend [41]. Figure 3.5 shows the anomalies identified for the BEVs.

Using this approach, key anomalies were identified in the BEV registrations:

- **December 2022:** A sharp spike in registrations as consumers rushed to benefit from expiring BEV tax exemptions, leading to record BEV sales before the new fiscal policies took effect [42].
- **January 2023:** A significant decline in overall auto sales following the introduction of new taxes on heavier and high-end BEVs, along with stricter penalties on CO_2 emitting vehicles, reflecting the immediate impact of tax policy shifts [43].
- **April 2023:** A noticeable increase in BEV registrations driven primarily by the ongoing effects of the January tax changes. The surge was amplified by improved Tesla logistics (notably Model Y deliveries) and the registration of pre-tax-change orders placed months earlier [44].

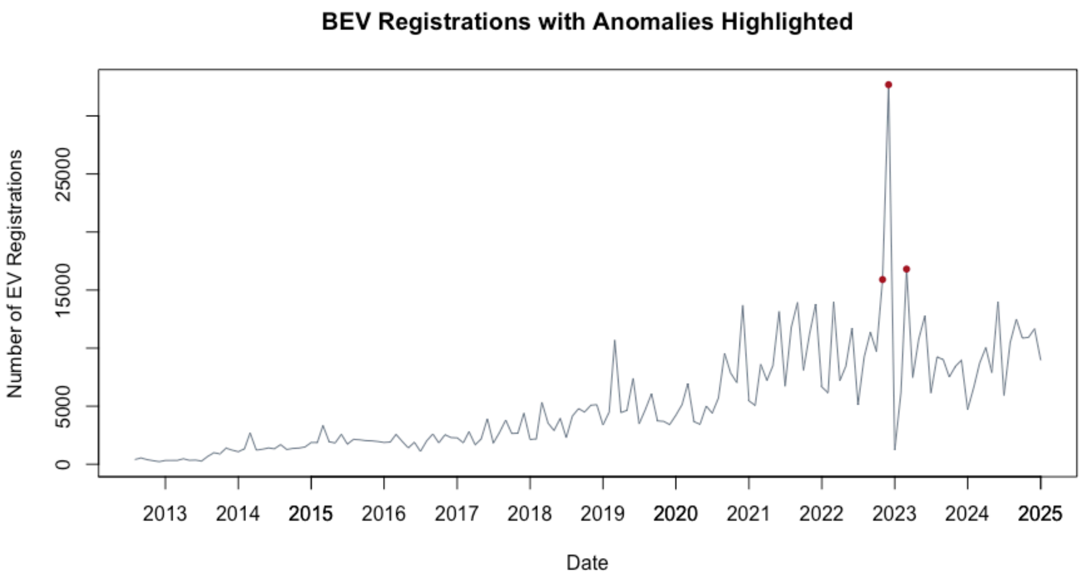

Figure 3.5: BEV Registrations with Anomalies Highlighted

The results confirm that the adoption of BEVs is heavily influenced by external interventions, such as policy changes and major vehicle launches, rather than organic consumer trends alone. The seasonal component also suggests that purchasing patterns are shaped by the timing of financial incentives and tax adjustments.

The exploratory data analysis reveals key trends in Norway's transition from ICE vehicles to BEVs. BEV adoption is largely policy-driven, with financial incentives and tax regulations shaping consumer behaviour. Fluctuations in registrations align with subsidy changes, highlighting market responsiveness. A recurring year-end surge suggests that consumers optimise purchases before policy shifts. Additionally, sharp spikes and declines in BEV sales correspond to major policy changes and vehicle launches. These insights form a foundation for forecasting BEV adoption using innovation diffusion models, as well as statistical and machine learning approaches.

4
Results from Innovation Diffusion Models

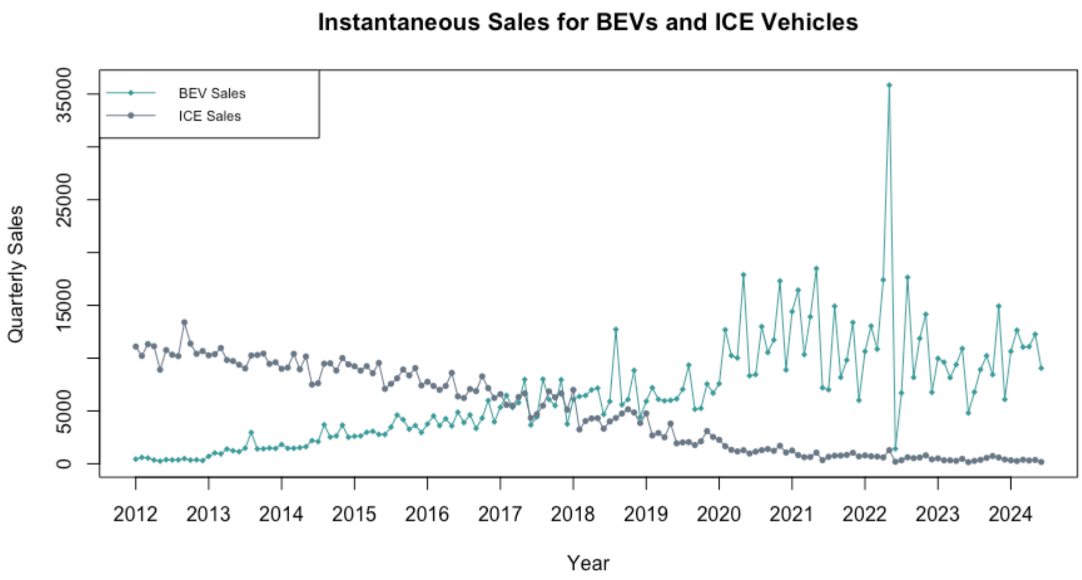

Figure 4.1: Instantaneous Sales for BEVs and ICE Vehicles

This section introduces the innovation diffusion models applied to the BEV and ICE datasets to analyse their market behaviour. The time-series data for BEVs and ICE vehicles, which form the basis of the modelling process, are presented in the plot 4.1.

4.1 Bass Model (BM)

The Bass Model (BM), Generalized Bass Model (GBM), and UCRCD model are designed to capture first-time adoption. Consequently, only new vehicle registration data was utilised for modelling purposes.

The Bass Diffusion Model [3] was used to analyse the trajectory of adoption of battery electric vehicles (BEVs) and the decline of Internal Combustion Engine (ICE) vehicles in Norway. Given the dataset includes multiple vehicle categories, the following steps were taken to consolidate the data before applying the model:

- **BEV Adoption:** To examine the electrification trend in a comprehensive way, the sales data of battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) were aggregated. This grouping provides a more holistic perspective on the transition to electric mobility.
- **ICE Vehicle Decline:** To assess the phase out of fossil fuel-powered transport, the registrations of petrol and diesel vehicles were combined. This approach captures the overall decline in ICE vehicle adoption rather than focussing on individual fuel types.

By grouping these categories, the broader market transition is captured, allowing for a more representative modelling approach. From this point on, BEV and ICE refer to the aggregated data, and the models based on this aggregation will be applied.

The estimated Bass Model parameters for BEVs are presented in Table 4.1. In general, if the confidence intervals do not include zero, this indicates that the parameter is statistically significant at the level 5%. The value of R^2 of 0.999625 is derived from cumulative sales data, which explains why it reaches such a high level.

Coefficient	Estimate	Std. Error	Lower	Upper
m	1388522.5	20206.3	1348918.7	1428126.3
p	0.00056	0.0000078	0.00055	0.00058
q	0.032	0.00040	0.031	0.033

$R^2 = 0.999625$

Table 4.1: Bass Model Summary for BEV Adoption

Figure 4.2 shows the BM's fit to the instantaneous sales of BEVs. According to the models' predictions, BEV sales peaked in 2022, followed by a decline. The estimated market potential, $m = 1388522.5$, represents the maximum number of sales achievable throughout the lifecycle of the BEV. The parameters p and q correspond to the innovative and imitation behaviours within the diffusion process. The relatively low p value of 0.00056, well below the typical starting value of 0.001, suggests a weak influence of innovators, leading to a slow initial uptake. Similarly, the q value of 0.032, lower than the standard benchmark of 0.1, indicates a less pronounced imitation effect in the later diffusion phase. Since both parameters fall below their expected ranges, the diffusion process is likely progressing at a slower pace, with market saturation occurring over an extended period.

Overall, these values indicate a gradual adoption process, where both innovators and imitators play a limited role. This suggests that stronger external drivers, such as policy incentives, infrastructure development, or shifts in consumer preferences, may be required to accelerate market penetration.

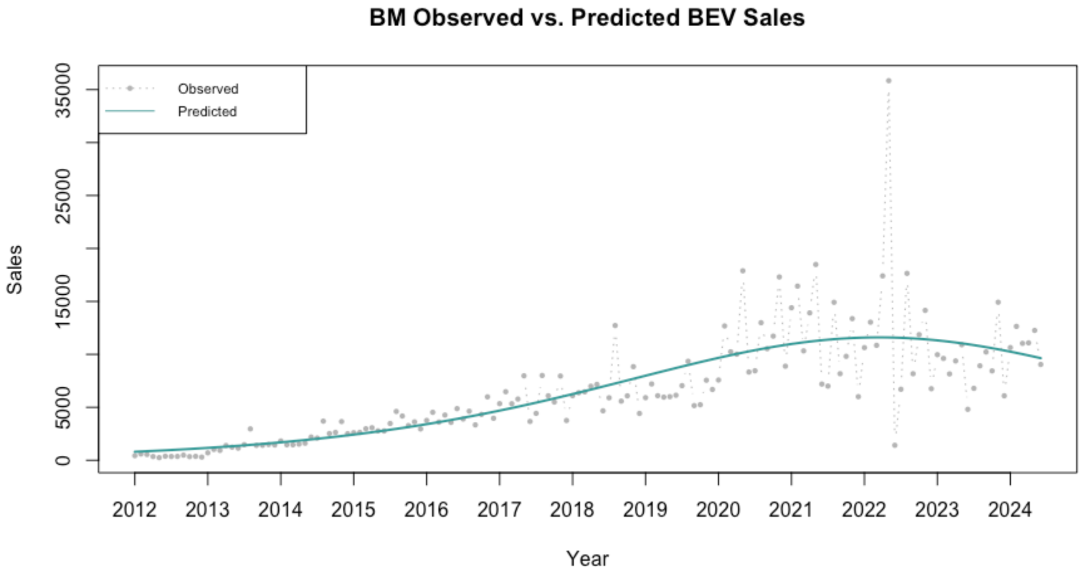

Figure 4.2: BM for BEVs on Instantaneous Sales

The estimated BM parameters for the ICE vehicles are presented in Table 4.2. The market potential ($m = 758661.3$) represents the total potential decline, indicating the estimated minimum level that the ICE vehicle market may reach. While the BM is traditionally used to model growth, in this context, it illustrates how the market shifts towards a lower equilibrium as electric vehicles replace ICE vehicles. The innovation coefficient ($p = 0.012$) is significantly higher than the typical starting value of 0.001, suggesting that the initial phase of the decline was strongly influenced by external factors. Consumers rapidly moved away from ICE vehicles due to technological advances, environmental concerns, and regulatory policies. A high value of p typically means a rapid initial transition leading to a sharp drop in ICE sales.

Conversely, the imitation coefficient ($q = 0.023$) is considerably lower than the typical value of 0.1, indicating that imitation played a minor role in the later stages of the decline. In most diffusion models, adoption is primarily influenced by imitation; however, in this case, the phase-out of ICE vehicles appears to have been driven more by external pressures than by social reinforcement. The model's goodness of fit ($R^2 = 0.999898$) was measured using cumulative sales data, confirming the observed decline in ICE vehicles.

These BM parameters suggest that the decline in ICE vehicles was initially driven by external factors such as technological advancements, environmental policies, and economic incentives that promote alternative technologies. The high innovation coefficient (p) indicates a rapid initial drop, while the lower imitation coefficient (q) suggests that this decline was not primarily reinforced by consumer imitation but rather by regulatory and economic shifts.

Coefficient	Estimate	Std. Error	Lower	Upper
m	758661.3	1412.2	755893.4	761429.2
p	0.012	0.00012	0.0122	0.0126
q	0.023	0.00052	0.0227	0.0247

$R^2 = 0.999898$

Table 4.2: Bass Model Summary for ICE Decline

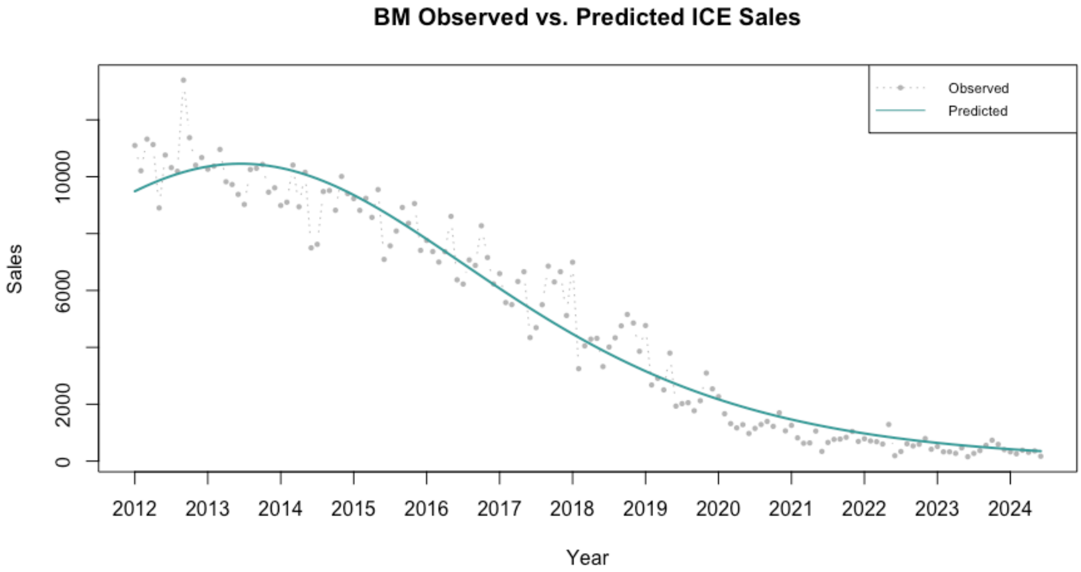

Figure 4.3: BM for ICE Vehicles on Instantaneous Sales

The peak in ICE vehicle sales around 2013 marks the turning point before the transition away from combustion engines. This supports the notion that government incentives, emerging electric vehicle alternatives, and increasing environmental concerns played a crucial role in accelerating the decline. Overall, these findings highlight a structural transition in the automotive industry, where the decline of vehicles with internal combustion engines is largely driven by policy and is not entirely dependent on social diffusion effects.

Figure 4.3 presents the observed and predicted decline of instantaneous sales of the ICE vehicles.

The Bass Model (BM) requires sufficient historical data for accurate parameter estimation. Estimating market potential (m) is challenging with limited data, and reliable estimates often emerge only after peak adoption, reducing its usefulness in forecasting.

A key limitation of BM is its assumption of a constant market potential (m), ignoring its possible evolution over time. Furthermore, the model does not account for marketing strategies such as pricing and advertising, focussing solely on innovation and imitation.

The Bass Model (BM) struggles to account for external shocks, such as economic fluctuations, policy changes, or technological advancements, limiting its ability to capture real-world market dynamics. To overcome this, the Generalized Bass Model (GBM) incorporates external influences, providing a more flexible framework for diffusion analysis.

Additionally, BM models adoption as a univariate process, overlooking the competitive interactions between technologies. To address this limitation, the UCRCD Model was developed, explicitly capturing competition and substitution effects between products.

The following sections analyse the trends of BEV and ICE adoption using both the GBM and UCRCD models, offering deeper insights into their market evolution.

4.2 Generalized Bass Model (GBM)

One major limitation of the Bass Model (BM) is its inability to incorporate marketing mix variables under executive control, such as pricing strategies and advertising. The key improvement of the GBM is its ability to explicitly account for the impact of these strategies. The GBM achieves this by introducing an integrable and non-negative intervention function, $x(t)$, which represents external shocks. In general, if $0 < x(t) < 1$, the diffusion process slows down and if $x(t) > 1$, the diffusion accelerates.

The function $x(t)$ can model different types of shocks, such as exponential and rectangular, and can also accommodate mixed shocks for a more comprehensive analysis. The following section examines BEV adoption and ICE decline using exponential, rectangular, and mixed shocks within the GBM framework.

4.2.1 Generalized Bass Model with one Exponential Shock

As a general guideline, the parameters m, p, and q were set equal to those estimated using the BM, since the BM is nested within the GBM. These estimates were selected as a reliable starting point for the non-linear least squares (NLS) estimation of the GBM. Table 4.3 presents the estimated parameters for BEV and ICE vehicles within the GBM framework, incorporating an exponential shock that will be referred to as GBM1e from now on.

Parameter	Estimate	Std. Error	Lower Bound	Upper Bound
BEV (Battery Electric Vehicles)				
m	1242882.2	11807.4	1219740.06	1266024.3
p	0.00051	0.0000088	0.00049	0.00053
q	0.038	0.00055	0.036	0.039
a_1	82.25	0.65	80.98	83.53
b_1	-0.208	0.045	-0.29	-0.12
c_1	-1.09	0.19	-1.47	-0.71
R^2 = 0.999686				
ICE (Internal Combustion Engine Vehicles)				
m	739136.5	585.5	737988.9	740284.2
p	0.014	0.00012	0.014	0.014
q	0.014	0.00063	0.013	0.016
a_1	38.92	0.91	37.13	40.71
b_1	0.030	0.0014	0.027	0.033
c_1	0.17	0.013	0.14	0.19
R^2 = 0.999898				

Table 4.3: Estimated Parameters for the Generalized Bass Model (GBM) with an Exponential Shock

Parameters a_1, b_1, and c_1 have been defined to ensure a clear and meaningful interpretation. The parameter a_1 represents the onset of the shock, indicating the point in time when it begins. The parameter b_1 reflects the *memory* of the shock and is typically negative, signifying an exponentially decaying effect. Lastly, the parameter c_1 denotes the *magnitude* of the shock, which may be either positive or negative, depending on the nature of the intervention. The exponential shock is designed to capture sudden and significant disruptions in diffusion dynamics. These can have a positive effect, such as boosting sales through marketing strategies and incentive measures, or a negative impact, such as a sharp decline in sales due to competition from alternative products, a sudden reputational loss, or the effects of an economic crisis.

It can be seen in Table 4.3 that the model achieves satisfactory performance for both vehicle types, with $R^2 = 0.999686$ for BEVs and $R^2 = 0.999898$ for ICE vehicles. Additionally, all estimated parameters are statistically significant, as confirmed by the confidence interval analysis. The statistical significance of the shock-related parameters further highlights the relevance of external shocks in the diffusion process.

For BEVs, the estimated shock onset occurs around 2019, as indicated by $a_1 = 82.25$, with negative intensity $c_1 = -1.09$ and negative memory $b_1 = -0.208$. This suggests that the system tends to "forget" the effects of the shock over time, eventually returning to the behaviour dictated by the diffusion parameters p and q. The data show a slight spike in BEV sales around the year 2019, caused by a small spike in the diffusion process. This positive perturbation aligns with the observed surge in the adoption of BEV in Norway. In 2019, BEVs represented 42. 4% of the total of new car registrations, up from 31.2% in 2018 [45, 46].

For ICE vehicles, the estimated shock onset is around 2016, given that $a_1 = 38.92$, with a positive intensity $c_1 = 0.17$ and positive memory $b_1 = 0.03$, indicating that its effect is not yet absorbed in time. The presence of a positive exponential shock implies that the adoption of the ICE vehicle was influenced by external factors that supported its diffusion. This aligns with the introduction of the Norwegian government's 2018-2029 National Transport Plan

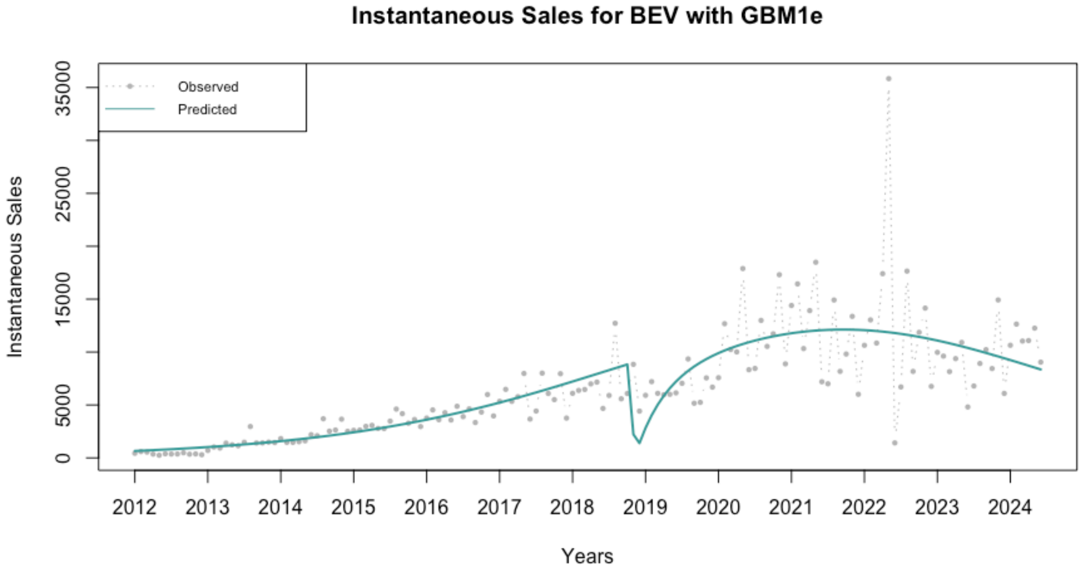

Figure 4.4: GBM for BEV on Instantaneous Sales with an Exponential Shock

(NTP), which aimed to reduce greenhouse gas emissions from the transportation sector by approximately 50% by 2030 [47].

Regarding the diffusion parameters m, p, and q, the low innovation coefficient ($p = 0.00051$) confirms that the BEV diffusion process in Norway had a slow start, suggesting that BEVs were not market leaders at the time. This finding is consistent with the estimated shock, indicating that external interventions were necessary to stimulate an otherwise sluggish diffusion process. The estimated market potential $m = 1242882.2$ in the GBM is lower than in the BM 1388522.5, suggesting that the inclusion of a shock moderates long-term diffusion expectations.

Figure 4.4 illustrates the GBM with a single exponential shock applied to instantaneous and cumulative sales data for BEVs, while Figure 4.5 presents the corresponding results for ICE vehicles.

To evaluate whether the GBM with an exponential shock (GBM1e) provides a better explanation for the diffusion of BEV than the BM, we examine $\tilde{R}^2$. Typically, if $\tilde{R}^2 > 0.2$, a more complex model is justified. However, in this case, $\tilde{R}^2 = 0.16$, indicating a slight improvement in explaining the diffusion process, but not enough to justify the adoption of a more complex model.

For ICE vehicles, the values of p and q remain the same, suggesting that ICE diffusion is in the maturity phase and undergoing a steady decline. The value of $\tilde{R}^2$ for ICE vehicles (BM vs. GBM1e) is 0, meaning that the GBM with exponential shock does not improve on the BM. This suggests that external shocks do not significantly influence the diffusion of the ICE vehicle and their adoption follows a more predictable trajectory.

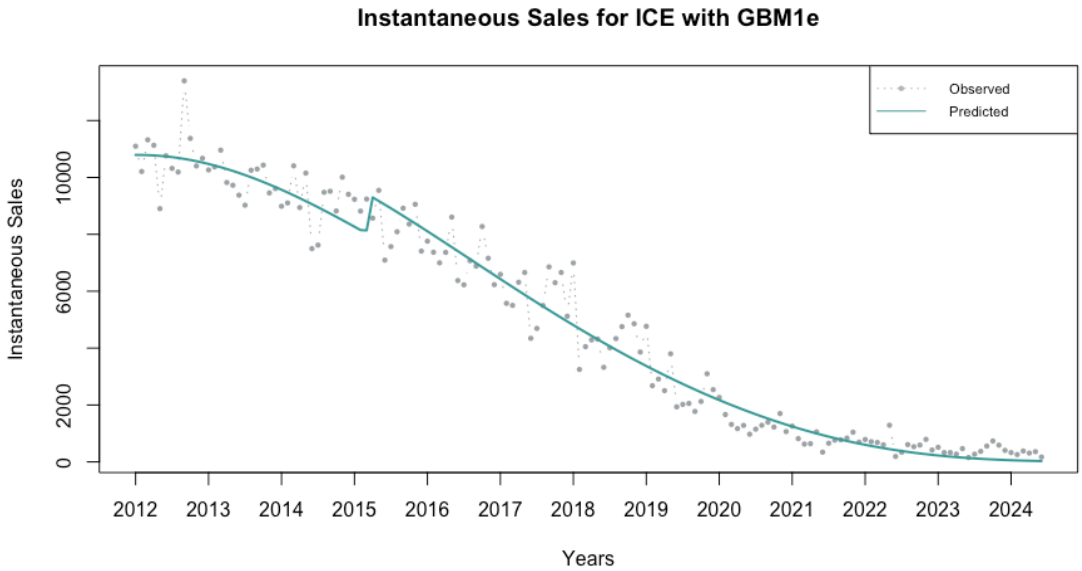

Figure 4.5: GBM for ICE on Instantaneous Sales with an Exponential Shock

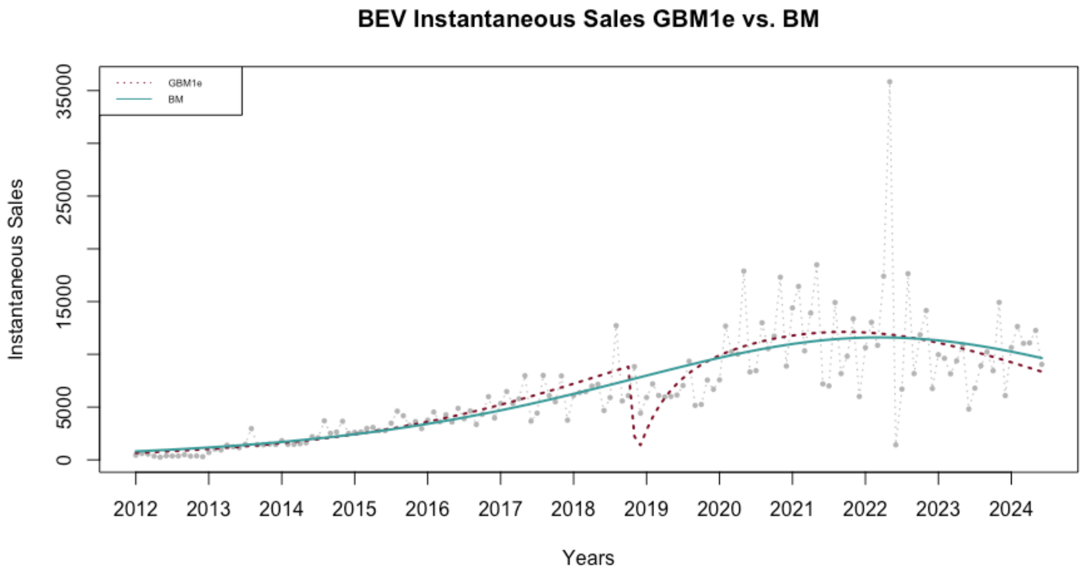

Figure 4.6: GBM with an Exponential Shock vs. BM for BEVs on Instantaneous Sales

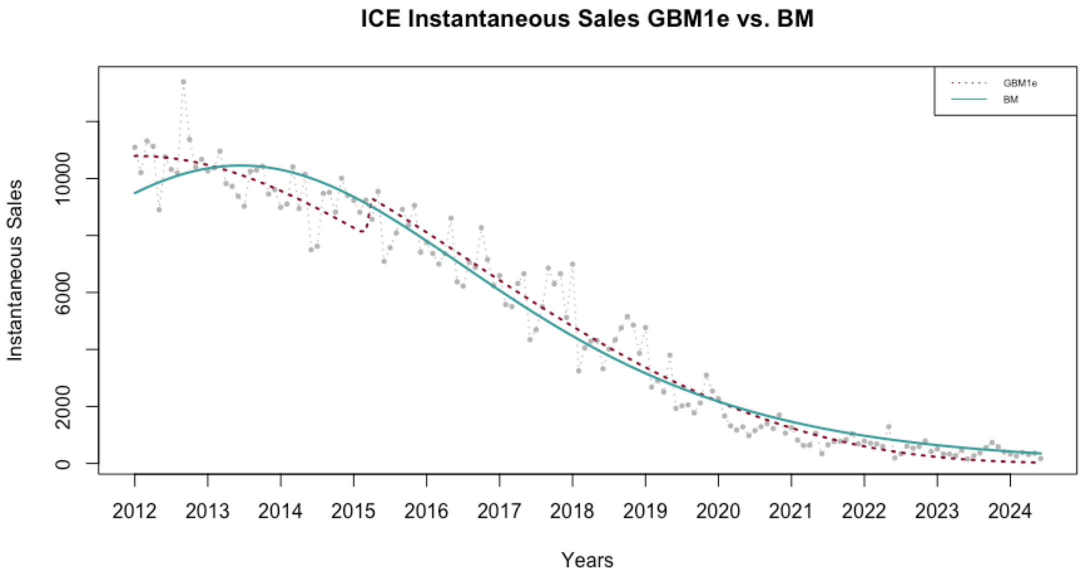

Figure 4.7: GBM with an Exponential Shock vs. BM for ICE on Instantaneous Sales

Overall, while both models yield similar estimates for fundamental diffusion parameters, the GBM with a single exponential shock introduces some flexibility by incorporating external influences. The observed differences in q and the market potential suggest that external effects can alter the diffusion trajectory, particularly for BEVs.

4.2.2 Generalized Bass Model with one Rectangular Shock

In some cases, a perturbation may exhibit a more stable pattern over time rather than being abrupt and intense, occurring within a defined time span. In such scenarios, a rectangular shock provides a more appropriate modelling choice.

The parameters a_1 and b_1 define the start and end times of the shock, while the parameter c_1 represents its magnitude, which can be either positive or negative. The rectangular shock is particularly suitable for disturbances that persist over an extended period, such as those driven by advertising campaigns or the implementation of policies and regulations within a specific time frame.

Table 4.4 presents the results of the GBM with a rectangular shock applied to BEVs and ICE vehicles. From this point onwards, the GBM with a rectangular shock will be referred to as GBM1r.

Overall, the model achieves $R^2 = 0.999614$ for BEVs and $R^2 = 0.999904$ for ICE vehicles, suggesting a strong fit. In addition, all estimated parameters are statistically significant. However, it is important to note that R^2 is calculated using cumulative sales data, which may influence the evaluation of model performance.

For BEVs, the introduction of a rectangular shock has been particularly effective in capturing

Parameter	Estimate	Std. Error	Lower Bound	Upper Bound
BEV (Battery Electric Vehicles)				
m	3041423.9	526467.7	2009566.1	4073281.6
p	0.00030	0.000044	0.00021	0.00039
q	0.013	0.0011	0.011	0.016
a_1	27.00	2.97	21.17	32.82
b_1	128.50	0.60	127.31	129.68
c_1	0.69	0.068	0.55	0.82
$R^2 = 0.999614$				

ICE (Internal Combustion Engine Vehicles)				
m	753151.0	801.7	751579.7	754722.3
p	0.013	0.000070	0.013	0.013
q	0.018	0.00031	0.017	0.018
a_1	55.65	0.56	54.55	56.75
b_1	99.85	2.16	95.60	104.10
c_1	0.31	0.012	0.28	0.33
$R^2 = 0.999904$				

Table 4.4: Estimated Parameters for the GBM with a Rectangular Shock for BEVs and ICEs

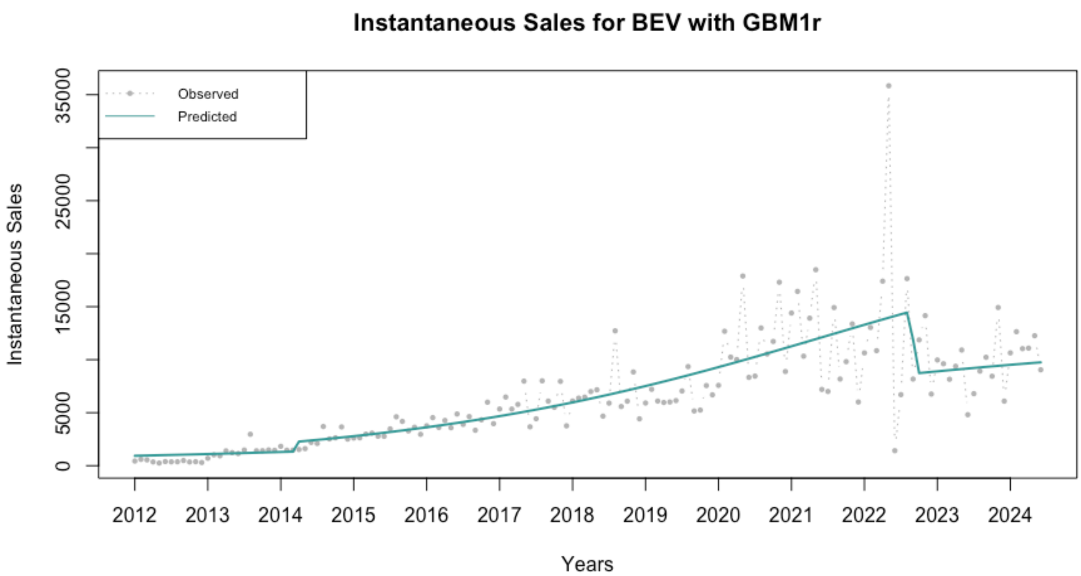

Figure 4.8: GBM with a Rectangular Shock on the BEV on Instantaneous Sales

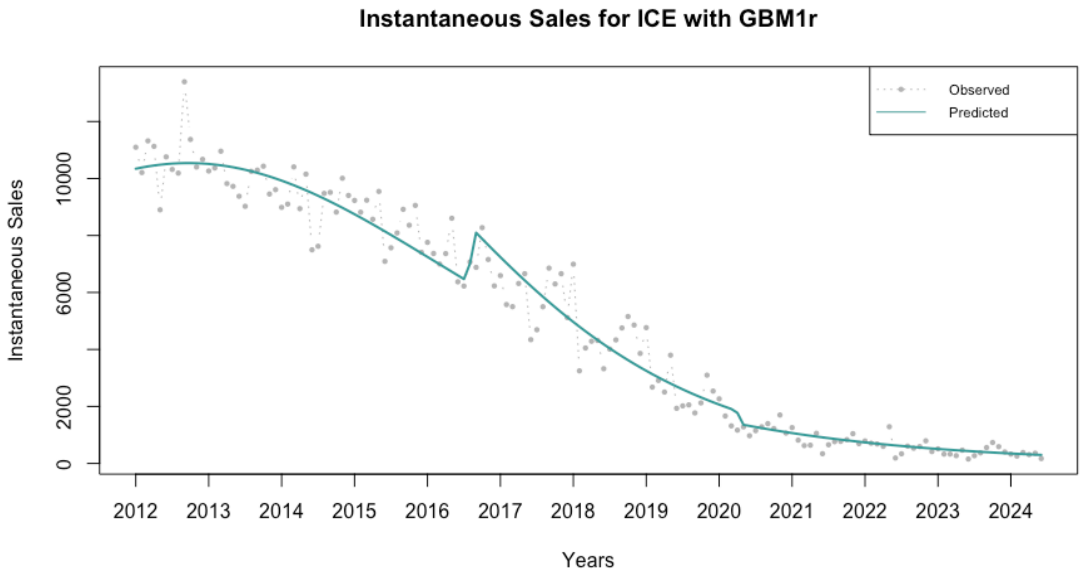

Figure 4.9: GBM with a Rectangular Shock for ICE on Instantaneous Sales Data

the sharp increase in sales due to policy changes at the end of 2022 and the beginning of 2023. Figure 4.8 presents the implementation of GBM1r in BEVs. However, it is estimated that the positive shock $c_1 = 0.69$ began in 2014 ($a_1 = 27.00$) and ended in 2023 $b_1 = 128.50$. The comparison between BM and GBM1r, as illustrated in Figures 4.10 and 4.11 highlights the improvements brought about by GBM1r over BM. The computed $\tilde{R}^2 = -0.029$ suggests that the sales changes were primarily sudden and driven by governmental incentives and policy interventions, rather than gradual shifts over a long period. To further explore the long-term impact of policies, the next section introduces mixed shocks to assess the compatibility of the model.

For ICE vehicles, the implementation of a rectangular shock effectively captures sales fluctuations, beginning in 2016 $a_1 = 55.65$ and ending around 2020 $b_1 = 99.85$, with a positive intensity of $c_1 = 0.31$. The visual comparison between GBM1r and BM, presented in Figure 4.10, demonstrates that GBM1r provides a slightly better fit, with a computed $\tilde{R}^2 = 0.058$. This suggests that the rectangular shock model offers a slight improvement in capturing the variability in ICE vehicle sales compared to BM.

However, to justify the selection of a more complex model, the criterion $\tilde{R}^2 > 0.2$ must be met, which is not the case in this instance. Nevertheless, the rectangular shock is more effective than the exponential shock in explaining the underlying data structure. This finding aligns with the characteristics of rectangular shock, as the decline in ICE vehicle sales was not a sudden shift but rather a gradual policy-driven transition towards BEVs. The visual representation of these effects is provided in Figure 4.9.

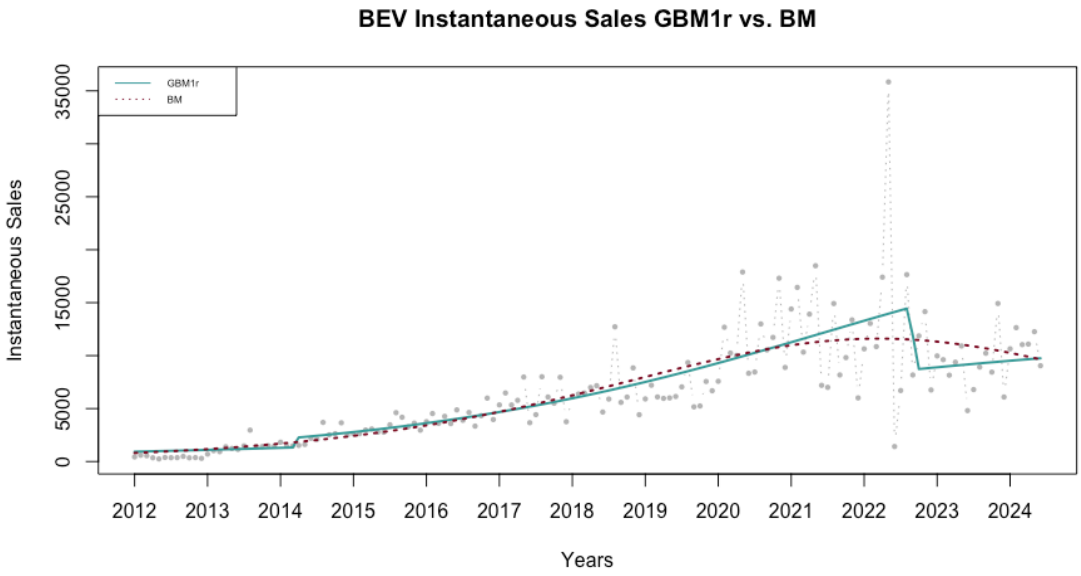

Figure 4.10: GBM vs. BM for BEV on Instantaneous a Sales with a Rectangular Shock

Overall, the BM provides a more optimistic long-term projection, while the GBM introduces greater flexibility by accounting for external shocks. The rectangular shock model proves more effective in explaining the decline of ICE vehicles compared to the exponential shock model, which is better suited for capturing short-term disruptions that amplify imitation effects in BEV adoption. However, the rectangular shock alone was insufficient to fully explain the underlying structure of BEV adoption.

These differences highlight the adaptability of the GBM in adjusting diffusion estimates based on external influences, making it a more robust framework for analysing dynamic market conditions and policy-driven transitions. In the following section, mixed shocks, incorporating both exponential and rectangular components, are applied to both vehicle types to gain deeper insight into the diffusion process.

4.2.3 Generalized Bass Model with Mixed Shocks

These applications are further extended to gain a deeper understanding of the underlying diffusion process of BEVs and ICE vehicles by introducing a second shock. This approach, referred to as GBM with mixed shocks, incorporates both an exponential and a rectangular shock. From this point on, it will be denoted as GBM1e1r for BEVs and ICEs.

The results of this application, including the estimated parameters, are presented in Table 4.5 and visually displayed in Figure 4.12 for BEV and Figure 4.13 for ICE vehicles.

The model achieves $R^2 = 0.999832$ for BEVs and $R^2 = 0.999967$ for ICE vehicles, suggesting a strong fit. Additionally, all estimated parameters are statistically significant. However, it is important to note that R^2 is calculated using cumulative sales data, which may influence the

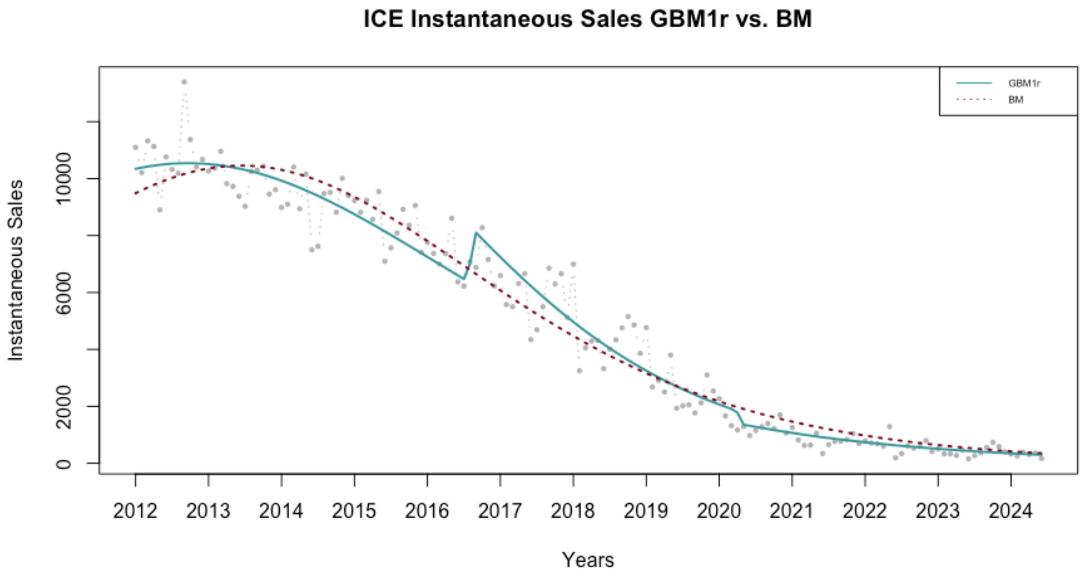

Figure 4.11: GBM vs. BM for ICE on Instantaneous a Sales with a Rectangular Shock

evaluation of model performance.

The exponential shock for BEVs, which begins at $a_1 = 132.80$ in 2023, exhibits a negative memory effect $b_1 = -0.25$, indicating that its influence gradually decreases over time. Moreover, its intensity $c_1 = -0.57$ suggests a negative perturbation, which means that the shock had an adverse impact on the trends of adoption of BEVs. This decline can be attributed to multiple factors, including changes in tax policy, a shift in consumer preference, market saturation, and economic challenges such as inflation.

In contrast, the rectangular shock for BEVs occurs over a period of 2018 to 2020, starting at $a_2 = 72.64$ and ending at $b_2 = 97.10$. This time frame reflects an external intervention, such as policy measures or incentives, that influenced adoption rates over a sustained period rather than a sudden impact. The intensity of the rectangular shock $c_2 = -0.27$ is also negative, indicating that during this time window, adoption was hindered, potentially due to regulatory changes, economic factors, or changes in consumer incentives. The decline in BEV registrations from 2018 to 2020 in Norway was primarily due to a market transition phase, where initial fiscal incentives began to lose their effectiveness as the market matured. Changes in tax policies, charging infrastructure limitations, and global supply chain constraints also played a role. Despite the slowdown, BEVs still remained dominant, but their rapid growth rate was beginning to stabilise as Norway approached a more mature phase of BEV adoption.[48]

The GBM1e1r captures the influence of both exponential and rectangular shocks on the diffusion process of ICE vehicles. The estimated parameters provide insights into how these external shocks influence market behaviour over time.

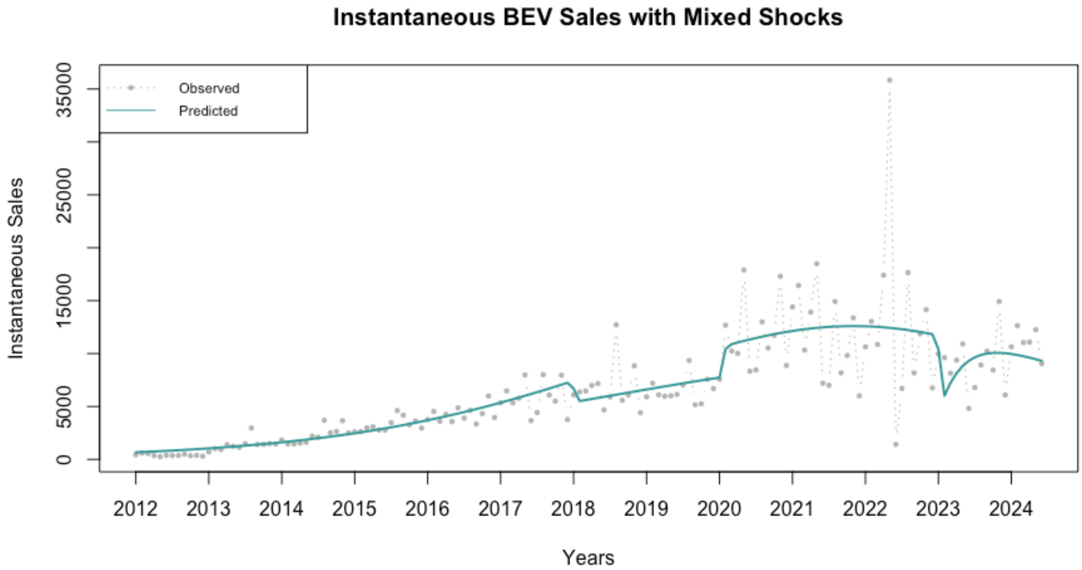

Figure 4.12: GBM for BEVs with Mixed Shocks

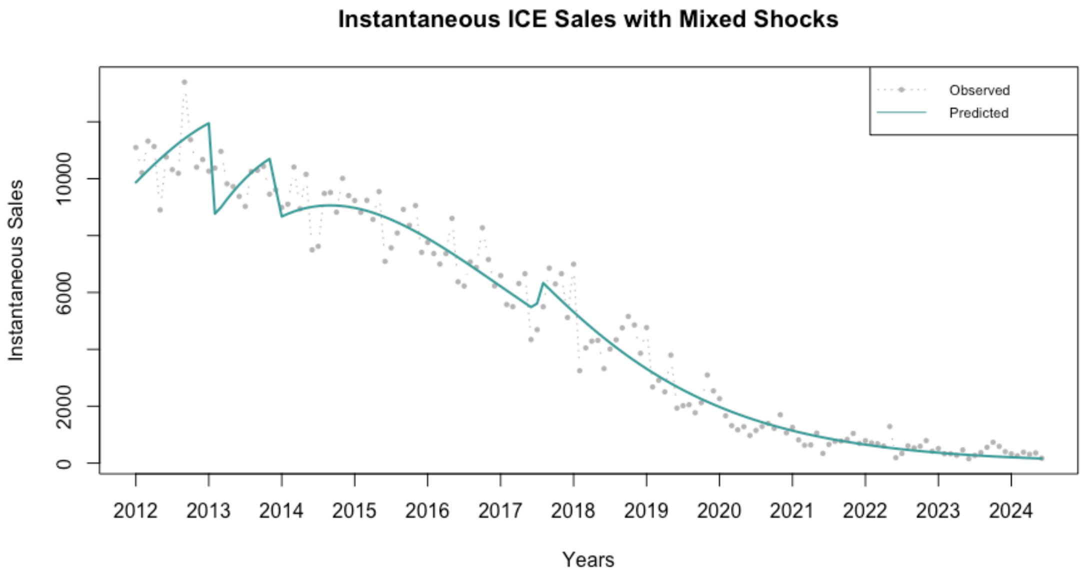

Figure 4.13: GBM for ICE Vehicles with Mixed Shocks

Parameter	Estimate	Std. Error	Lower Bound	Upper Bound
BEV (Battery Electric Vehicles)				
m	1288197.15	23506.19	1242125.84	1334268.45
p	0.00050	0.0000059	0.00049	0.00051
q	0.038	0.00065	0.036	0.039
a_1	132.80	0.66	131.49	134.10
b_1	-0.25	0.11	-0.48	-0.027
c_1	-0.57	0.17	-0.92	-0.22
a_2	72.64	1.03	70.61	74.66
b_2	97.10	0.73	95.65	98.54
c_2	-0.27	0.014	-0.29	-0.24
$R^2 = 0.999832$				
ICE (Internal Combustion Engine Vehicles)				
m	744461.79	366.65	743743.16	745180.42
p	0.013	0.000070	0.012	0.013
q	0.035	0.00046	0.034	0.0365
a_1	13.022	0.38	12.26	13.77
b_1	-0.077	0.014	-0.10	-0.048
c_1	-0.28	0.026	-0.34	-0.23
a_2	23.48	0.47	22.56	24.41
b_2	66.76	0.61	65.55	67.98
c_2	-0.18	0.010	-0.20	-0.16
$R^2 = 0.999967$				

Table 4.5: Estimated Parameters for the Generalized Bass Model (GBM) with Mixed Shocks

The exponential shock begins at $a_1 = 13.022$ in 2013, indicating an early-stage disruption in the diffusion process. The memory effect $b_1 = -0.077$ is negative, suggesting an exponentially decaying impact. The intensity of the exponential shock $c_1 = -0.28$ is also negative, indicating an adverse effect on the adoption of ICE vehicles at the time of the occurrence.

In contrast, the rectangular shock spans a defined period, beginning in 2014 $a_2 = 23.48$ and concluding around 2018 $b_2 = 66.76$. This suggests that external interventions, such as policy changes or regulatory measures, influenced the diffusion process over a sustained period rather than through abrupt interruption. The intensity of the rectangular shock $c_2 = -0.18$ is negative, indicating that during this period, the diffusion process faced obstacles, possibly due to changes in governmental incentives, taxation policies, or declining consumer demand for ICE vehicles. Figure 4.13 shows the visual representation of these shocks.

The computed value $\tilde{R}^2$ for ICE when comparing the Bass Model (BM) and the Generalized Bass Model (GBM) with mixed shocks is 0.676. Since this value is significantly greater than the threshold of 0.2, it indicates that the GBM with mixed shocks provides a well-performing model for explaining the decline of ICE vehicles in the market. This suggests that incorporating both exponential and rectangular shocks enhances the model's ability to capture the external factors influencing the phase-out of ICE technology.

BM vs. GBMs with Different Shock Structures

Comparison	$\tilde{R}^2$ **for BEV**	$\tilde{R}^2$ **for ICE**
BM vs. GBM1E	0.1627	0.0000
BM vs. GBM1R	-0.0293	0.0588
BM vs. GBM1E1R	0.5520	0.6765
GBM1E vs. GBM1R	-0.2293	0.0588
GBM1E vs. GBM1E1R	0.4649	0.6765
GBM1R vs. GBM1E1R	0.5648	0.6563

Table 4.6: $\tilde{R}^2$ Comparisons Between Models for BEV and ICE

The $\tilde{R}^2$ values offer a comprehensive perspective on the performance of the model across different specifications. For BEVs, GBM1E1R stands out as the most effective model compared to the baseline BM, with a value of 0.552, above the 0.2 threshold, indicating a statistically significant improvement. In contrast, both GBM1E and GBM1R perform worse relative to BM, with negative or near-zero differentials in pairwise comparisons. This reinforces that only the mixed-shock model (GBM1E1R) consistently enhances the explanatory power for BEV adoption.

In contrast, ICE diffusion reveals a different narrative. Here, GBM1E1R again achieves the highest improvement over BM, with a $\tilde{R}^2$ value of 0.6765. Positive values in pairwise comparisons, such as GBM1E vs. GBM1E1R (0.6765) and GBM1R vs. GBM1E1R (0.6563), further confirm that incorporating both exponential and rectangular shocks provides the best fit for ICE decline dynamics.

Thus, while BEV adoption is best explained by the inclusion of both short and long-term shocks through GBM1E1R. This underscores the differing nature of BEVs and ICEs in the market, which requires tailored modelling approaches to reflect each trajectory's underlying complexity.

4.3 Unbalanced Competition and Regime Change Diachronic Model (UCRCD)

The models presented so far have treated the diffusion of BEVs and ICE vehicles as a univariate process, where the adoption dynamics depends solely on internal parameters and potentially on external shocks such as government incentives, tax policies and other market interventions that influence the speed of adoption. However, the univariate approach employed by the BM, GBM, and similar diffusion frameworks is limited in that it does not explicitly consider the competitive interactions between BEVs and ICEs, which are fundamental to understanding market transitions.

Competition plays a pivotal role in shaping the diffusion of vehicle technologies, acting both as a barrier and an opportunity in the transition from ICE vehicles to BEVs. On the one hand, the persistence of ICE sales and the well established infrastructure supporting them may hinder the widespread adoption of BEVs, delaying the expected market shift. However, the increasing presence of BEVs can expand consumer awareness, accelerate technological advancements, and reinforce policy measures aimed at phasing out ICE vehicles. This dual nature of competition underscores its critical importance in modelling the diffusion of new automotive technologies. UCRCD Model, considers the competition between two products, that enter the market at different times, the so-called diachronic competition. The model assumes that the diffusion process is characterised by two stages: an initial one where only one product is in the market and a second one when the second product enters the market giving rise to competition.

Hence, incorporating competition explicitly into diffusion models is essential to accurately capture market evolution and technological transitions. Table 4.7 presents the parameters of the UCRCD model that extend traditional univariate approaches by incorporating the interdependencies between BEVs and ICEs. This enables a more comprehensive representation of market dynamics through key parameters, including market potential (m), innovation effects (p), imitation effects (q), replacement effects (δ), and adoption boosts (γ). These parameters provide deeper insight into the competitive interactions and substitution effects between BEVs and ICEs.

Parameter	Double	Unique	Description
m_c	2110509.51	2645323.29	Market potential in competition
p_{1c}	0.0054	0.0041	Innovation of 1 in competition
p_2	0.00048	-0.00038	Innovation of 2
$q_{1c} + \delta$	-0.00024	0.00064	Within imitation of 1 in competition
q_{1c}	-0.014	-0.015	Cross imitation of 2 on 1
q_2	0.052	0.025	Within imitation of 2
$q_2 - \gamma$	-0.0022	0.0093	Cross imitation of 1 on 2
δ	0.0139	0.0161	Replacement effect
γ	0.054	–	Adoption boost
R^2	0.746	0.727	Multiple R^2

Table 4.7: Estimation Results for the UCRCD Model

The results of the UCRCD model provide key information on the competitive dynamics between BEVs and ICE vehicles. The market potential in competition is estimated to be 2110509.51 in the double parameter model and 2645323.29 in the unique parameter model, indicating a substantial market expansion when competitive interactions are simplified.

The innovation effect of ICEs in competition (p_{1c}) remains relatively strong, estimated at 0.0054 in the double model and 0.0041 in the unique model, while the innovation effect of BEVs (p_2) is much lower and even negative in the unique model. This suggests that direct innovation alone does not drive the adoption of BEVs, highlighting the greater importance of external policies and imitation effects.

The imitation effects reveal a marked divergence between the two vehicle types. For ICE vehicles, the internal imitation effect ($q_{1c} + \delta$) is slightly negative in the double model, indicating a weak or potentially adverse influence of word of mouth within the competitive context. This may be attributed to several factors, including the maturity and possible saturation of the ICE market, the growing anticipation of a technological shift toward electrification, and the increasingly negative perceptions associated with ICE vehicles due to emissions and fuel costs. As ICEs are no longer considered innovative or forward-looking, the positive peer influence that typically drives new adoptions appears to be minimal.

In sharp contrast, BEVs exhibit strong positive internal imitation effects, with estimates of 0.0523 and 0.0254 in the double and unique models, respectively. These figures highlight the significant role of social influence and peer dynamics in accelerating BEV adoption. Positive user experiences, combined with the desire to align with an emerging and socially endorsed trend, appear to act as powerful motivators in encouraging the diffusion of electric vehicles.

The cross-imitation effects further demonstrate the interdependence between the two technologies. The negative coefficient for q_{1c} (-0.0142 in the double model and -0.0155 in the unique model) indicates that BEVs are directly in full competition with ICEs. Similarly, the effect of the decline in ICE on BEV adoption ($q_2 - \gamma$) is slightly positive in the unique model (0.00925), suggesting that as ICE sales decrease, a portion of consumers move toward BEVs.

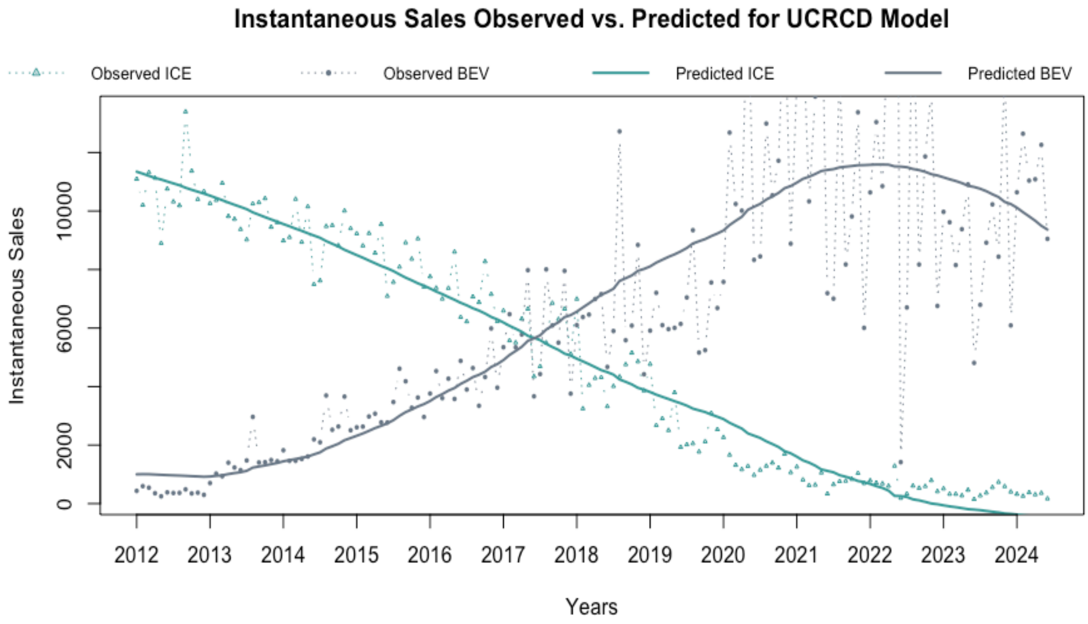

Figure 4.14: Instantaneous Sales Observed vs. Fitted for UCRCD Model for Both Vehicles Types

The replacement effect (δ) is estimated at 0.0139 (double model) and 0.0161 (unique model), reinforcing the notion that ICE users are gradually switching to BEVs. Furthermore, the adoption boost effect (γ), estimated at 0.0544 in the double model, highlights the significant role of external interventions, such as government incentives, subsidies and tax exemptions, in accelerating BEV adoption.

In terms of overall model performance, the multiple R^2 values indicate that both models provide a strong fit to the data, and the double-parameter model achieves a slightly better fit ($R^2 = 0.746$) compared to the unique model ($R^2 = 0.727$). This suggests that while the more complex model captures market dynamics more accurately, the unique model offers a more parsimonious approach.

In conclusion, the findings indicate that the adoption of BEVs is predominantly influenced by imitation effects and external policies, rather than direct innovation. In contrast, the decline in ICE sales is largely driven by the increasing adoption of BEVs. These results highlight the critical role of market potential expansion, replacement effects, and government interventions in shaping the competitive dynamics of the automotive industry. The visual representations of the UCRCD (double) model fit are presented in Figure 4.14 for instantaneous sales.

5

Results of Statistical and Machine Learning Models

This section applies six forecasting algorithms to forecast BEV and ICE sales over a sixty-month horizon. These algorithms include ARIMA-based models, Prophet, Random Forest, XGBoost, LightGBM and LSTM. The configuration details of each model, their respective methodological strengths, and the forecasting results are presented and compared.

5.1 ARIMA-Based Models

This section presents a classical time series modelling approach using ARIMA and its extensions to forecast BEVs and ICE sales over a sixty-month horizon. The models include ARIMA, ARMAX, and various SARMAX configurations, some of which integrate external regressors and seasonal components. Their configurations and performance are systematically compared and the most accurate models are selected to generate long-term forecasts.

BEV Forecasting Models

Multiple ARIMA-based models were evaluated to forecast BEV sales, each progressively incorporating more structure to capture policy shocks, seasonality, and behavioural substitution.

ARIMA: A baseline model estimated using `auto.arima()` on the monthly `EV_sales` series. Although providing a reasonable fit, it lacked explanatory variables and structural awareness.

ARMAX: Extended the baseline model by including external regressors: ICE sales and binary dummies for the December 2022 policy spike, January 2023 tax reform, and the Tesla-related delivery effect in April 2023. This model improved interpretability and reduced forecast error.

SARMAX (111)(111): Incorporated seasonal autoregressive and moving average components to model monthly cyclicality, along with exogenous regressors.

SARMAX (111)(110) and **SARMAX (111)(011)**: Alternative seasonal configurations tested to assess sensitivity to different seasonal lag structures.

SARMAX (Final): The best-performing model, SARMAX (1,1,1) (1,1,1) [12], integrated ICE sales in advance and behind, as well as policy-related dummies. It achieved the lowest AIC (2514.86), a competitive RMSE (1808.70), and stable residual autocorrelations.

Table 5.1 summarises the error metrics for each model. The final SARMAX model demonstrated the highest overall accuracy and was selected to forecast future BEV sales.

Model	ME	RMSE	MAE	MAPE	MASE	ACF_1	AIC	BIC
ARIMA	205.17	2842.16	1581.48	26.73	0.750	-0.033	2863.89	2875.98
ARMAX	110.37	1847.59	1237.57	35.09	0.587	-0.013	2762.91	2793.22
SARMAX (111)(111)	-6.25	1799.55	1161.47	17.45	0.551	-0.013	2531.16	2557.63
SARMAX (111)(110)	0.10	1917.83	1263.52	19.63	0.599	-0.011	2543.94	2567.48
SARMAX (111)(011)	-14.25	1802.76	1161.09	17.47	0.551	-0.013	2529.85	2553.38
SARMAX (Final)	**-12.09**	**1808.70**	**1172.27**	**17.93**	**0.553**	**-0.013**	**2514.86**	**2541.27**

Table 5.1: Comparison of ARIMA-Based Models for BEV Forecasting

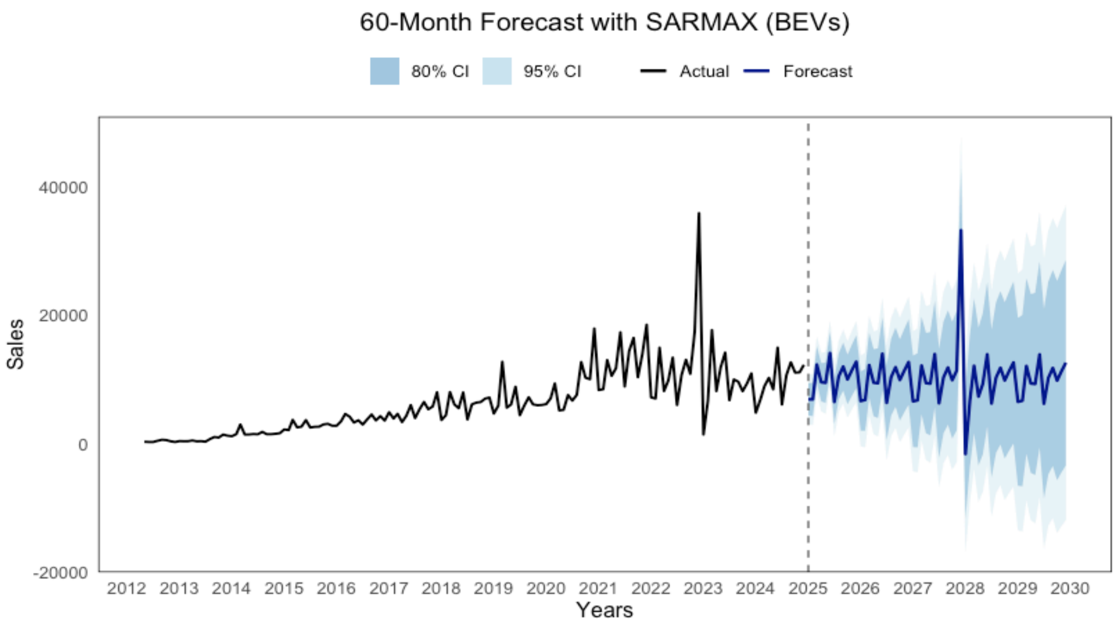

Figure 5.1: 60-Month Forecast with SARMAX Model for BEV Sales

ICE Forecasting Models

Following a similar procedure, ARIMA-based models were tested for ICE sales, incorporating trend, seasonality, and interactions with BEV demand.

ARIMA: A univariate model capturing the temporal structure without external variables.

ARMAX: Integrated `EV_sales` and policy shock dummies (December 2022, January 2023, April 2023) to explain ICE fluctuations.

SARMAX (Final): The selected specification was ARIMA(1,1,1)(1,1,1)[12] with exogenous variables. This model outperformed others in terms of RMSE (583.21), MAE (410.42), and AIC (2231.02), while maintaining acceptable autocorrelation behaviour.

Table 5.2 presents the comparative evaluation of ICE models.

Model	ME	RMSE	MAE	MAPE	MASE	ACF_1	AIC	BIC
ARIMA	-93.50	629.12	439.38	15.67%	0.689	-0.022	2410.44	2428.58
ARMAX	-96.12	626.04	431.17	**13.80%**	0.677	-0.024	2416.95	2447.19
SARMAX (0,1,1)	-23.95	640.24	450.57	22.08%	0.707	0.123	2237.94	2261.48
SARMAX (Final)	**-42.34**	**583.21**	**410.42**	22.46%	**0.644**	**0.121**	**2231.02**	**2257.50**

Table 5.2: Comparison of ARIMA-Based Models for ICE Forecasting

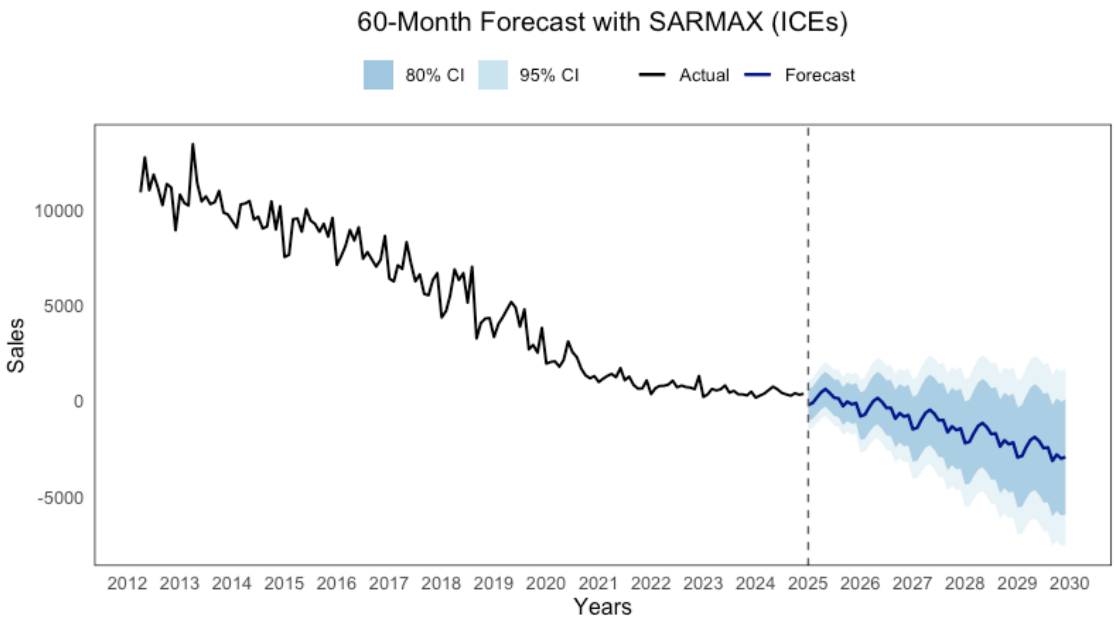

Figure 5.2: 60-Month Forecast with SARMAX Model for ICE Sales

All ARIMA-based models were evaluated using multiple error metrics and residual diagnostics. While ARIMA served as a baseline, the inclusion of exogenous variables and seasonal structure via SARMAX models led to substantial accuracy improvements. For BEV sales, the SARMAX model incorporating policy shocks and ICE dynamics captured nonlinear transitions more effectively than simpler specifications. Similarly, the ICE SARMAX model revealed strong explanatory power and stable residuals, suggesting that classical statistical models remain competitive for structured, policy-influenced time series forecasting tasks.

5.2 Prophet Model

A comprehensive time series forecasting framework was implemented using Facebook Prophet. Prophet is a decomposable additive model incorporating components for trend, seasonality, holidays, and user-defined regressors. It is particularly well suited to modelling monthly vehicle sales data due to its flexibility in accommodating structural changepoints and incorporating known external events. In this section, multiple Prophet model configurations employed for forecasting both BEVs and ICE sales are described, and their relative performances are evaluated.

BEV Forecasting Models

Five Prophet-based models were applied to forecast BEV sales, each progressively incorporating additional features to assess their contribution to predictive performance.

Model `m_base`: A benchmark model with logistic growth (cap set to 40,000) and yearly seasonality. No regressors, changepoints, or holidays were included.

Model `m`: Extends `m_base` by including `ICE_sales` as a multiplicative regressor, reflecting potential substitution effects between BEV and ICE markets.

Model `m_1`: A reduced version of `m` without changepoints, used to assess whether a smooth logistic trend and multiplicative seasonality are sufficient for capturing BEV sales dynamics.

Model `m_holiday`: Incorporates both official holidays and key policy-related events (e.g., December 2022, January 2023, April 2023) as regressors, with no changepoints.

Model `m_full`: Combines logistic growth, seasonality, policy events, changepoints, and lagged `ICE_sales` to model delayed market responses and structural shifts in adoption.

Table 5.3 presents the error metrics for each model, with `m_full` emerging as the best-performing configuration. This model achieved an RMSE of 1325.47, an MAE of 993.66, and a MAPE of 40.61%, along with an R^2 value of 0.9303. Based on this performance, `m_full` was selected to generate the five-year forecast, as illustrated in Figure 5.3.

Model	RMSE	MAE	MAPE (%)	R^2
m_base	2852.56	1838.29	73.80	0.6777
m	2856.34	1813.20	70.01	0.6768
m_1	2785.84	1804.57	74.57	0.6926
m_holiday	2072.20	1503.98	67.92	0.8299
m_full	**1325.47**	**993.66**	**40.61**	**0.9303**

Table 5.3: Performance Metrics for BEV Forecasting Models

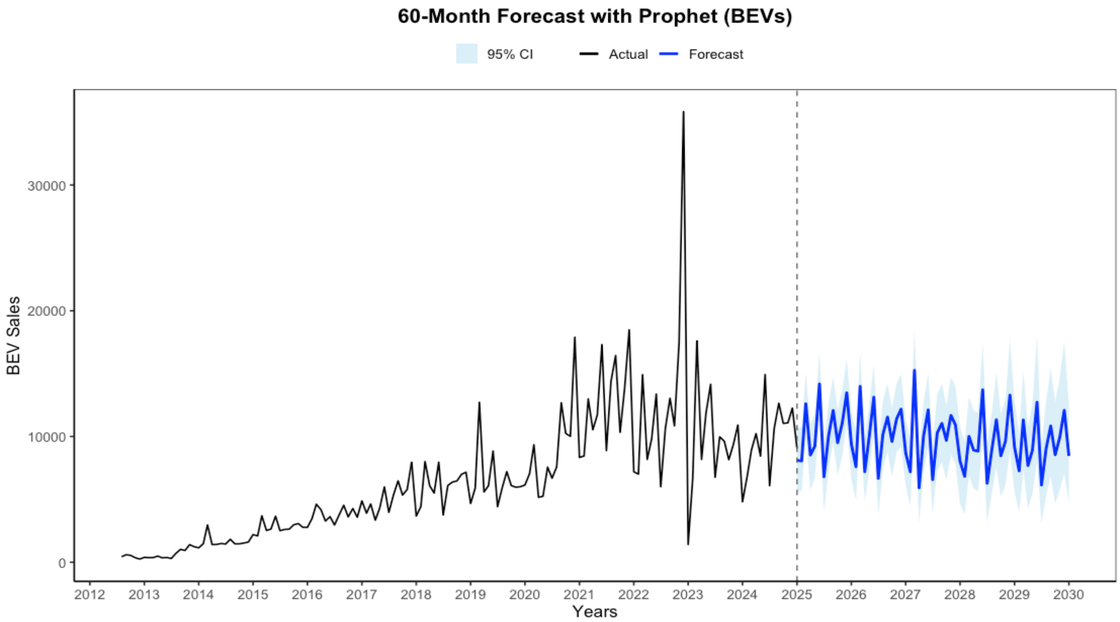

Figure 5.3: 60-Month Forecast with Prophet Model for BEVs Sales

ICE Forecasting Models

Three Prophet-based models were tested to forecast ICE vehicle sales, each designed to capture different aspects of market behaviour and long-term decline trends.

Model `ice_base`: This baseline model employs logistic growth and yearly seasonality, without incorporating regressors or holiday effects. It serves both as a control for comparison and as the source of projected ICE values used in BEV models.

Model `ice_full`: This extended configuration includes `BEV_sales` as a multiplicative regressor and accounts for holidays, based on the hypothesis that increasing BEV adoption and public holidays influence ICE sales. Changepoints are included to model structural shifts and behavioural substitution effects.

Model `ice_floor`: This version integrates a floor parameter (set to 0.5) to simulate a long-term phase-out of ICE vehicles, reflecting residual baseline demand. It uses additive seasonality and a conservative changepoint strategy to model a smoother, gradual decline.

Table 5.4 presents the error metrics for each model applied to forecast ICE vehicle sales. Among all configurations, the `ice_base` model demonstrated the best overall performance. Despite excluding external regressors and holiday effects, it achieved the lowest RMSE (766.52) and MAE (600.77), as well as the highest R^2 value (0.9607). Although the `ice_floor` exhibited a slightly lower MAPE (29.74%), its overall predictive accuracy was inferior to that of `ice_base`. Therefore, the `ice_base` model was selected as the most reliable and balanced option for generating the sixty-month forecast, as illustrated in Figure 5.4.

All models were evaluated based on historical fit using Mean Absolute Error (MAE), Root

Model	RMSE	MAE	MAPE (%)	R^2
ice_base	766.52	600.77	32.60%	0.9607
ice_full	1044.53	787.91	41.36%	0.9270
ice_floor	885.37	665.37	29.74%	0.9476

Table 5.4: ICE Forecast Model Performance Comparison

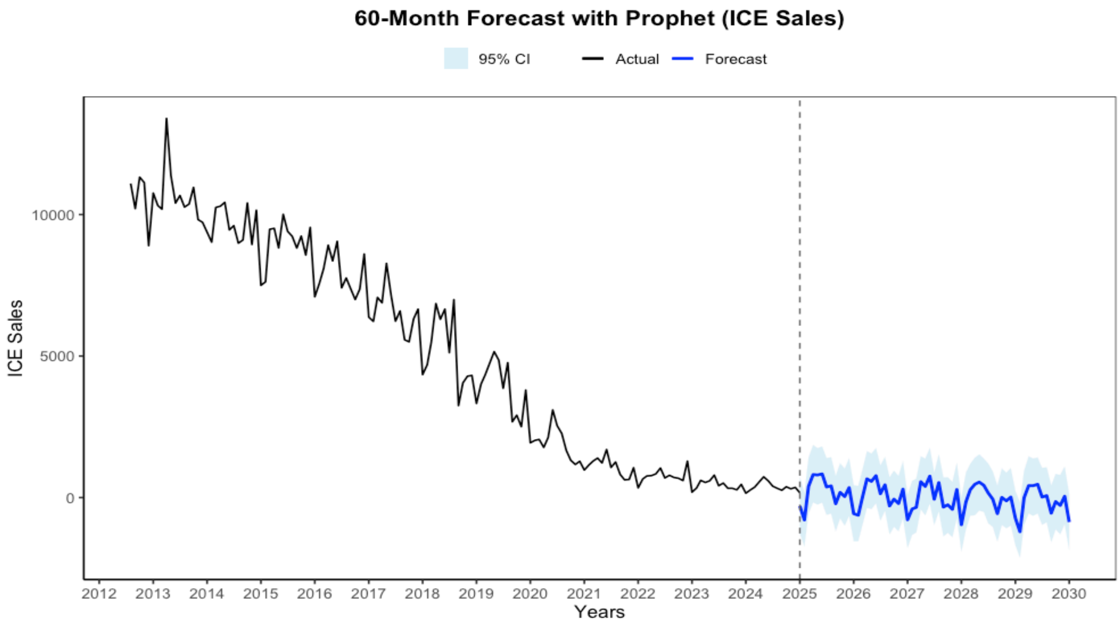

Figure 5.4: 60-Month Forecast with Prophet Model for ICE Sales

Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2). Time-series cross-validation was conducted with an initial five-year training window, a five-year forecasting horizon, and evaluation intervals of six months to ensure robust performance comparison under realistic forecasting conditions.

5.3 Random Forest Model

In this section, Random Forest was applied to forecast monthly sales of BEVs and ICE vehicles over a sixty-month horizon. Random Forest is a tree-based ensemble method that captures non-linear dependencies and variable interactions effectively. Although it is not inherently designed for time series forecasting, it can be adapted through manual feature engineering and recursive prediction frameworks. The methodological steps, model configurations, and forecasting results for both BEV and ICE sales are presented and evaluated below.

Model	RMSE	MAE	MAPE (%)	R^2
BEV	509.81	431.03	4.55	0.9532
ICE	68.49	57.88	16.03	0.7687

Table 5.5: Performance Metrics for Random Forest Forecasting Models

BEV Forecasting Models

Two Random Forest models were developed to forecast BEV sales: a full model with all engineered features and a filtered model with reduced feature dimensionality based on variable importance.

Full Model: A comprehensive set of predictors was constructed, including lag variables (lag_1 to lag_{24}), rolling statistics (3-month and 6-month means and standard deviations), cumulative sales, seasonal indicators (month and quarter) and binary flags for known policy-related events (December 2022, January 2023, and April 2023). The training and test sets were defined chronologically, with the final twelve months reserved for out of sample evaluation. Hyperparameter tuning was carried out using a rolling origin cross-validation procedure to preserve temporal structure.

Filtered Model: Feature selection was performed using variable importance rankings obtained from the trained full model. The top 15% of the predictors were retained, along with lag_1 to lag_{12}, which were considered structurally essential to capture temporal dependencies. This reduced model exhibited improved performance across all error metrics, particularly in terms of generalisability.

Random forests are inherently one-step-ahead forecasters and do not natively support multi-horizon prediction. To address this, a recursive forecasting strategy was implemented in which each monthly forecast was used as input for subsequent months. After each prediction, the feature set was dynamically updated to reflect the new lag structure, recalculated rolling statistics, updated cumulative totals, and refreshed seasonal and event variables. This allowed us to simulate month-by-month forecasts for a five-year (60-month) horizon. The sixty-month forecast produced by the best model is illustrated in Figure 5.5.

ICE Forecasting Models

A similar modelling strategy was adopted for ICE sales. The same engineered features and validation procedures were used. However, the ICE model exhibited a weaker generalisation performance.

Recursive forecasting was again utilised to generate the sixty-month projections, shown in Figure 5.6, while a zoomed plot of BEV and ICE forecasts is provided in Figure 5.7.

The Random Forest models for both BEV and ICE vehicles were trained on the full training set using the optimal hyperparameters. Evaluation of the test set was performed using RMSE, MAE, MAPE, and R-squared metrics. While the full models demonstrated acceptable performance on BEV sales, the ICE model showed poorer generalisation, likely due to a smaller target

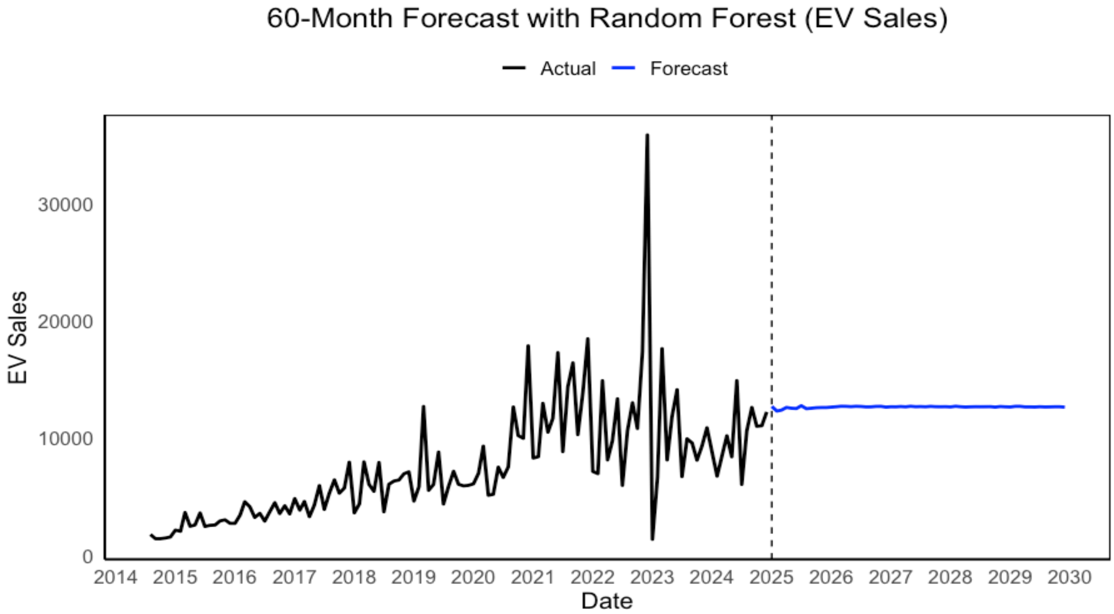

Figure 5.5: 60-Month Forecast with Random Forest Model for BEV Sales

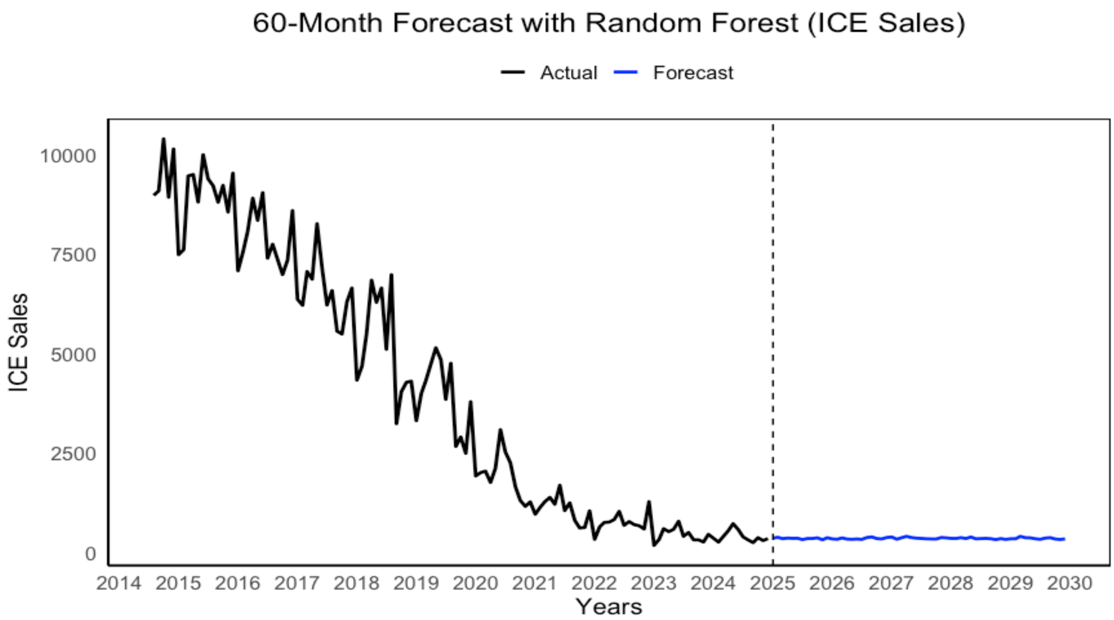

Figure 5.6: 60-Month Forecast with Random Forest Model for ICE Sales

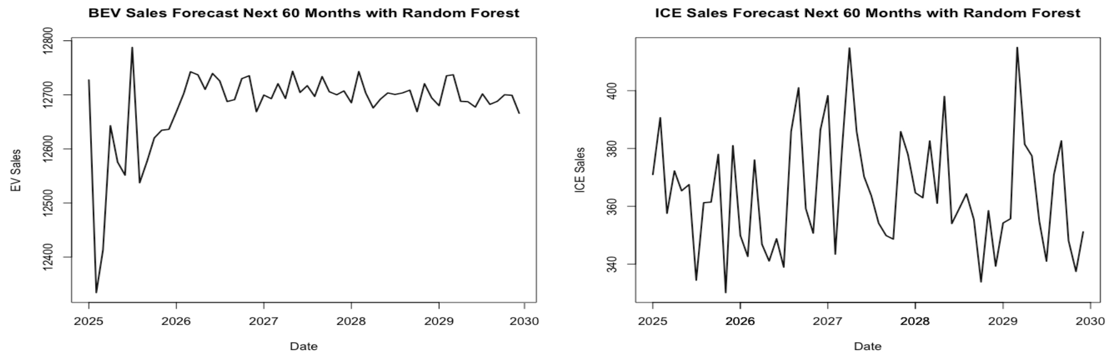

Figure 5.7: 60-Month Forecast with Random Forest Model for BEV and ICE Sales (Zoomed View)

magnitude.

Long-term forecasts produced by Random Forest were relatively flat and lacked visible trend dynamics. This outcome is consistent with the known limitations of tree-based models, which do not extrapolate beyond the range of training data and tend to revert to the historical mean. As such, although Random Forest proved useful for capturing short-term patterns and interactions, its long-horizon projections must be interpreted with caution.

5.4 Extreme Gradient Boosting (XGBoost)

This section outlines the implementation and evaluation of the Extreme Gradient Boosting (XGBoost) algorithm for forecasting monthly sales of BEVs and ICE vehicles over a sixty-month horizon. XGBoost is a scalable and efficient machine learning method based on gradient-boosted decision trees, particularly well-suited to handling nonlinear relationships and heterogeneous data features. In this section, multiple XGBoost configurations are described for both BEV and ICE forecasting tasks, and their respective performances are compared based on established error metrics.

BEV Forecasting Models

Three XGBoost models were constructed to forecast BEV sales, each incorporating increasing levels of complexity to evaluate the impact of feature engineering and hyperparameter tuning:

Baseline Model: A preliminary model using raw time-based predictors without feature engineering or tuning. It served as a reference point to benchmark later improvements.

Feature-Engineered Model: Extended the baseline configuration by incorporating seasonality (via sine and cosine transformations), lag variables, and rolling statistics (e.g., rolling mean and standard deviation), which are known to enhance temporal signal extraction in machine learning models.

Tuned Model: The final model employed 5-fold time-series cross-validation to optimise key hyperparameters (e.g., learning rate, max depth, number of rounds). This configuration

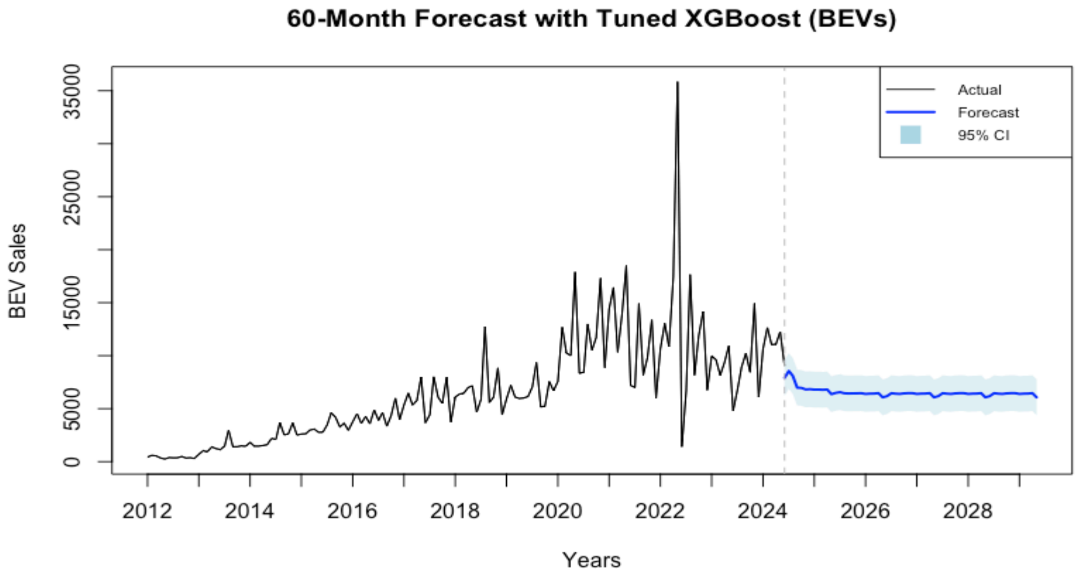

Figure 5.8: 60-Month Forecast with XGBoost for BEVs Sales

delivered the best performance across all evaluation metrics, with an RMSE of 1012.67, MAE of 900.90, and MAPE of 9.06%, achieving an R^2 score of 0.821.

Table 5.6 summarises the error metrics, highlighting the superior accuracy of the tuned XGBoost model for BEV forecasting. Based on this result, the tuned model was used to generate the sixty-month forecast, as visualised in Figure 5.8.

These findings underscore the importance of both advanced feature engineering and hyperparameter tuning in boosting model accuracy, especially in forecasting time series data affected by seasonal trends and policy-driven shocks.

Model	RMSE	MAE	MAPE (%)	R^2
BEV	1012.67	900.90	9.06	0.821
ICE	63.05	47.52	11.49	0.828

Table 5.6: XGBoost Model performance metrics for BEV and ICE sales forecasting

ICE Forecasting Models

A single XGBoost model was developed for ICE sales, incorporating the same engineered features and tuning methodology applied to the BEV models. This approach allowed for capturing long-term decline trends and short-term fluctuations driven by seasonality and policy interventions.

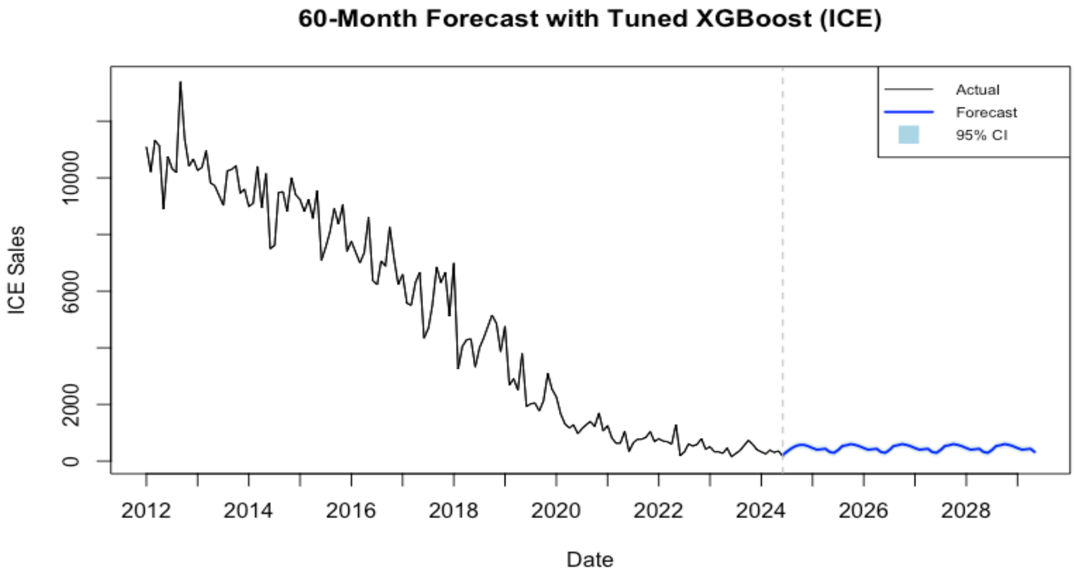

Figure 5.9: 60-Month Forecast with XGBoost for ICE Sales

The ICE model achieved strong predictive performance, with an RMSE of 63.05, MAE of 47.52, and MAPE of 11.49%, accompanied by an R^2 score of 0.828. These results suggest that the XGBoost algorithm effectively captured the temporal dynamics of ICE sales, outperforming simpler benchmark models. The corresponding sixty-month forecast is presented in Figure 5.9.

All models were evaluated using standard performance metrics, including RMSE, MAE, MAPE, and R^2, with time-series cross-validation applied to ensure generalisability. Results confirmed the importance of feature engineering and tuning for boosting model accuracy, especially in time series domains influenced by both regular seasonality and policy-driven disruptions.

5.5 Light Gradient Boosting Machine (LightGBM)

This section presents the application of the Light Gradient Boosting Machine (LightGBM) algorithm for forecasting monthly sales of BEVs and ICE vehicles over a sixty-month horizon. LightGBM is a fast, scalable gradient boosting framework based on decision trees and is particularly effective in capturing complex feature interactions and non-linear relationships. In this study, LightGBM models were developed using comprehensive feature engineering, time series cross-validation, and grid search optimisation. Recursive multi-step forecasts were then produced with confidence intervals.

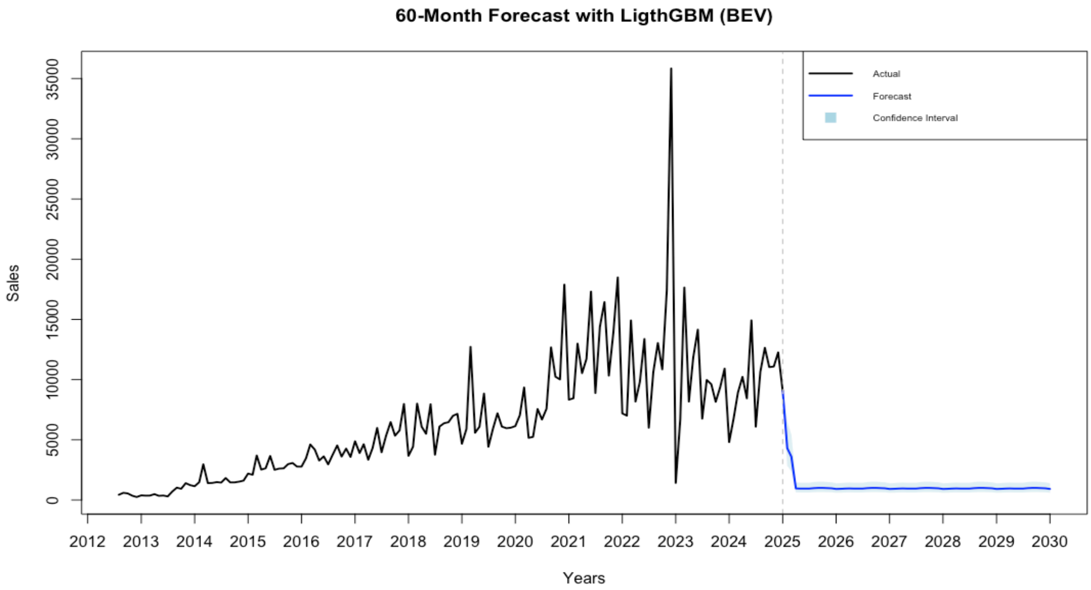

Figure 5.10: 60-Month Forecast with LightGBM Model for BEV Sales

BEV Forecasting Models

The LightGBM model for BEV sales was trained on engineered features including lagged sales values (lag_1 to lag_3), moving averages, first differences, seasonal transformations (sine/cosine of the month), and binary policy shock indicators. A grid search over key hyperparameters (number of leaves, learning rate, maximum depth) was performed using 5-fold time-series cross-validation. The model was trained on the full dataset excluding the final twelve months, which were reserved for evaluation.

Recursive multi-step forecasts were generated by feeding each predicted value back into the feature set for subsequent predictions. Prediction intervals were constructed using residual standard deviation from the training set. Figure 5.10 presents visualisation of the resulting forecast.

ICE Forecasting Models

A similar model was developed for ICE sales. In addition to lag and rolling statistics, trend-based features and policy dummies were included to capture structural shifts in ICE demand. The final model configuration was selected using cross-validation, and forecasts were generated recursively over a 60-month horizon Figure 5.11 presented the result.

Despite effective feature engineering and parameter tuning, LightGBM models did not outperform XGBoost or Random Forest in long-horizon forecasting. However, they provided reasonably accurate results for BEVs and ICEs, with the added benefit of confidence interval estimation. Recursive forecasting led to slight error accumulation over time, but the models remained competitive, especially for short- to mid-term projections.

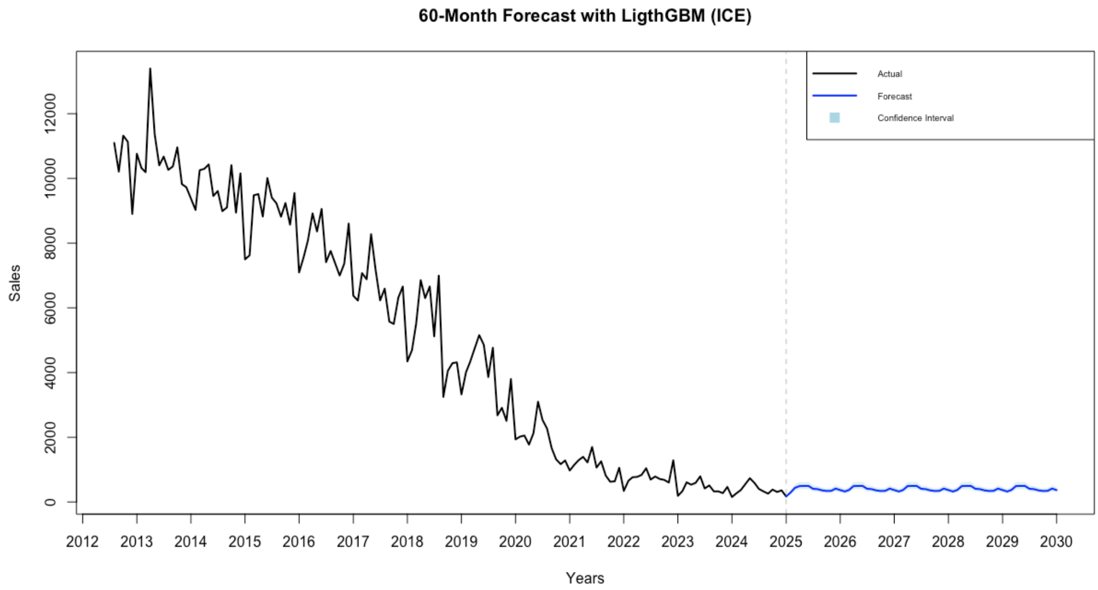

Figure 5.11: 60-Month Forecast with LightGBM Model for ICE Sales

Model	MAE	RMSE	MAPE (%)	R^2
BEV	1361.06	1655.56	13.96	0.5216
ICE	90.35	108.84	25.99	0.4879

Table 5.7: LightGBM Forecasting Performance for BEV and ICE Sales

5.6 Long Short-Term Memory (LSTM) Model

This section presents the application of a LSTM neural network for forecasting monthly sales of BEVs and ICE vehicles over a sixty-month horizon. LSTM is a class of RNN designed to model sequential dependencies and is well suited for time series data with long-term temporal patterns. A direct multi-step forecasting framework was employed, using a sequence-to-vector architecture optimised separately for BEV and ICE targets.

Data Preparation and Feature Engineering

To enhance predictive performance, several features were engineered:

- **Lagged features:** One-month and three-month lag values of BEV and ICE sales were included to capture recent trends.
- **Seasonality:** Sine and cosine transformations of the month index were used to represent annual cycles.

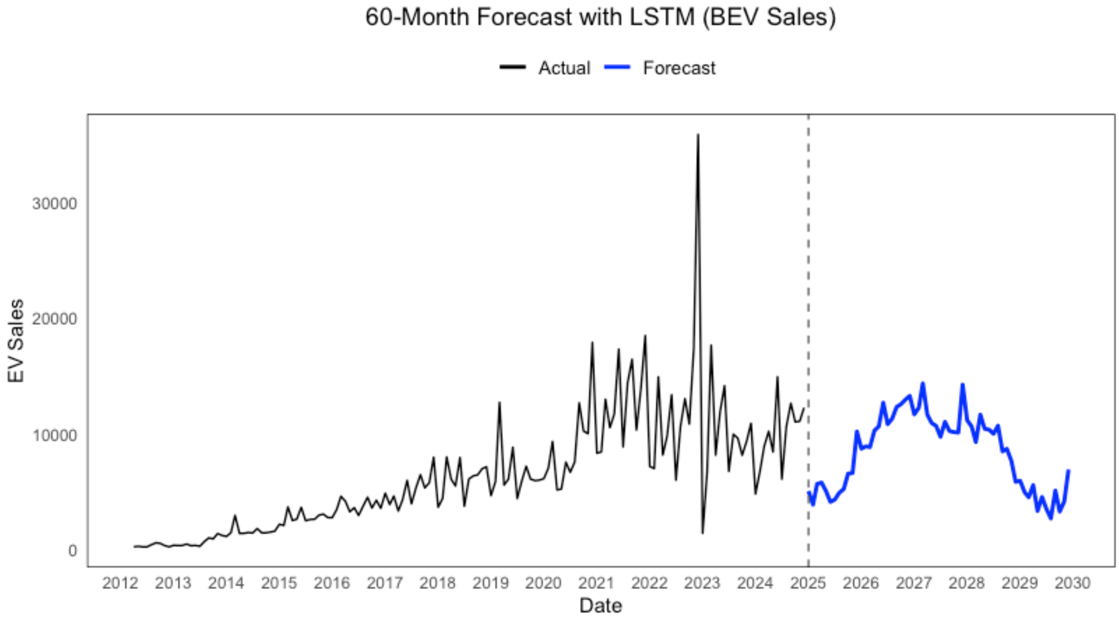

Figure 5.12: 60-Month Forecast with LSTM Model for BEV Sales

- **Event indicators:** Binary dummy variables were introduced for key policy-related disruptions, including the December 2022 incentive deadline, the January 2023 tax change, and the Tesla delivery shock in April 2023.

All features were normalised using min-max scaling. Input sequences of 18 months were constructed to forecast the subsequent 60 months. This structure enabled the model to learn both local and global temporal dependencies.

Model Architecture and Training

The final LSTM architecture was designed using grid search across 64 hyperparameter combinations. The best model, achieving the lowest validation loss, had the following configuration: 64 units in the bidirectional LSTM layer, 32 units in the stacked LSTM layer, 32 units in the final LSTM layer, 0.1 dropout rate, a batch size of 4, and a learning rate of 0.0005.

The architecture consisted of:

A **bidirectional LSTM layer** to capture forward and backward temporal signals.

A **stacked LSTM layer** to enrich temporal representation.

A final **LSTM layer with dropout** to mitigate overfitting.

A **dense output layer** to generate the sixty-month forecast.

The model was trained using early stopping and learning rate reduction strategies. Visualisation of the resulting forecasts is presented in Figures 5.12 and 5.13.

Table 5.8 reports the final evaluation metrics for the optimised LSTM model. The model achieved stronger performance on ICE sales, as expected given their more stable and trend-

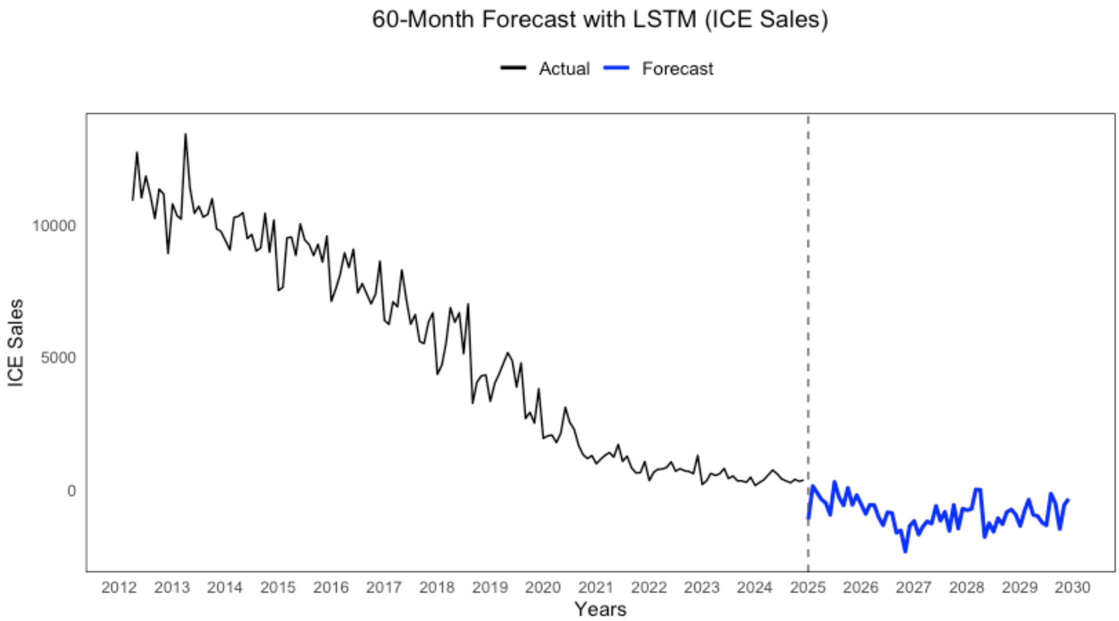

Figure 5.13: 60-Month Forecast with LSTM Model for ICE Sales

driven behaviour. For BEV forecasts, despite extensive tuning and feature engineering, prediction accuracy remained moderate. This outcome is consistent with the volatile and policy-sensitive nature of BEV adoption, which remains challenging for autoregressive sequence models to capture in long-horizon scenarios.

Several alternative modelling strategies were also explored to improve BEV performance, including the integration of multivariate inputs (e.g., ICE sales as an additional input series), the addition of further exogenous regressors, and the use of recursive and multistep forecasting variants. However, none of these approaches led to a significant improvement. In particular, long-term predictions tended to flatten over time, a known limitation of LSTM models when forecasting non-stationary, shock-prone time series such as BEV sales[49]. Sequence-to-sequence models with recursive decoding were also evaluated; however, these too resulted in flat forecasts. This suggests that the model was unable to generalise dynamic long-term trends under recursive self-conditioning, a known challenge when training LSTM architectures on volatile time series without strong external signals[50].

The LSTM-based approach demonstrated potential for long-term vehicle sales forecasting, particularly for ICE vehicles where demand exhibits steady seasonal and structural trends. For BEVs, future work may explore architectures such as Transformers or probabilistic LSTM variants, or the integration of more detailed policy and economic signals, to improve long-horizon forecasting accuracy.

Model	RMSE	MAE	MAPE (%)	R^2
BEV	3046.98	1854.70	27.07	0.5050
ICE	860	684.00	31.79	0.9110

Table 5.8: Performance Metrics for LSTM Forecasting Models

6 Discussion and Conclusion

This thesis set out to comprehensively analyse the transition from Internal Combustion Engine (ICE) vehicles to Battery Electric Vehicles (BEVs) in Norway using a two-pronged methodological approach. The first objective was to uncover the behavioural and structural mechanisms behind the historical adoption of these technologies using innovation diffusion models. The second objective focused on forecasting future monthly sales using a suite of statistical and machine learning (ML) techniques. Together, these approaches offered complementary insights for capturing both the explanatory depth of past adoption patterns and the predictive capability necessary for forward-looking analysis.

To address the first objective, three main classes of innovation diffusion models were employed: the classical Bass Model (BM), several Generalized Bass Models (GBMs), and the Unbalanced Competition and Regime Change Diachronic (UCRCD) model. The BM demonstrated high R^2 values and revealed fundamental diffusion trends, but was limited by its assumptions of constant market potential and inability to accommodate external shocks.

To overcome these constraints, GBMs were applied. These incorporated exponential, rectangular, and mixed shock structures to model real-world events such as tax incentives, supply chain fluctuations, and policy announcements. Among the variants, the GBM1e1r model featuring both exponential and rectangular shocks proved the most effective, with partial correlation coefficients ($\tilde{R}^2$) of 0.552 for BEVs and 0.676 for ICEs relative to the BM. These results underscored the need for hybrid shock structures to adequately reflect both short-term disruptions and long-term systemic changes.

The UCRCD model further deepened the analysis by explicitly modelling competition between BEVs and ICEs. It revealed that BEV adoption is accelerated by social imitation and policy boosts, while ICE vehicles suffer from reduced peer influence and direct substitution effects. The significance of the replacement effect (δ) and policy-related boost (γ) confirmed the critical role of coordinated interventions in shaping technology transitions.

In pursuit of the second objective, six forecasting algorithms ARIMA-based, Prophet, Random Forest, XGBoost, LightGBM and Long Short-Term Memory (LSTM) were employed to predict BEV and ICE sales over a 60-month horizon. Each model was rigorously tuned and assessed using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

For BEVs, the most accurate model was the tuned XGBoost algorithm, achieving an RMSE of 1012.67, MAE of 900.90, and MAPE of 9.06%. Random Forest followed with the lowest MAPE of 4.55%, although it exhibited flat long-term forecasts due to its tendency to revert to historical means. LightGBM achieved a respectable MAPE of 13.96% with balanced performance, but did not surpass the predictive accuracy of XGBoost or Random Forest. Prophet, while highly interpretable and responsive to policy events, showed a high MAPE of 40.61%, while indicating moderate accuracy, still constrains its effectiveness for long-range forecasting. SARMAX achieved moderate accuracy with a MAPE of 17.93%, excelling in interpretability and structured shock modelling. LSTM was the weakest performer, with an RMSE of 3046.98 and MAPE of 27.07%, reinforcing the difficulty of applying deep learning models to volatile, policy-sensitive time series.

ICE sales, by contrast, were more predictable. XGBoost again yielded the best accuracy, with an RMSE of 63.05 and MAPE of 11.49%. Random forest followed with an RMSE of 68.49 and a MAPE of 16.03%. LightGBM offered competitive performance with an RMSE of 108.84 and MAPE of 25.99%. Prophet's baseline model, though interpretable, showed the highest RMSE (766.52). SARMAX and LSTM performed reasonably, with MAPEs of 22.46% and 31.79%, respectively.

Category	Model	RMSE	MAE	MAPE (%)
BEV	SARMAX	1808.70	1172.27	17.93
	Prophet (m_full)	1325.47	993.66	40.61
	XGBoost	1012.67	900.90	9.06
	LightGBM	1655.56	1361.06	13.96
	Random Forest	509.81	431.03	4.55
	LSTM	3046.98	1854.70	27.07
ICE	SARMAX	583.21	410.42	22.46
	Prophet (ice_base)	766.52	600.77	32.60
	XGBoost	63.05	47.52	11.49
	LightGBM	108.84	90.35	25.99
	Random Forest	68.49	57.88	16.03
	LSTM	860.00	684.00	31.79

Table 6.1: Performance Comparison of Forecasting Models for BEV and ICE Sales

Overall, XGBoost emerged as the most accurate and generalisable forecasting model across both vehicle types. Its performance benefited from robust feature engineering and its ability to handle non-linearities and interactions. Random Forest and LightGBM performed strongly in short-term projections but displayed limitations in longer horizons due to their mean-reverting tendencies. SARMAX offered a transparent and interpretable structure particularly well-suited to policy-aware forecasting. Prophet proved valuable for exploratory modelling and policy simulation, though it was less precise in long-range forecasts. LSTM, despite its complexity, was outperformed by simpler models due to the challenges of modelling erratic sales behaviour in the absence of consistent signals.

From a forecasting perspective, these 60-month projections should be interpreted as conditional paths based on historical dynamics. XGBoost forecasts a continued rise in BEV adoption, while SARMAX anticipates steady ICE decline, both aligning with Norway's official plan to end the sale of new ICE vehicles by 2030 [51]. However, it is important to emphasise that all forecasts are uncertain and subject to change with shifts in regulations, macroeconomic factors, or technological disruptions.

The main result of this thesis is that Norway's transition from ICE to BEV vehicles is not only measurable through data-driven models but also strongly aligned with the country's ambitious policy goals. The use of innovation diffusion models confirmed that policy shocks and social imitation are key accelerators of BEV adoption, while ICE vehicles show a steady decline under substitution pressure. Forecasting results support this trajectory: XGBoost consistently delivered the most accurate predictions, indicating continued BEV growth and an ICE phase-out consistent with Norway's plan to ban new ICE sales by 2030. These findings collectively highlight that the electrification strategy, driven by fiscal incentives, infrastructure expansion, and clear regulatory targets, is effective and reflects empirical sales dynamics. In this context, combining behavioural insight with advanced forecasting enables not only reliable prediction but also policy validation and planning for a zero-emission future.

Future Work

There are several promising directions for extending this research:

- **Incorporating macroeconomic and behavioural signals:** Including variables such as energy prices, household income, or consumer sentiment could enhance the explanatory power and adaptability of forecasting models, especially under uncertain policy conditions.

- **Testing ensemble and hybrid models:** Combining machine learning models (e.g. XGBoost, LSTM) with interpretable statistical frameworks (e.g., SARMAX, GBM) may produce robust forecasts that balance accuracy and interpretability.

- **Exploring Transformer-based and probabilistic neural models:** Recent developments in deep learning, such as attention mechanisms and Bayesian LSTMs, could better model the data volatility and quantify forecast uncertainty, particularly for BEV trends.

- **Extending counterfactual policy analysis:** While this thesis incorporated key policy shocks into models such as SARMAX and Prophet, future work could explore a broader set of counterfactual scenarios (e.g., earlier phase-out of ICEs, staggered incentive removal) and evaluate their projected impact through structured scenario simulations.

Future research can build on these extensions to support more robust, adaptive, and policy-relevant forecasting systems in the context of sustainable mobility transitions.

A

Appendices

Below are additional comments that provide further insight into the trends in BEV adoption.

A.0.1 Bass Model for Each Variables

This section presents the application of the Bass Model to each vehicle category in the dataset, along with a detailed explanation of the corresponding parameter estimates.

Vehicle Type	Market Potential (m)	Innovation (p)	Imitation (q)
BEV	1,360,521	0.00048	0.0303
Petrol	291,543	0.0104	0.0340
Diesel	444,611	0.0149	0.0171
Non-Plugin Hybrid	182,651	0.0028	0.0281
Plugin Hybrid	215,568	0.00069	0.0478

Table A.1: Summary of Bass Model Parameters for Vehicle Types

Table A.1 presents the estimated Bass Model parameters for five vehicle types in Norway, namely Battery Electric Vehicles (BEVs), Petrol, Diesel, Non-Plugin Hybrid, and Plugin Hybrid vehicles. The three key parameters include market potential (m), the coefficient of innovation (p), and the coefficient of imitation (q).

The **market potential** (m) reflects the estimated maximum number of adopters or cumulative sales that can be achieved throughout the product's life cycle. The **innovation coefficient** (p) captures adoption driven by external influences, such as advertising, media exposure, or policy incentives, and is independent of previous adopters. The **imitation coefficient** (q) represents the influence of previous adopters, capturing social contagion effects such as peer influence, word of mouth, and network effects. In most empirical applications of the Bass Model, q exceeds p, indicating that adoption tends to be socially reinforced rather than independently motivated.

- **Battery Electric Vehicles (BEVs)** exhibit the highest estimated market potential ($m = 1{,}360{,}521$), indicating robust long-term demand. The innovation parameter is notably low ($p = 0.00048$), suggesting that early adoption was not driven primarily by external stimuli. In contrast, the imitation coefficient ($q = 0.0303$) is substantially higher, yielding a ratio q/p of approximately 63. This indicates that the diffusion of BEVs has been largely driven by peer influence and social learning, rather than spontaneous adoption, a typical pattern of policy-driven and infrastructure-sensitive innovations.

- **Petrol Vehicles** demonstrate a significantly lower market potential ($m = 291{,}543$) than BEVs. The innovation coefficient is relatively high ($p = 0.0104$), with imitation at $q = 0.0340$, yielding a ratio of q/p of approximately 3.3. This suggests that adoption was somewhat more balanced between innovation and imitation, with a relatively greater role played by external influences, possibly reflecting earlier stages of automotive diffusion.

- **Diesel Vehicles** possess a moderate market potential ($m = 444{,}611$). In particular, they have the highest innovation coefficient in all vehicle types ($p = 0.0149$) and a relatively low imitation coefficient ($q = 0.0171$), resulting in a q/p ratio close to 1.15. This implies that both innovation and imitation mechanisms contributed similarly to their adoption, which may reflect the role of functional considerations and policy neutrality during their growth phase.

- **Non-Plugin Hybrids** exhibit the lowest market potential ($m = 182{,}651$). The innovation coefficient is modest ($p = 0.0028$), while imitation is stronger ($q = 0.0281$), producing a ratio of q/p of approximately 10. This points to a diffusion process predominantly driven by peer influence, though less so than for BEVs or Plugin Hybrids.

- **Plugin Hybrids** have a moderate market potential ($m = 215{,}568$), higher than Non-Plugin Hybrids. Their innovation coefficient is extremely low ($p = 0.00069$), while their imitation coefficient is the highest among all categories ($q = 0.0478$), giving rise to a q/p ratio of nearly 69. This highlights a diffusion process heavily reliant on social dynamics and possibly shaped by transitional policy incentives promoting plug-in technology as a bridge to full electrification.

In summary, BEVs and Plugin Hybrids display classic imitation-driven diffusion patterns, in which social influence outweighs independent innovation. By contrast, Petrol and Diesel vehicles show relatively higher innovation coefficients, suggesting a stronger role for independent adoption in earlier phases. These findings confirm that adoption of BEV in Norway has been mainly driven by policy and socially reinforced, while the transition away from ICE vehicles reflects declining market potential and structural saturation.

A.0.2 Generalized Bass Model with two Exponential Shocks

To gain a more comprehensive understanding of BEV adoption and the decline of ICE vehicles, GBM with two exponential shocks, hereafter referred to as GBM2E applied to the data. The parameters for this model are provided in Table A.2.

Parameter	Estimate	Std. Error	Lower Bound	Upper Bound
BEV (Battery Electric Vehicles)				
m	971021.13	7717.36	955895.39	986146.87
p	0.00081	0.000017	0.00078	0.00084
q	0.034	0.00037	0.033	0.034
a_1	100.00	1.23	97.59	102.41
b_1	0.042	0.0042	0.034	0.051
c_1	0.28	0.033	0.21	0.34
a_2	139.43	11.21	117.46	161.39
b_2	0.56	0.20	0.17	0.96
c_2	0.14	0.99	-1.80	2.085
$R^2 = 0.999670$				
ICE (Internal Combustion Engine Vehicles)				
m	746488.49	9381.40	728101.29	764875.68
p	0.014	0.00017	0.014	0.014
q	0.013	0.00056	0.012	0.014
a_1	32.71	0.68	31.36	34.06
b_1	0.041	0.0039	0.033	0.048
c_1	0.10	0.0058	0.092	0.11
a_2	91.11	0.63	89.87	92.35
b_2	0.044	0.0014	0.041	0.047
c_2	-0.87	0.10	-1.08	-0.66
$R^2 = 0.999982$				

Table A.2: Estimated parameters for the Generalized Bass Model (GBM) with two exponential shocks for BEV and ICE.

In this framework, the parameters a_i, b_i, and c_i (for $i = 1, 2$) denote the starting time, memory, and intensity of each shock, respectively. While a_i identifies when the shock occurs, b_i governs its persistence, and c_i reflects the direction and magnitude of its impact on the diffusion curve.

The model achieves $R^2 = 0.999670$ for BEVs and $R^2 = 0.999982$ for ICE vehicles, suggesting a strong fit. Additionally, all estimated parameters are statistically significant.

For BEVs, the first exponential shock occurred at $a_1 = 100.00$, aligning with the year 2020. This was characterised by a modest but sustained acceleration $b_1 = 0.042$ and a significant positive intensity $c_1 = 0.28$, probably reflecting favourable external factors such as policy incentives. A second shock emerged around 2023 at $a_2 = 139.43$, with an even stronger memory effect $b_2 = 0.56$ and a moderate intensity $c_2 = 0.14$, further amplifying the diffusion process. These developments underscore the reinforcing role of policy and infrastructure improvements

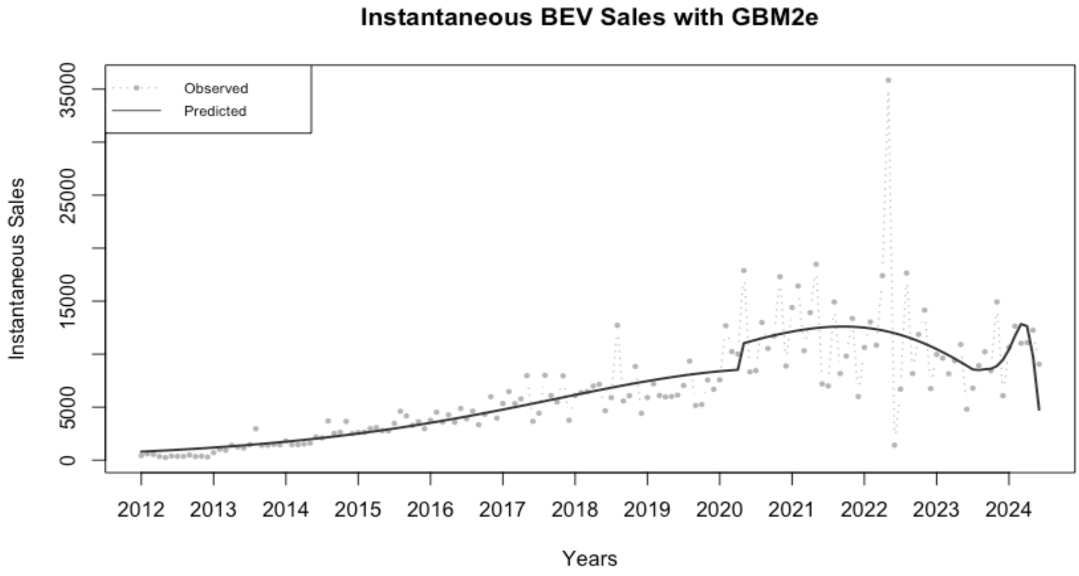

Figure A.1: GBM with two Exponential Shocks for BEV Adaption

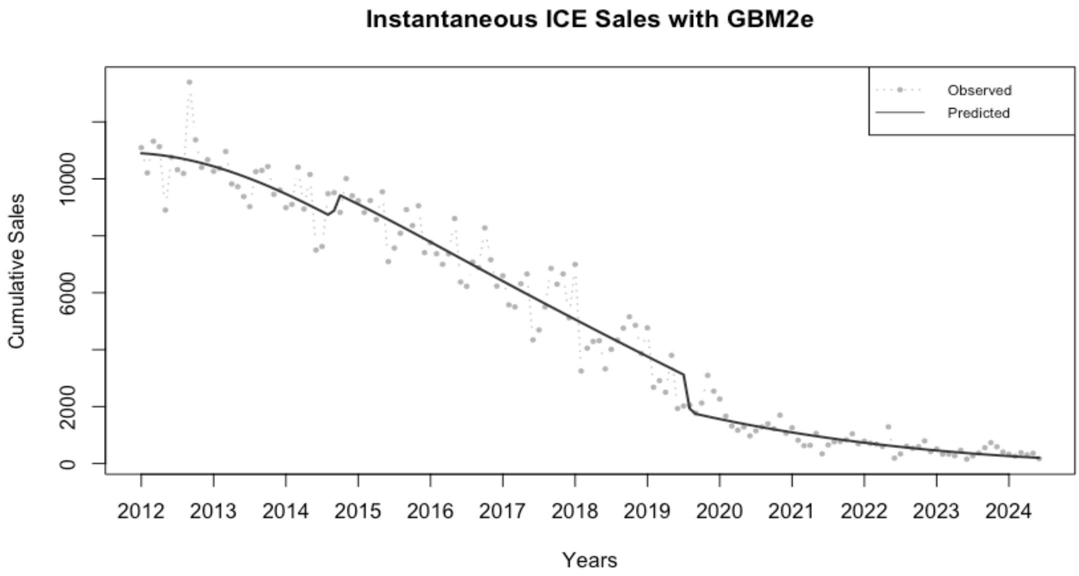

Figure A.2: GBM with two Exponential Shocks for ICE Decline in driving the adoption of BEVs. The improved fit of the model resulting from the inclusion of a second shock, as illustrated in Figure A.1, captures the evolving market dynamics with greater precision.

Regarding ICE vehicles, the first exponential shock is observed at $a_1 = 32.71$, corresponding to the period between 2014 and 2015. This early intervention shows a positive memory effect of $b_1 = 0.041$ and a moderate intensity of $c_1 = 0.10$, indicating a brief increase in the momentum of adoption. A more significant shift occurs with the second shock at $a_2 = 91.11$, around 2019–2020, where a similarly low memory effect of $b_2 = 0.04$ is combined with a pronounced negative intensity of $c_2 = -0.87$. This reflects a gradually intensifying decline in ICE diffusion initially mild, but increasingly evident over time, it is also aligning with the broader transition towards electrification. The enhanced model, illustrated in Figure A.2, captures this downturn more accurately, reinforcing the conclusion that ICE vehicles have entered a decline phase.

For the ICE dataset, it is evident from the $\tilde{R}^2$ values that the GBM2E model consistently outperforms the alternatives, showing improvements over BM ($\tilde{R}^2 = 0.8235$), GBM1E ($\tilde{R}^2 = 0.8235$), and GBM1R ($\tilde{R}^2 = 0.8125$). This suggests that, so far, GBM2E is the most appropriate model to explain the variance in ICE registrations.

In contrast, for the adoption of BEVs, none of the comparisons involving GBM2E exceed the commonly accepted threshold of $\tilde{R}^2 > 0.2$, although the graphical representation suggests a visually better fit. This indicates that the additional complexity introduced by GBM2E does not result in a substantial improvement in the performance of the model. Therefore, it is not necessary to adopt the more complex model for the BEV data, and the simpler BM may be sufficient.

A.0.3 Generalized Bass Model with three Exponential Shocks

The inclusion of three exponential shocks allows for a more detailed and realistic characterisation of the response function $x(t)$, capturing complex shifts in diffusion dynamics. The estimated parameters associated with this extended model are reported in Table A.3.

In this formulation, the parameters a_i, b_i, and c_i (for $i = 1, 2, 3$) correspond to the time, memory, and intensity of onset of each respective shock. Specifically, a_i indicates the timing of the shock, b_i describes the duration and persistence of its effect, and c_i determines both the direction and magnitude of its influence on the diffusion trajectory.

The model demonstrates excellent fit, achieving $R^2 = 0.999707$ for BEVs and $R^2 = 0.999988$ for ICE vehicles. Furthermore, nearly all estimated parameters are statistically significant, supporting the robustness of the model.

For BEVs, the first exponential shock is observed at $a_1 = 99.99$, corresponding approximately to the year 2020. This shock is characterised by a small but positive intensity of $c_1 = 0.18$ and a memory effect of $b_1 = 0.14$. These values suggest a modest but steadily increasing influence on the diffusion process over time. The second shock, which occurs at $a_2 = 110.74$ around 2021, introduces a decelerating effect, as indicated by the negative intensity of $c_2 = -0.62$, although memory remains positive at $b_2 = 0.15$, implying a delayed but diminishing

Parameter	Estimate	Std. Error	Lower Bound	Upper Bound
BEV (Battery Electric Vehicles)				
m	973205.03	8363.67	956812.53	989597.54
p	0.00081	0.000016	0.00078	0.00084
q	0.034	0.00036	0.033	0.034
a_1	99.99	2.01	96.05	103.94
b_1	0.14	0.018	0.10	0.17
c_1	0.18	0.07	0.03	0.33
a_2	110.74	0.91	108.95	112.53
b_2	0.15	0.01	0.12	0.18
c_2	-0.62	0.15	-0.93	-0.31
a_3	138.22	0.97	136.31	140.13
b_3	0.30	0.03	0.23	0.38
c_3	1.83	0.96	-0.05	3.72
$R^2 = 0.999707$				
ICE (Internal Combustion Engine Vehicles)				
m	746720.93	230.0473	746270.0520	747171.821
p	0.0030	0.00028	0.0025	0.0036
q	0.039	0.00049	0.03	0.04
a_1	-0.21	0.11	-0.43	0.011
b_1	-0.11	0.0017	-0.12	-0.11
c_1	3.08	0.24	2.59	3.56
a_2	80.43	0.34	79.76	81.11
b_2	-0.26	0.05	-0.36	-0.16
c_2	0.89	0.14	0.60	1.18
a_3	69.42	0.45	68.53	70.31
b_3	-0.67	0.33	-1.33	-0.013
c_3	0.85	0.38	0.09	1.61
$R^2 = 0.999988$				

Table A.3: Estimated parameters for the Generalized Bass Model (GBM) with three exponential shocks for BEV and ICE.

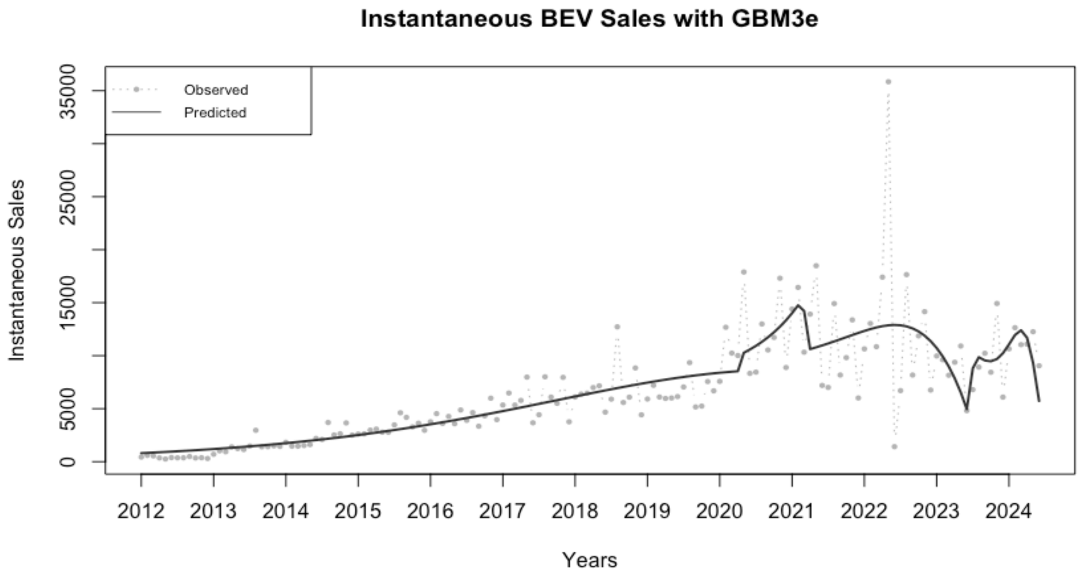

Figure A.3: GBM with three Exponential Shocks for BEVs Adaption

impact. The third shock, which began at $a_3 = 138.22$ in 2024, has a pronounced positive influence, with a strong intensity of $c_3 = 1.83$ and a relatively persistent effect at $b_3 = 0.30$, indicating a substantial acceleration in adoption once the shock has reached its peak. The inclusion of three exponential shocks improves the model's ability to visually capture the fluctuations observed in the dataset. The $\tilde{R}^2$ value of 0.2187 for GBM3E for BEV, when compared to the baseline BM, indicates a slight improvement in model performance, just surpassing the commonly accepted threshold of 0.2. A similar level of enhancement is observed in comparison with GBM1R, which yields a $\tilde{R}^2$ difference of 0.2409.

In the case of ICEs, the first shock appears at $a_1 = -0.21$, which, although not statistically significant, can be interpreted as a theoretical indication that the decline may have commenced prior to the observed data period. The corresponding memory effect $b_1 = -0.11$ implies an exponentially decaying influence, while the large positive intensity $c_1 = 3.08$ signals a sharp early acceleration, potentially marking the onset of the decline phase. The second shock, located at $a_2 = 80.43$ in the year around 2018, is moderately strong $c_2 = 0.89$ but short-lived due to the decay rate $b_2 = -0.26$. Finally, the third shock begins at $a_3 = 69.42$, accompanied by a substantial decay rate $b_3 = -0.67$ and intensity $c_3 = 0.85$, suggesting a rapidly decreasing but still impactful force accelerating the downturn in the adoption of ICE. For ICE vehicles, the GBM3E model surpasses all other models in terms of the value $\tilde{R}^2 = 0.8824$, indicating the highest explanatory power among the alternatives evaluated.

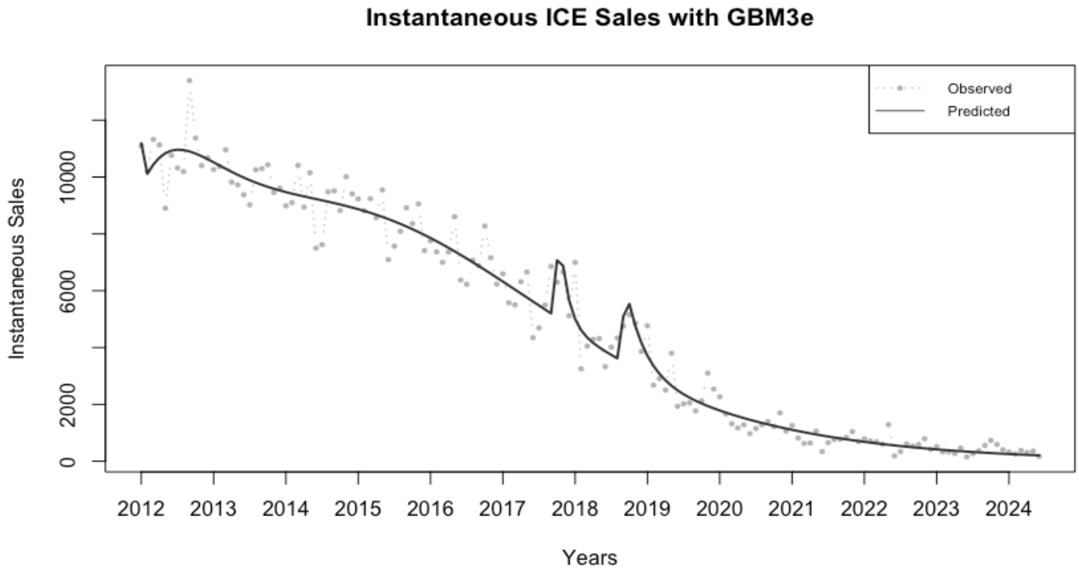

Figure A.4: GBM with three Exponential Shocks for ICE Decline

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Acknowledgments

I would like to express my deepest gratitude to my supervisor, Prof. Mariangela Guidolin, whose guidance, encouragement, and insightful feedback made the completion of this thesis possible. Her immense expertise, boundless patience, and genuine care for her students have significantly enriched my study experience. It has truly been an honour and a privilege to work alongside such an inspiring mentor.

A very special thank you goes to my family, whose endless love, support, countless FaceTime calls, and unwavering belief in me made every obstacle feel conquerable. Your presence, even from afar, has been the heartbeat of my motivation and the shield that protected me from giving up.

My heartfelt appreciation extends to all the beautiful souls that I had the privilege of meeting during my master's journey here in Padova. Your warmth, kindness, and companionship have left a lasting mark on my heart. You made this chapter of my life not only meaningful but truly magical and unforgettable. The laughter we shared, the tears we dried, and the memories we created will always remain with me. I believe Galileo and I have one thing in common, we both spent the best times of our lives in Padova, and it's all because of all of *you. Grazie mille a tutti.*