Analysis of Factors Influencing Electric Vehicle Sales Based on the Multiple Linear Regression Model

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Abstract: As electric vehicles are at the core of the global automotive industry's transformation and significantly reduce greenhouse gas emissions, understanding the owners of electric vehicle sales is important for policymakers and corporate partners. The main objective of this study is to examine the key drivers of electric vehicle (EV) sales, with a particular focus on market penetration and stock dynamics. To achieve this, the study employs multiple linear regression (MLR) analysis, a statistical technique that models the relationship between a dependent variable and multiple independent variables using a linear equation. Utilizing detailed information from 2010 to 2024 and predictions that extend to 2035, this research examines how combined EV stock, EV sales share, and EV stock share affect regular EV sales across different areas. The results indicate that combined EV stock and EV stock share are important indicators of EV sales, addressing the importance of boosting EV market presence to drive adoption. By measuring these associations, this study provides valuable insights for governments, businesses, and owners who want to encourage EV implementation through appropriate legislation changes. These results support more extensive efforts to promote responsible travel and decrease global carbon emissions.

1 INTRODUCTION

Electric vehicles (EVs) are receiving increased attention for their capacity to curb air pollution and decrease dependency on fossil fuels (Li & Ouyang, 2021). According to Ford (2023), large-scale datasets of global EV trends indicate a sharp rise in both EV stock and charging infrastructure from 2010 onward, underscoring how supportive conditions can powerfully shape market trajectories. The analysis of factors affecting electric vehicles sales is of great significance. In European contexts, Zhou and Li (2022) argue that income levels and shifting fuel costs substantially influence EV purchase decisions, highlighting how financial considerations can differ by region. Meanwhile, Kang and Park (2020) emphasize the role of social dynamics and environmental awareness, showing that broader public support can accelerate EV adoption.

Zhang and Lu (2020) illustrate that in China, the presence of robust charging networks corresponds directly to higher EV uptake, suggesting that accessible infrastructure stands out as a key determinant. Chen and Chou (2022) find that in the United States, range anxiety remains a core consumer concern, although lower operating costs still motivate a growing segment of buyers. Wu and Zhao (2021) contend that battery innovations, particularly those improving driving range and energy density, have steadily reduced technological barriers, making EVs more palatable to mainstream markets.

Beyond these early adoption drivers, recent analyses shine a fresh light on how EV sales, EV stock, and market share metrics shape overall growth. The International Energy Agency (IEA) (2022) reports that total EV sales have been climbing steadily, driven by a combination of cost reductions and growing infrastructure investment. According to BloombergNEF (2023), forecasts through the early 2030s suggest that EVs will likely dominate new car registrations in several leading markets, pushing EV stock share upward even in regions currently dominated by internal combustion engines. Jin and

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Slowik (2021) find that such expansions in EV market share often track closely with government incentive programs, underscoring the importance of strategic policy intervention. In parallel, Yang, Liao, and van Wee (2020) confirm that subsidies and tax rebates can significantly boost local EV sales, influencing both consumer decisions and automaker production choices. Sakti, Jaller, and Lee (2021) note that as EV sales share rises, reinforcing charging infrastructure and supply chains becomes critical to sustaining the momentum.

In light of this global perspective, the adoption of electric vehicles differs considerably. It is influenced by several regional factors, including promoting relationships, marketing trends, and charging infrastructure. This research uses a multiple linear regression approach to identify and analyze the main factors that affect EV sales. We use robust standard errors (HC3) and log transformations to increase model reliability and address non-linearity and heteroscedasticity. To aid the transition to sustainable transportation systems, this study uses quantitative measures like EV sales, EV sales share, EV stock, EV stock share, and charging station size to provide helpful insights to stakeholders, including urban planners, automobile manufacturers, and governments. Manufacturers and urban planners are looking to accelerate the transition to sustainable transportation systems.

2 METHODOLOGY

2.1 Data Source and Description

This study uses the IEA Global EV Data dataset from Kaggle and the comprehensive data on electric vehicle (EV) adoption across various regions between 2010 and 2024. Also, the database includes projections for 2035. Along with EV sales, EV stock prices, EV sales share, and EV stock share, analytical variables like having details are included in the database. The data covers a range of geographical regions and years and thoroughly examines how significant factors driving car implementation are. According to uniformity, the factors measured on several scales, such as the range of vehicles versus the percentages, are standardized and similar across several years and regions. The key features and information from this study are summarized in Table 1.

Table 1: Definition of variables.

Variable	Description	Range
EV Sales (y)	Total number of EVs sold in the region (annual)	[0.001, 62000000]
EV Charging points (x_1)	Total publicly accessible EV charging points in the region	[0.1, 15000000]
EV Sales Share (x_2)	Percentage of EV sales in the total vehicle market	[0.0000320, 93]
EV Stock (x_3)	Cumulative stock of EVs in the region.	[1, 44000000]
EV Stock Share (x_4)	Percentage of EVs in the total vehicle stock.	[0.0000150, 58]

2.2 Method Introduction

Given the continuous nature of EV sales, this study employs Multiple Linear Regression (MLR) as the primary method to assess the key factors influencing electric vehicle (EV) sales. Multiple linear regression can be used to model a regiment variable's relationship to several separate parameters. This technique is especially useful for examining how variations in EV sales are influenced by charging infrastructure, combined EV stock, EV sales share, and EV stock share. The dependent variable (EV Sales) is represented by a linear combination of independent variables in multiple linear regression models expressed as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \tag{1}$$

Where y represents the total EV sales, x_i are the independent variables that capture key economic and infrastructural factors, β_i are the regression coefficients measuring the strength and direction of influence, and ε is the error term, accounting for variations not explained by the model. To estimate the coefficients, this study employs the Ordinary Least Squares (OLS) method, which minimizes the discrepancy between actual and predicted sales values. The objective function for optimization is given by:

$$\hat{\beta} = \arg\min_{\beta} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{2}$$

Which represents the estimation of regression coefficients using the Ordinary Least Squares (OLS) method. Here, $\hat{\beta}$ denotes the estimated coefficients that minimize the sum of squared residuals, where each residual is the difference between the observed value y_i and the predicted value $\hat{y}_i$. The term β represents the set of regression coefficients being optimized. The important work ensures that the chosen coefficients provide the best possible right match by reducing the regiment variable's common error. The characteristics that best capture the contact between the different and answer guidelines are created in multiple linear regression. The research software enables a deeper understanding of the impact of each indicator on EV sales while avoiding forecast error.

Given the continuous nature of EV sales and the potential for non-linearity in the relationships between predictors and the response variable, this study employs a log-linear multiple regression model as an extension of multiple linear regression. By applying logarithmic transformations to both the dependent variable and key predictors, the model effectively captures proportional relationships and reduces heteroscedasticity. The log-linear model takes the following form:

$$log(y) = \beta_0 + \beta_1 log(x_1) + \beta_2 log(x_2) + \cdots + \beta_n log(x_n) + \varepsilon \quad (3)$$

Applying this transformation allows us to interpret the coefficients in terms of elasticity, meaning that a 1% increase in a predictor corresponds to an approximate β_i% change in EV sales, holding all other factors constant.

3 RESULTS AND DISCUSSION

3.1 Visualization Analysis

To gain insights into the distribution of electric vehicle (EV) sales across different regions, we first conducted a preliminary data quality assessment, which included checking for missing values and ensuring the dataset's integrity. After confirming the dataset's completeness and reliability, we proceeded with data visualization to better understand the regional disparities in EV sales. The bar chart (Figure 1) presented below provides a comparative analysis of total EV sales worldwide, with a focused examination of the top ten countries contributing most significantly to global EV adoption. This approach ensures clarity and highlights the dominant regions in the EV market.

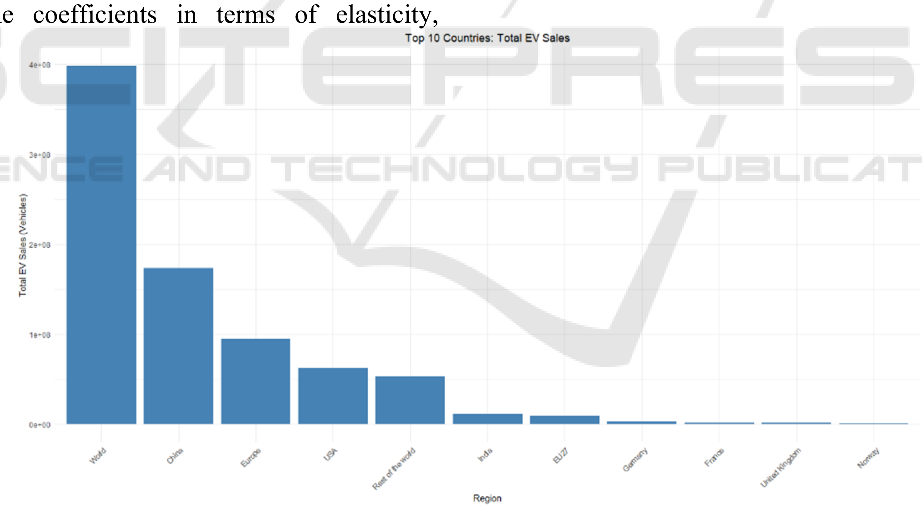

Figure 1: Total EV Sales Worldwide and in the Top 10 Countries (Photo/Picture credit: Original).

3.2 Model Result

Understanding the factors influencing EV sales is crucial for policymaking, infrastructure development, and market forecasting in an electric vehicle (EV) market analysis. To achieve this, a log-linear regression model was developed to measure the relationship between EV sales and its essential factors, including EV stock share, EV sales share, EV stock, and EV charging points. With the aid of the log-linear regression model, it can be determined whether or not each indicator impacts the growth of EV sales and whether these correlations are statistically significant. The log-linear regression model is expressed as follows:

$$\log(y) = -0.559 + 0.055\log(x_1) + 0.194\log(x_2) + 0.905\log(x_3) - 0.396\log(x_4) \quad (4)$$

Table 2 presents the ordinary least squares (OLS) regression results with heteroscedasticity-responsive (HC3) standard errors to understand EV sales' main determinants. For each indicator, the columns report the estimated factor, strong common mistake, t-statistics, p-value, and 95 percent trust period (CI), and each row represents a model-independent variable.

Table 2: OLS Regression Results table.

Feature	Coefficient	Robust SE	t	p-value	[0.025	0.975]
const	-0.559	0.118	-4.725	0.000***	-0.791	-0.327
Log EV charging points	0.055	0.025	2.209	0.027**	0.006	0.104
Log EV sales share	0.194	0.031	6.308	0.000***	0.134	0.254
Log EV stock	0.905	0.025	35.413	0.000***	0.855	0.955
Log EV stock share	-0.396	0.045	-8.745	0.000***	-0.485	-0.307

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively. The Standard Errors are heteroscedasticity robust (HC3).

The intercept of the model is negative and significant, meaning that when all predictors are zero, the expected dependent variable value is negative. A 1% increase in EV charging points is associated with a 0.055% increase in the dependent variable. The effect is statistically significant at the 5% level. Similarly, a 1% increase in the share of EV sales correlates with a 0.194% increase in the dependent variable. This relationship is strongly significant. A 1% increase in EV stock is associated with a 0.905% increase in the dependent variable. This has the largest effect and is highly significant. A 1% increase in EV stock share correlates with a 0.396% decrease in the dependent variable, suggesting a negative effect.

Table 3 shows the VIF.

Table 3: Variance Inflation Factor (VIF) Analysis.

Feature	VIF
const	20.036037
Log EV charging points	3.869944
Log EV sales share	3.275625
Log EV stock	4.786732
Log EV stock share	2.909117

Table 4 shows the model fit.

Table 4: Model Fitness.

R-squared	Adj. R-squared	F-statistic	Prob (F-statistic)
0.958	0.958	2591	2.20e-281

The variance inflation factor (VIF) analysis in Table 3 indicates that multicollinearity is manageable, ensuring the model's stability. These findings reinforce the status of EV market penetration and infrastructure expansion in generating potential EV sales adjustments. Table 4 shows the model fit. The R-squared is 0.958, which shows that the data fits the regression model well. The F-statistics (2591) indicate that the model is highly statistically significant in explaining log (EV sales).

4 DISCUSSION

The Breusch-Pagan test confirms the presence of heteroscedasticity in the model (LM Statistic = 21.1939, p-value = 0.0002898), necessitating the use of heteroscedasticity-robust standard errors (HC3) for valid statistical inference. The results from Table 2 show that all features are statistically significant, highlighting the importance of EV stock, EV stock share, and EV sales share in predicting EV sales. Despite having a statistically significant impact, the fairly minimal index of EV charging points suggests that market penetration interactions play a secondary part in EV implementation.

This research mainly analyzes the IEA Global EV Data. Although this dataset contains information on EV sales and ownership in many regions around the world, it may still have limitations in terms of geographical coverage or data segmentation. For example, the real situation of some emerging markets or countries with large regional differences may not be fully reflected. To further improve external validity, consider multi-source data integration: Integrate public databases (such as IEA (2022), BloombergNEF (2023), etc.) with official statistics released by transportation departments and automobile associations of various countries/regions to obtain more detailed and representative data. Supplement key segmentation indicators: For example, quantitative indicators such as supplementary fiscal subsidies, regional income levels, and consumer environmental awareness indexes can help explain possible unobserved heterogeneity in the model.

Although charging infrastructure exerts a statistically significant positive impact, it shows a smaller elasticity compared to EV stock and market share. This may be partly explained by the fact that consumers weigh other factors (e.g., policy incentives, vehicle cost, perceived reliability) even more heavily when deciding on an EV purchase (Coffman, Jaller, and Wee, 2017). Past studies in Norway have demonstrated that targeted incentives like free parking, road toll exemptions, and tax benefits can greatly stimulate EV uptake, particularly in the early stages of market development (Bjerkan, Nørbech and Nordtømme, 2016). Therefore, a balanced approach that combines infrastructure deployment with well-designed demand-side policies (e.g., tax rebates, direct subsidies) is essential for sustaining or boosting EV sales across different market maturity phases (Narassimhan and Johnson, 2018).

This research uses a (logarithmic) multiple linear regression model, which can effectively reveal the linear relationship between EV sales and core variables but may be insufficient when exploring more complex dynamic processes or interactive effects. Despite offering valuable insights, the current research omits certain variables like consumer preference evolution, oil price fluctuations, and vehicle resale values that could further elucidate EV adoption dynamics. Existing studies indicate that such factors, along with regional socio-economic conditions, strongly mediate EV growth trajectories (Figenbaum, 2017). Future work could broaden the dataset to include these additional covariates, employ panel or longitudinal models to capture time-lag effects, and integrate qualitative methods (e.g., consumer surveys) for a deeper understanding of behavioral nuances. This expanded scope may yield a more holistic view of how public policy, consumer sentiment, and infrastructure co-evolve in shaping the global EV landscape.

5 CONCLUSION

In summary, this research uses a multiple linear regression model with logarithmic transformation to analyze and underscores that cumulative EV stock, EV stock share, and EV sales share exert the strongest influence on annual EV sales. The paper also performs data visualization and checks for multicollinearity. Notably, the positive and significant effect of EV stock highlights how a growing fleet fuels further market growth by enhancing consumer awareness and confidence. However, the negative coefficient associated with EV stock share suggests that higher saturation levels can dampen new sales, indicating the possibility of a diminishing return once EVs become more mainstream. Although charging infrastructure plays an important role, its comparatively smaller impact points to the complexity of consumer decisions—where vehicle availability, supportive policies, and market maturity can outweigh charging accessibility. For policymakers and industry stakeholders, these findings emphasize the importance of strategically expanding EV stocks and aligning infrastructure investments with demand. Doing so will help sustain healthy sales trajectories as electric vehicles continue evolving from an emerging segment into a well-established cornerstone of global transportation systems.

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