Causal Effects of Electric Vehicles Around the World

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Introduction

In the Global EV Outlook 2024 (EVO2024), published on April 23, 2024, the IEA projected that by the end of the year, one in every five cars sold globally would be electric. Worldwide sales of this powertrain class were expected to peak at 17 million units, reflecting an increase from 18% of all car sales in the previous year. While these figures suggest a world undergoing rapid yet consistent change, they risk oversimplifying the situation, as the agency also reported that more than half of all electric vehicles were manufactured in China, a market that accounted for 60% of all EV sales during the same period.

The same report also highlighted a critical point: "The pace at which electric car sales pick up in emerging and developing economies outside China will determine their global success." While in contrasting sentiment, the New York Times quoted the director of the Center for Automotive Research in Bochum, Germany, who observed, "The Chinese are winning market share, and the Germans are losing." [1]

By the last quarter of 2024, the European Union had imposed heavy tariffs on several Chinese automakers, a move aimed at addressing a growing competitive imbalance, "starting to hit the safe places that Western carmakers had," with many European factories reportedly "making fewer cars than they were built to produce." Anton Spisak of the Centre for European Reform [2] claims that at the core of China's competitive advantage lies its lower battery production costs, a significant factor driving its dominance in the EV sector, further questioning if the EU's course of action was adequate to meet its stated goal of regaining competitiveness in the automotive industry within a five-year period.

This geopolitical and economic rivalry raises a pertinent question: if public perception exalts the triumph of EVs as inevitable, should it not be possible to explain a substantial portion of EV sales using simple macroeconomic and demographic indicators? Such a notion suggests that the EV's rise might be more easily predictable than the complexities of global competition imply. [3]

Research Question

To what extent can macroeconomic and demographic indicators predict the growth in Electric Vehicle (EV) sales across different countries, and how do these relationships vary when accounting for individual country characteristics (Fixed Effects) and unobserved country-specific heterogeneity (Random Effects)?

Methodology

To address this research question, we initially selected variables based on the criteria and methodologies outlined in [4] and [5]. Subsequently, we identified and added new variables that we believed could provide additional insights. Our first step was to evaluate the relationships among these variables, specifically checking for high correlations between any of the newly introduced variables and those from our original selection. The data for this analysis, which included electric vehicle sales, macroeconomic indicators (e.g., GDP), air pollution, and renewable energy consumption, was collected from various sources. [6] [7] [8]

The dataset was mostly complete, with very few missing entries, which were imputed using linear interpolation of the respective country's time series. We explored various mathematical transformations, such as squaring, square roots, logarithms, and first differences, to identify those that could be useful for our model specification.

We began with a baseline specification that included all academically validated variables to test different model types using statistical tests. The model that performed the best on the statistical tests was then selected, and a final specification that optimized for maximized explained variance (R^2) and minimized robust standard errors was chosen.

The models tested were Pooled OLS, Fixed Effects, Random Effects and Mixed Effects and the statistical tests were Lagrange Multiplier, Breusch-Pagan, Robust Hausman and the Breusch–Godfrey Test. When applicable, robust standard errors were computed using the covariance matrix appropriate for the statistical properties of each model.

Results

The plot shows a clear exponential growth curve with respect to the sale of electric vehicles, as we would expect, given the analysis provided by the IEA in EV Outlook 2024. This immediately placed a ceiling on the expected utility of our modelling, as exponential growth phenomena can only be approximated by linear models in the short term.

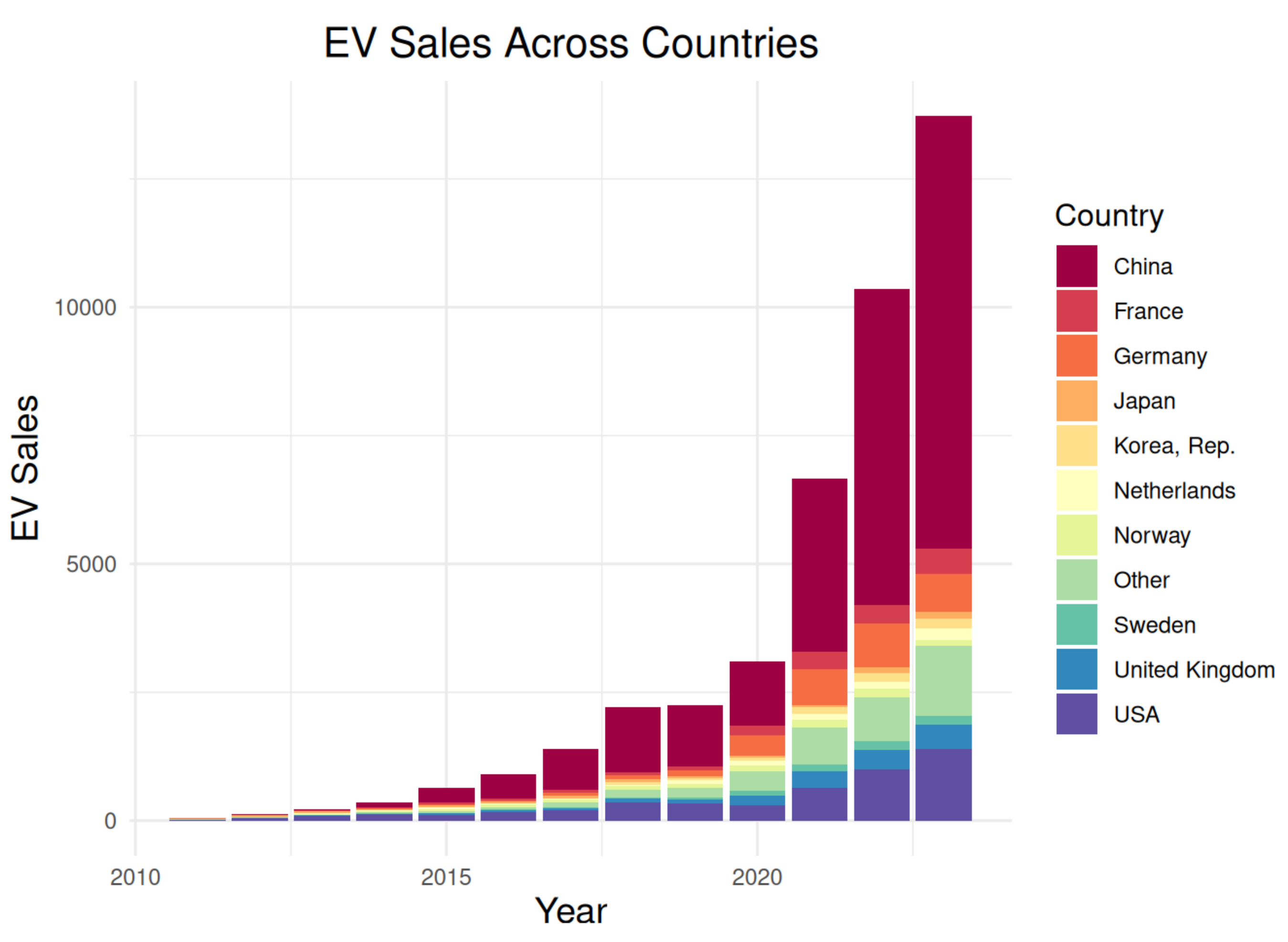

Figure 1: Figure 1 - EV Sales across countries

First, we assessed the presence of panel effects in our data applying the Lagrange Multiplier test to the Pooled OLS model. Having confirmed the presence of panel effects, we proceeded to compute the Breush Pagan and the Breush Godfrey tests for all models. We concluded that there was heteroskedasticity and residual serial correlation, independent of the model used. To account for this, we report the robust standard errors using HC3 - moderately penalizing high leverage observations - and the Arellano method specifically designed to address the computation of the covariance matrix under the assumption of heteroskedasticity and serial correlation.

Table 1 - Panel Data Analysis

Test	P-value	H0	Conclusion
Lagrange Multiplier	$1.726e^{-10}$	No Panel Effects	Has Panel Effects
Breusch Pagan (all models)	$2e^{-16}$	Homoskedasticity	Heteroskedasticity
Breusch Godfrey (all models)	$2e^{-16}$	No Residual Serial Correlation	Residuals serially correlated
Robust Hausman	0.4675	Use Random Effects	Use Random Effects

Below, we report the models results, featuring the estimators' importance.

Table 2 - Estimator importance

Model	gdp	pm25exp_square	co2emit	co2emit_diff	factor (Country)
Pooled OLS	0.03756 *	0.03184 *	$2e^{-16}$ ***	$2e^{-16}$ ***	-
FE	0.008461 **	0.009028 **	$2e^{-16}$ ***	$2e^{-16}$ ***	-
Robust FE	.05482 .	$3.377e^{-5}$ ***	$5.023e^{-5}$ ***	0.27481	-
RE	0.03691 *	0.03123 *	$2e^{-16}$ ***	$2e^{-16}$ ***	-
Robust RE	0.120033	0.020965 *	0.0007998 ***	0.361396	-
Mixed FE	$2e^{-16}$ ***	$1.653e^{-14}$ ***	$2e^{-16}$ ***	$2e^{-16}$ ***	Yes
Robust Mixed FE	$2.388e^{-6}$ ***	0.2254487	$5.123e^{-14}$ ***	0.0848060 .	Yes
Mixed RE	$2e^{-16}$ ***	$2e^{-16}$ ***	$2e^{-16}$ ***	$2e^{-16}$ ***	Yes
Robust Mixed RE	$4.551e^{-5}$ ***	0.2452769	$5.227e^{-13}$ ***	0.1347671	Yes

Table 3 - Best Model Specification

Robust Mixed FE	gdp *	pm25exp_square	co2emit *	co2emit_diff	factor (Country) *
Estimate	0.46899	0.39887	0.90779	-1.9012	Yes
Robust SE	0.097758	0.32847	0.11561	1.1	Yes

The Robust Mixed Fixed Effects (RMFE) model provided a balance between the performance of the Fixed Effects model while accounting for heteroskedasticity of the data. It was able to explain 86% of the variability (adjusted R^2 of 0.86) of the outcome variable (*evsales*), with a very high F-statistic (69.8968, 36, 348), associated with the low p-value of $2.22e^{-16}$, indicating an overall jointly statistically significant model.

Conclusions

Overall, the academically validated variables proved to be a good baseline for modelling. However, the RMFE model only showed significance for GDP and CO2 emissions, as well as intrinsic country effects, in the explanation of electric vehicles sales.

Despite the promising results, because mixed effects models are hard to compare against fixed effects models directly, under our assumptions, we fail to conclude definitively on the best model.

Regardless, these results are clear evidence that much of the variability in the sale of electric vehicles can be explained by making use of rather simple macroeconomic indicators.

Next Steps

In the future, this work would greatly benefit of testing mixed effects linear regression models using a more dedicated library, such as *lme4*, or even other types of non-linear regression models.

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