POLITECNICO DI TORINO

Master's Degree in Management Engineering

Master's Degree Thesis

"Understanding the Drivers of Electric Vehicle Demand: A Cross-Country Analysis"

Supervisor **Candidate**

Prof. Francesco NICOLI **Doga GUNGOR**

October 2025

Acknowledgements

Firstly, I would like to express my gratitude to my supervisor, Prof. Francesco Nicoli, for his guidance and encouragements which were crucial for me to keep going during the preparation of this thesis.

I want to thank Nurcanim and Murat, for being the best parents I could ever ask for. At each step of my journey, I know you are there for me. Even if it includes moving kilometers away from home when I was only 17. I know that my dreams are also your dreams and always will be.

Next, I want to say thank you for everyone who made Torino my second home in these last 6 years. In good days and in bad days, always sticking together and moving ahead. Thank you especially Pinpin, you became my sister who I met after 17 years of my life and one of the most important pieces of my university life.

Lastly, I also have to thank to myself, no? Good job! We did it!

Abstract

The global transformation toward sustainable mobility has made Electric Vehicles (EVs) an important tool for decreasing transport-related emissions. Yet EV adoption rates are not homogeneous and differ across countries, shaped by many economic, political, and infrastructural conditions. This thesis focuses on the factors affecting EV Market Share using a panel dataset consisting of 38 countries over a ten-year period from 2013 until 2023. A fixed-effects regression framework has been chosen in order to control for country-specific heterogeneity and examine the role of income, income inequality, public charging infrastructure, EV-supportive policies, and gasoline prices.

The obtained results show that higher income levels and availability of public charging points significantly increase EV adoption, while inequality does not display a direct effect on Market Share. Gasoline prices are also a strong driver, with increasing prices accelerating the shift away from traditional internal combustion vehicles. The effectiveness of EV-supportive policies resulted as uneven: in high-income countries they complement each other with gasoline price signals and already established baseline infrastructure, while in low-income contexts the infrastructural investment show stronger results than policies. Robustness checks reveal an inverted-U relationship between charger density and EV Market Share, suggesting diminishing returns in wealthier regions, while no saturation point is observed in lower-income countries.

These results emphasize that EV adoption is shaped by both structural and socioeconomic contexts. The study provides empirical evidence that strategic decisions should be tailored by optimizing the location of infrastructure and proposing related incentives in high-income regions, and prioritizing infrastructure expansion in low-income regions, to accelerate the global EV transition.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction & Literature Review

Over the last decade there has been a significant shift in global sustainability goals and efforts. The concept of 'sustainability' has evolved significantly from being a secondary concern of some specific industries to a central pillar of global policymaking. Governments, institutions, and private sectors are intensifying their efforts every other day to mitigate, or at least slow down, the outcomes of climate change. As Singh (2022, p. 944) mentions, "*changes in the global climate are a manifestation of unsustainable development, specifically resulting from our dependence on fossil fuel-based energy sources,"*. This points out how the current reliance for carbon-intensive energy sources accelerates the negative trend, thus a transition to more sustainable options is crucial.

The transportation sector alone is responsible for approximately 23–25% of global energy-related CO_2 emissions, with around 75% of this coming from road transport such as cars, trucks, or buses (IEA, 2023; IPCC, 2022). It is important to keep an eye on this sector in order to reach the globally set targets and goals. As an action plan, **Electric vehicles (EVs)** are strongly promoted to decrease transportation-related emissions. According to the International Energy Agency (IEA) projections, the total number of electric vehicles in the world is expected to reach 250 million in 2030 and 525 million in 2035. As a result, more than one in four cars running on the streets is expected to be electric by 2035 (Cui and Zhao, 2024).

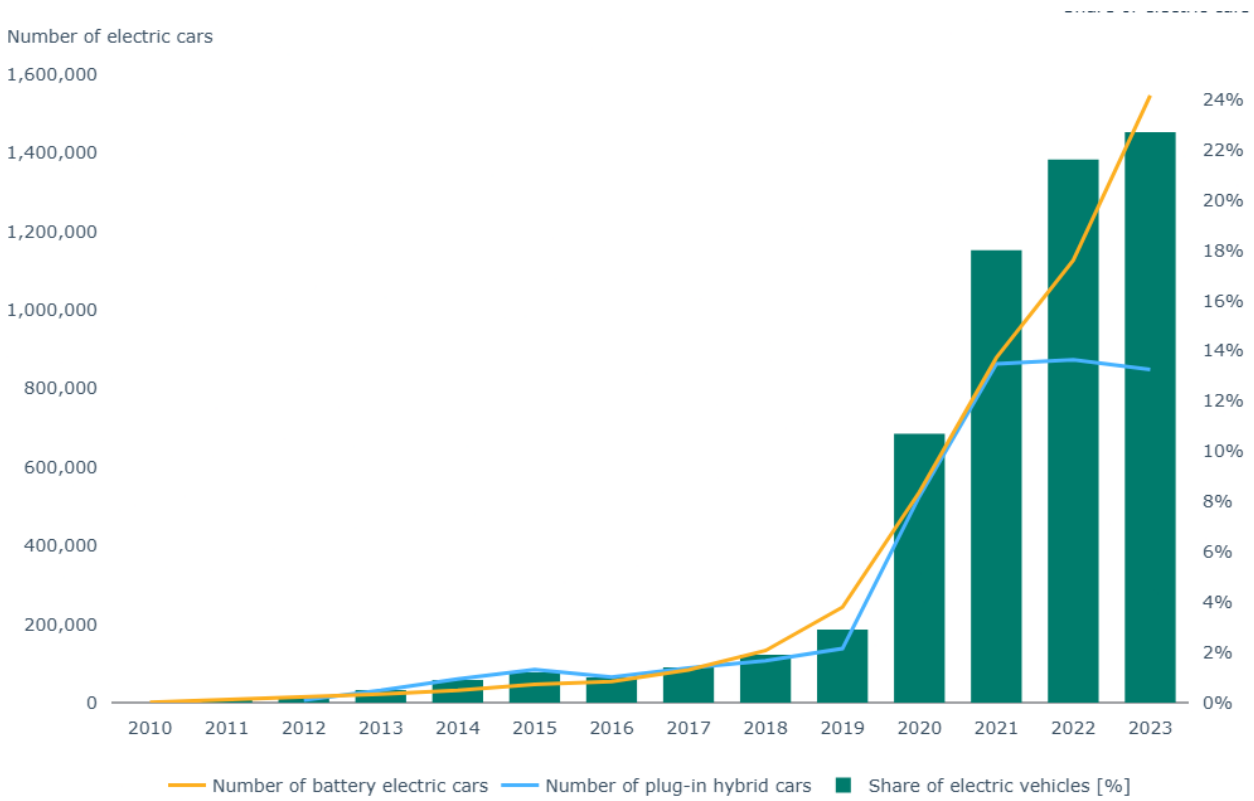


Figure 1: Share of newly registered battery cars in the EU-27 (2010-2023) Source: European Environment Agency (2024)

Paris Agreement, as the first binding agreement bringing all nations together to combat climate change and its effects, states its goal as "*To hold the increase in the global average temperature to well below 2°C above pre-industrial levels*" and pursue efforts to "*limit the temperature increase to 1.5°C above pre-industrial levels*." It is noted that, in order to reach these goals, greenhouse gas emissions must decline 43% by 2030 (UNFCCC, 2024).

Several of United Nations Sustainable Development Goals (SDGs) can also be considered directly linked to the decarbonization of transportation. SDG 7 with the goal of affordable and clean energy, SDG 11 with sustainable cities and communities, and SDG 13 with climate action are underscoring the need to make transformative changes urgently. Each of these goals are supporting EV adoption as a pathway to reversing the climate change (European Guanxi, 2023).

However, EV adoption has not been consistent worldwide, despite rising awareness and support. While some countries have rapidly increased their EV usage, thus becoming less dependent to carbon-intensive energy sources, others are continuing to face probable barriers such as high costs, limited access to charging networks, or lack of policy support. This uneven progress across different countries forms a fundamental research question:

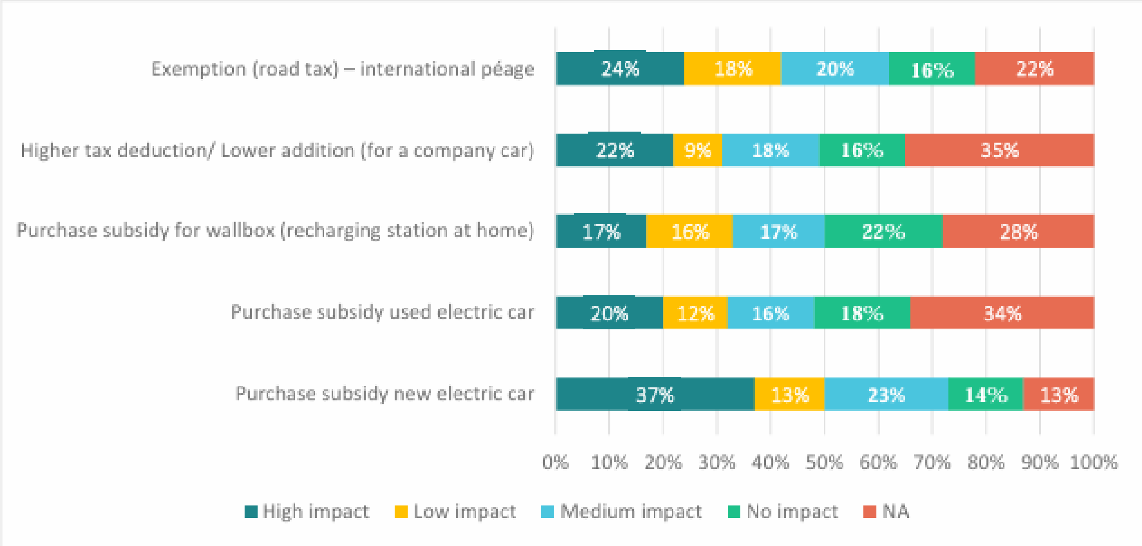
What drives the demand for EVs, and why does it vary so significantly across the world?

This thesis aims to investigate more deeply the effect of various factors, such as income, inequality, EV-supportive policies, infrastructure, and price of gasoline on EV Market Share. The chosen methodology is to apply an econometric analysis across multiple countries from 2013 to 2023, for a 10-year timeframe, aiming to research the EV transition pace.

Without any doubt, income is considered as one of the most important and obvious predictors for increasing EV adoption. A national-level study by Zou et al. (2024) demonstrates that wealthier populations tend to adopt green technologies earlier, while lower-income groups often face financial barriers that delay their participation in the transition. For instance, studies conducted in the United States indicate that sociodemographic factors, especially household income, has a significant effect on EV ownership trends (Sadeghvaziri et al., 2024). Similarly, in India, both per capita income and GDP have been associated to growing EV Market Share (Socio-Economic and Demographic Factors Affecting Adoption of Electric Vehicles in India, 2024), with wealthier regions such as Uttar Pradesh exhibiting stronger adoption patterns (Vyas and Kushwah, 2023). Even in highly developed EV markets such as Norway, the study shows that higher-income households are more likely to own multiple EVs, indicating a concentration among wealthier segment (Qorbani, Korzilius and Fleten, 2024).

When it comes to income inequality, according to the *World Inequality Report 2022*, the richest 10% of the population receives 52% of global income, while the bottom half earns just 8.5%. In the Middle East and North Africa (MENA), the top 10% hold as much as 58% of income, compared to 36% in Europe (WIR, 2022). These differences also lead to unequal access and adoption of sustainable solutions like EVs. As explained by Büchs and Schnepf (2013), lower-income segment is further away to invest in green technologies due to cost and information gaps. Aghion et al. (2019) also confirm that higher inequality can slow or even block the adoption of innovation.

EV-supportive policies are another important tool for increasing the adoption rate, especially in the early phases. As can be seen from Figure 4, there are different types of incentives with different levels of effectiveness according to European drivers surveyed. According to survey results, the most impactful type of policy seems to be purchase subsidies for new electric vehicles, followed by the exemption from road tax. While the least impactful policy results as the purchase subsidies for recharging stations at home, called wallbox.



Source: EAFO Consumer Monitor and Survey 2023.

Figure 2: Perceived impact of governmental incentives on EU drivers' decision to drive a full-battery electric vehicle. Source: EAFO Consumer Monitor and Survey (2023)

There are many researches done about this idea of government policies increasing the adoption of EV. Rietmann and Lieven (2019) analyzed 20 different countries and found that higher level and number of political incentives are leading to higher percentage of EV in that country. This pattern is mentioned also by Patil et al. (2024), who emphasize that subsidies, regulations, and supportive laws have helped to make EVs more financially accessible and attractive, especially when compared to internal combustion engine (ICE) vehicles. Countries like Norway, China, the USA, the EU, and India are highlighted as primary examples for this study. Similarly, Gao et al. (2023) support that environmental policies and financial incentives have been instrumental in growing the market for EVs. All together, these examples are highlighting that EV-supportive policies are essential for increasing EV adoption.

"Range anxiety" is one of the most significant mental barriers for drivers when switching from ICE vehicles to EVs. It is defined as the fear of being left on the road with an empty battery where there is no charging station (Dharmakeerthi et al., 2013). This concern was first pointed out in General Motor's project in 1997, and many studies have been done on this topic since then (van Haaren, 2011). Pevec et al.

(2019) argue that range anxiety is an important obstacle and addressing this anxiety requires strategically expanding the charging infrastructure. Similarly, Hou et al. (2024) found that, across U.S. states, the number of charging stations had the largest effect on EV Market Share, even more than income or education level. Together, these findings reinforce the positive impact of public charging points on EV adoption by reducing the range anxiety and boosting trust on EVs.

Fuel prices, especially gasoline, are a key variable for increasing EV Market Share. As highlighted by Peterson (2024), price fluctuations in fuel markets significantly influence purchasing behavior, with many consumers shifting toward fuel-efficient or electric vehicles when gasoline costs rise. Also Bushnell et al. (2022) found that, in regions like California, gasoline prices have a significantly greater impact on EV adoption, more than the impact of electricity prices. From another point of view, Mutascu et al. (2024) show that short-term drops in oil prices can temporarily reduce consumer interest in electric vehicles. These studies further confirm that increasing gasoline prices push customers to choose more affordable options like EVs, accelerating the transition to sustainable mobility.

In summary, as can be understood from the reviewed literature, there are multiple drivers affecting the rate of EV adoption. Higher income levels reduce the existing financial barriers and make investing in EVs easier for customers. In contrast, inequality can hinder the adoption of more sustainable green technologies by limiting the access for the segment with lower income. Governmental EV-supportive policies, especially purchase subsidies for new electric cars, are seen as vital catalysts for increasing market share. Investing in a strong infrastructural base is also found to be essential when trying to combat the so-called range-anxiety of drivers, mentioned by many papers as a crucial barrier. Last of all, changes in gasoline prices have an important impact on consumer behavior and decision-making process, pushing drivers to more cost-effective solutions. Together, all these variables demonstrate that EV adoption is a complex phenomenon and can be influenced by many factors. This thesis empirically analyzes the significance of all the variables in varying scenarios, in order to have a broader understanding of EV market characteristics and dynamics.

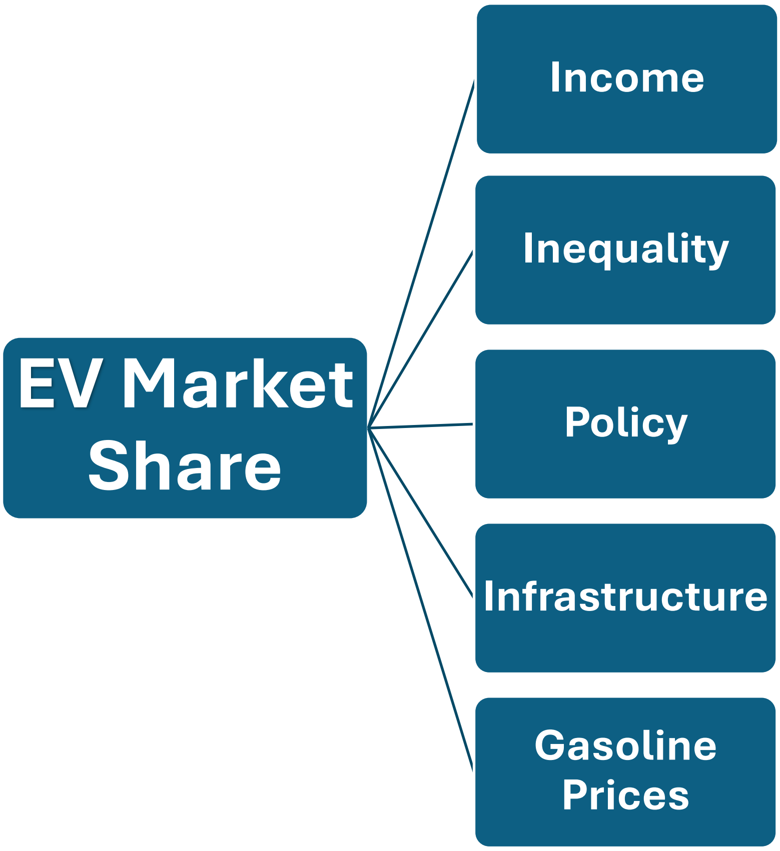


Figure 3: Main Variables Affecting Electric Vehicle Market Share

Chapter 2

Methodology and Research Method

For this thesis, a quantitative research approach will be adopted for examining the determinants of the market share percentage of electric vehicles (EVs) across 38 countries around the world over the years 2013-2023.

In order to address the research question, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Croatia, Czechia, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, India, Israel, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Turkey, UK and, US have been chosen for panel data. The idea behind this country selection strategy is preventing focusing only on one single geographic region of the world, which might show similar economic, policy, or infrastructural conditions with each other and, as a result, similar EV adoption rates. Instead, gathering data from different countries on different continents provides a broader perspective from all around the globe. This approach helps to make the study more comprehensive and decreases the possibility of regional bias, enabling meaningful cross-country comparisons. This way, the study allows for the examination of electric vehicle market dynamics across diverse socioeconomic and institutional contexts.

According to research company BloombergNEF, countries typically cross the electric vehicle (EV) “tipping point” when EVs account for at least 5% of new car sales (Randall,2022). This threshold is a sign of concluding the early adopter phases and start of mainstream adoption, often followed by a period of accelerated growth. In 2013, Norway became the first country to reach 5% threshold value and entered so-called “early maturity phase” of EV market (Ferris,2022).

Therefore, selecting 2013 as the starting year allows the analysis to begin at an important moment when EV adoption began transitioning into a new phase, one in which alternative-fuel electric vehicles were no longer seen as novel innovations, but instead became increasingly integrated into daily life of people. By concluding the study in 2023, a full decade of data is captured, which is a logical time frame to notice the changes in consumption behavior and trends.

The fixed-effects (FE) panel regression model has been chosen instead of the random-effects (RE) model. The logic behind this choice is that random-effects model is more straightforward while fixed-effects model controls for time-invariant heterogeneity between selected countries, such as cultural differences, variations in governance structures, or other conditions. If one believes that the country-specific effects can be treated as random noise and will not affect the outcome of the research question, random-effects model can also be adopted. But this is often an unrealistic assumption while investigating cross-country data. Without the use of fixed effects model, mentioned drivers can easily cause a bias for the results. By controlling these country-specific heterogeneities, the model isolates the effect of time-variant factors and provides more robust outcomes for the relationship between independent and dependent variables.

The dependent variable in this model is defined as the Market Share of electric vehicles measured every year for specified time frame. The target is monitoring the change of EV adoption and trying to come up with a common pattern across countries, despite having different backgrounds.

Meanwhile, the independent variables are chosen to resonate the difference in backgrounds mentioned:

1- **Income:** Measured as net average annual earnings of a full-time worker without children. This variable, sourced from Eurostat, indicates the average purchasing power. Given that, as of 2023, electric vehicles still had higher upfront purchase prices than their internal combustion engine (ICE) counterparts (IEA, 2024, p. 35), purchasing power thus justifies its important role as a critical factor influencing the EV Market Share. For modeling purposes, net average annual earnings are divided by 1000, which permits a clearer interpretation of regression coefficients.

2- **Gini Coefficient:** This index reflects the distribution of income of a country, ranging from 0 in case of perfect equality to 1 meaning full inequality. The study targets to investigate if high inequality creates a barrier of entry among households with lower income, or whether the wealthier segment can offset and result in high overall adoption of EV at country level. The coefficients are collected from *Our World in Data.*

3- **Policy Positive:** This is the only binary variable included in the model. It is coded as 1 if there exists at least one EV-supportive policy, like purchase incentives or tax reductions, in specified country and year. If no such policy is present, the index is equal to 0. The necessary information are sourced from *Our World in Data*. It is crucial to note that Policy Positive index gives an understanding about the presence or absence of the policy support from government and not the type, scope, or intensity.

4- **Infra1000:** Defined as the number of publicly accessible charging stations, both slow and fast, divided by 1000. This variable reflects the infrastructure accessibility, especially to recharge the battery of EV during longer travels. While the variable captures the number of public chargers, it does not contain information regarding geographical distribution. So, it does not analyze if they are more concentrated in bigger cities or equally dispersed. The division by 1000 extends the scale and helps interpret the regression coefficients easily.

5- **Gasoline Liter:** This variable is measured as the annual average price of one liter of gasoline in euros. Similar to the other independent variable Income, also this variable has a significant role while researching cost-driven substitution behavior between ICE vehicles and EVs. The Total Cost of Ownership (TCO) refers to all financial costs occurring during the whole lifetime of the product. So, it does not only consist of the purchase price but also possible maintenance or fuel costs. Logically, higher gasoline prices per liter increase the TCO of ICE vehicles and may increase interest in EV's, therefore leading to higher Market Share.

Together, this model structure provides a refined understanding of how EV Market Share evolves in response to economic situation, policy interventions, and infrastructural base, while controlling country-specific traits. The main questions investigated are as follows:

- Do higher income levels lead to greater EV adoption?
- Does income inequality, as measured by Gini Coefficient, accelerate, hinder, or have no direct effect on EV market growth?
- To what extent is the trend in EV Market Share influenced by policy support from government?
- Is there a significant relationship between number of available public charging points and EV Market Share?
- Are annual average fuel prices a significant driver of EV adoption?

Table 1: Description of the Main Variables

Variable	Unit of Measure	Symbol	Type
Market Share	% of total car sales	MarketShare	Dependent
Income	€ / 1000	Income	Independent
Gini Coefficient	0 to 1	GiniCoef	Independent
Policy Presence	Binary (0=No, 1=Yes)	PolicyPositive	Independent
Number of Public Charger Points	Number of charger points / 1000	Infra1000	Independent
Gasoline Price	€ / liter	GasolineLiter	Independent

In the next phases of analysis, three additional variables are introduced in order to address longer-term and possibly non-linear trends of infrastructural development on EV adoption. These independent variables are named as Infrastructure_lag, ChargerDensity, and ChargerDensity_sq. They serve as additions to the initial model and examined as a robustness check, and supplementary analysis. As they were not part of the original core model, they are not included in Table1 above, however it is important to include the definitions in order to understand the dynamics explored later on.

1- **Infrastructure_lag**: This variable captures the delayed effect of public charging infrastructure by using the one-year lag of Infra1000. The inclusion of this independent variable allows the model to observe whether the effect of new public charging points has a specific time delay rather than immediate results. This analysis provides valuable insights for authorities while considering the timing of returns on investments made.

2- **ChargerDensity**: This variable measures the number of publicly accessible EV charging stations relative to a country's land area (in chargers per km²). Unlike Infra1000, which reflects the scaled absolute number of chargers per 1,000 units, ChargerDensity adds another dimension to this study by capturing the dispersion of installed charging stations across the country. This distinction provides a more refined analysis of accessibility and regional equity.

3- **ChargerDensity_sq**: To explore potential diminishing returns of infrastructure expansion, the squared term of ChargerDensity is added. This variable helps to investigate if there exists a possible saturation point, where the marginal effect of additional chargers begins to decrease. A statistically significant and negative coefficient of ChargerDensity_sq would support the hypothesis of the explained relationship, in which infrastructure expansion has a positive effect up to a certain point but loses effectiveness thereafter.

Table 2: Description of the Additional Variables

Variable	Unit of Measure	Symbol	Type
Number of Public Charger Points (Lagged)	Number of charger points / 1000 (previous year)	Infrastructure_lag	Independent
Charger Density	Chargers per km^2	ChargerDensity	Independent
Charger Density Squared	(Chargers per km^2)^2	ChargerDensity_sq	Independent

Subscripts of regression equations

Before introducing empirical results, it is important to explain a few points about what a regression is and how one can comment on the outcomes. Regression analysis is a statistical method that helps quantify the relationship between a dependent variable and one or more independent variables. It allows researchers to estimate how changes in the explanatory variables are associated with changes in the outcome of interest, while controlling for other influencing factors (Frost, 2019).

In each regression, as in the example below, the subscript i refers to country while t refers to time variable, which in this case presents the year. This way, the model can account for the EV Market Share changes within each country over time. β_1 gives an idea about the extent of change each independent variable, like GasolineLiter or PolicyPositive, creates on the dependent variable. α_1 represents the fixed effects, while ϵ is the error term including all the other factors, not consisted in the model, that still influence EV market share.

$$MarketShare_{it} = \beta_1 X_{it} + \alpha_i + \epsilon_{it} \text{ (1)}$$

While interpreting each regression, the statistical significance is determined by looking at p-values. A p-value below 0.05 is commonly accepted as the threshold for statistical significance (Field, 2013). If p-value satisfies this threshold, the result is considered as "statistically significant", which mean the relationship between dependent and independent variables is unlikely to have happened by accident or luck.

On the other hand, if p-value is more than 0.05, the result is defined as "not statistically significant". In such situations, the outcome needs to be analyzed with proper attention. Even if the coefficient seems remarkable, it can just be due to a random variation.

Chapter 3

Empirical Results

This chapter consists of three subsections. At the first part, the effects of EV-supportive policy and charging infrastructure are analyzed separately. The aim of this distinction is the fact that increasing the number of public chargers on the road can also be interpreted as a government-led policy for promoting the use of EV's. For this reason, focusing on these two variables independently allows for a more specific understanding of their contributions.

In order to explore more if the socioeconomic situation of each country causes a positive or negative variation, the panel data is divided into 2 subgroups for every year from 2013 to 2023. If a country has net average earnings more than median, it is labeled as "High-income". On the contrary, if below than median, it is categorized as "Low-income".

In the second subsection, with the aim of deepening the analysis, regression models which investigate the interaction terms between key independent variables are performed. For the first subsection, the individual impacts of Policy Presence, Infrastructure, and Gini Coefficient are observed, while for the second part the focus is on whether the effect of one independent variable depends on another. As an example, the interaction between Policy Presence and Infrastructure explores if the presence of a supportive government legislation increases, or possibly decreases, the effectiveness of public charging point availability in enhancing EV adoption. By investigating also these interactions, the analysis can uncover the underlying dynamics that might remain hidden in additive models.

As the final step of this empirical analysis, third subsection investigates the trends of EV Market Share with respect to infrastructure development level. The previous models from first and second subsections focus on the role of policies, direct infrastructure availability, and their interactions, while this subsection introduces additional variables to explore the topic more profoundly. The purpose is to understand whether infrastructure effects are immediate or delayed, and whether the expansion of public charging points continues to have a linear relationship with EV adoption or is there a saturation point. These models also address effects in case of different income contexts just like in the first subsection.

3.1 Individual Impacts of EV Policy and Charging Infrastructure

3.1.1 General Regression with Policy Model

$$MarketShare_{it} = 2.00 \cdot PolicyPositive_{it} + 0.20 \cdot GiniCoef_{it} + 15.83 \cdot GasolineLiter_{it} - 26.16 + \alpha_i + \epsilon_{it} \quad (2)$$

Table 3: General Policy Regression Results

Variable	Coef.	Std. Err.	t	P > |t|	95% Conf. Interval
PolicyPositive	2.00	1.05	1.90	0.07	[-0.20; 4.21]
GiniCoef	0.20	0.65	0.31	0.76	[-1.15; 1.56]
GasolineLiter	15.83	2.62	6.04	0.00	[10.35; 21.31]
Cons	-26.16	21.00	-1.25	0.23	[-70.13; 17.80]

The first regression result suggests that having an EV-supporting policy in action is associated with a 2.00 percentage point increase in EV Market Share. It is important to note that this effect is only marginally statistically significant with p=0.07, which suggests a positive relationship, but with weaker statistical confidence compared to other variables.

The Gini Coefficient does not show a statistically significant (p=0.604) effect on EV Market Share, even if the positive coefficient results equal to 0.20.

The most significant effect comes from Gasoline Price, both in terms of coefficient magnitude and p-value significance. A one euro increase in the liter price of gasoline is linked with 15.83 percentage point increase in EV Market Share. This outcome aligns with the economic principle of cost-driven substitution: if and when traditionally used fuel gets more expensive, vehicle-owners start considering getting an EV and saving money in the long term. The operating costs play a critical role during consumers' decision-making process.

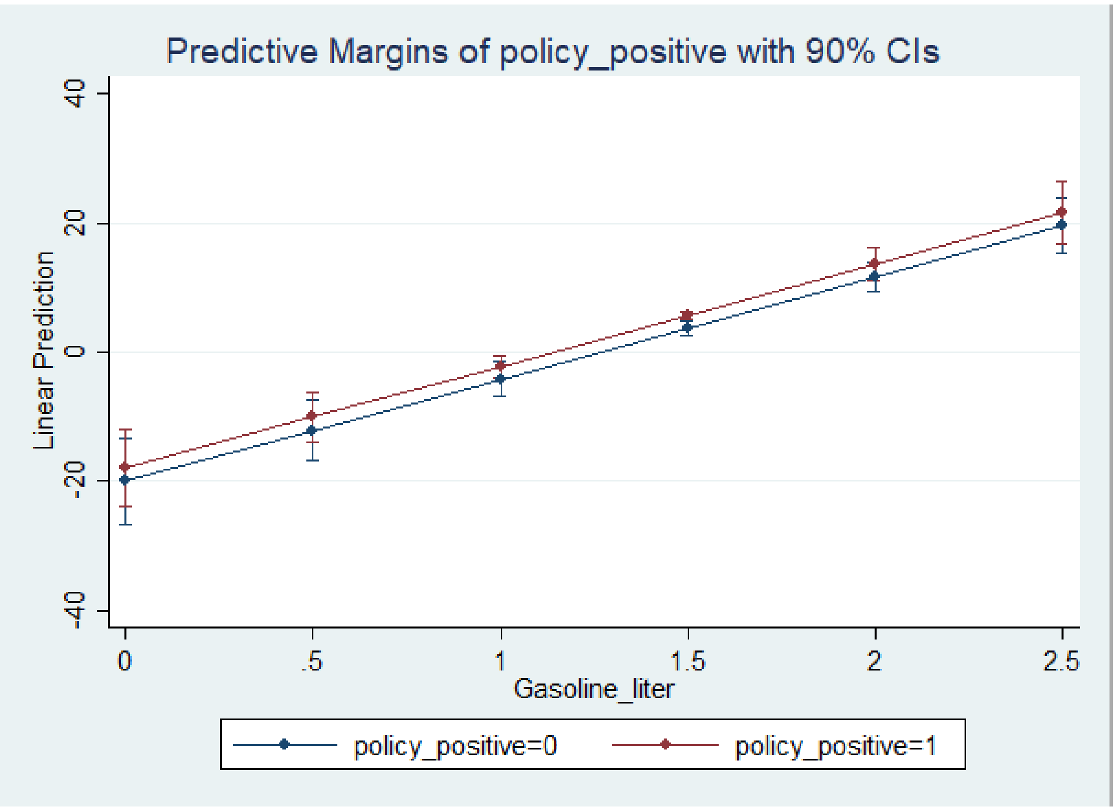


Figure 4: Predictive Margins of GasolineLiter and PolicyPositive on Market Share

As can be observed from the figure above, the main driver for Market Share is the Gasoline Price with a linearly increasing relationship. Additionally, when the binary variable for Policy Presence is equal to 1, the expected EV adoption is higher but marginal difference between policy and no-policy cases is only moderate. This result further indicates that policy has a positive effect, however, its impact is less influential than fuel prices for this regression.

3.1.2 General Regression with Infrastructure Model

$$MarketShare_{it} = 0.196 \cdot Infra1000_{it} + 0.20 \cdot GiniCoef_{it} + 10.11 \cdot GasolineLiter_{it} - 18.7 + \alpha_i + \epsilon_{it} \quad (3)$$

Table 4: General Infrastructure Regression Results

Variable	Coef.	Std. Err.	t	P > |t|	95% Conf. Interval
Infra1000	0.19	0.02	9.04	0.00	[0.15; 0.24]
GiniCoef	0.20	0.39	0.54	0.59	[-0.56; 0.98]
GasolineLiter	10.11	1.59	6.35	0.00	[6.97; 13.25]
Cons	-18.70	12.46	-1.5	0.13	[-43.29; 5.88]

The second general regression focuses on the effect of existing public charging infrastructure, together with two other independent variables, Gini Coefficient and Gasoline Price over a 10-year period.

Infrastructure with p=0.00 reveals a very strong and significant effect on EV Market Share. The coefficient indicates that for every 1000 public chargers installed by the government, the Market Share increases by 0.196 percentage point. Although a major increase of available chargers is needed to achieve a noticeable effect, it is important to emphasize that the relationship between Infrastructure and Market Share is significant and positive. The robust significance of this result can address one of the biggest barriers to EV adoption for customers, which is so-called ‘range anxiety’ explaining the concerns regarding the uncertainty about battery range and finding a charging point creating a mental burden for drivers. The existence of a well-developed charging network can decrease this concern, and as a result can promote EV adoption.

Again, like the first case, the Gini Coefficient has a p-value much higher than 0.05. It shows that, any direct link between inequality and EV adoption is not robust also in this equation. For both general equations with policy and infrastructure as independent variables, inequality is an irrelevant factor. The EV market is more responsive to economic factors like cost and structural situation like the number of chargers rather than distributional metrics. It is highly likely that inequality indirectly influences other significant independent variables; however, no direct relationship between inequality and the dependent variable can be observed.

Also Gasoline Price exerts a statistically significant effect with p=0.00. A one-euro price increase is linked with 10.11 percentage point increase. This shows a similar but slower trend with respect to the first general regression as can be observed from Figure 5 and Figure 6 below, still emphasizing the importance of fuel costs. The possibility of having lower Total Cost of Ownership (TCO) attracts people despite the higher initial investments required and increases the adoption rate of EV as a result.

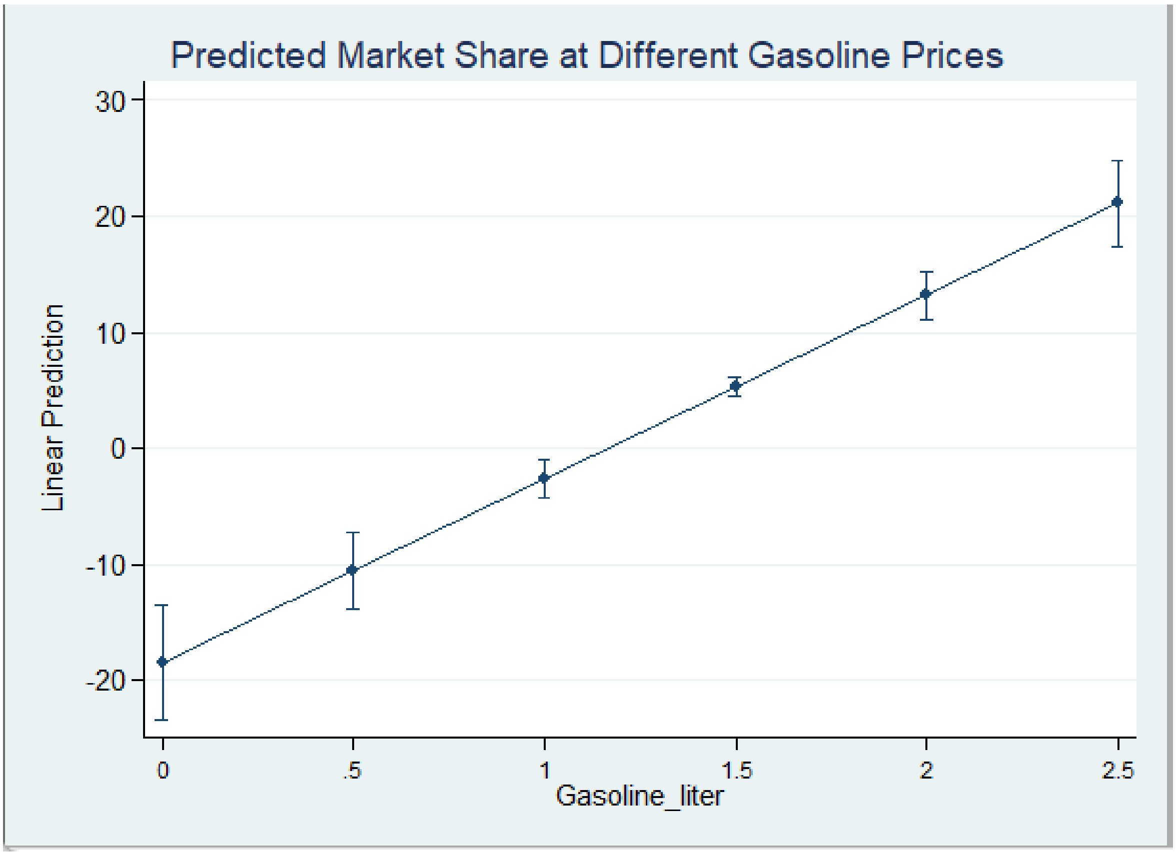


Figure 5:Predictive Margins of GasolineLiter for General Regression with Policy Model

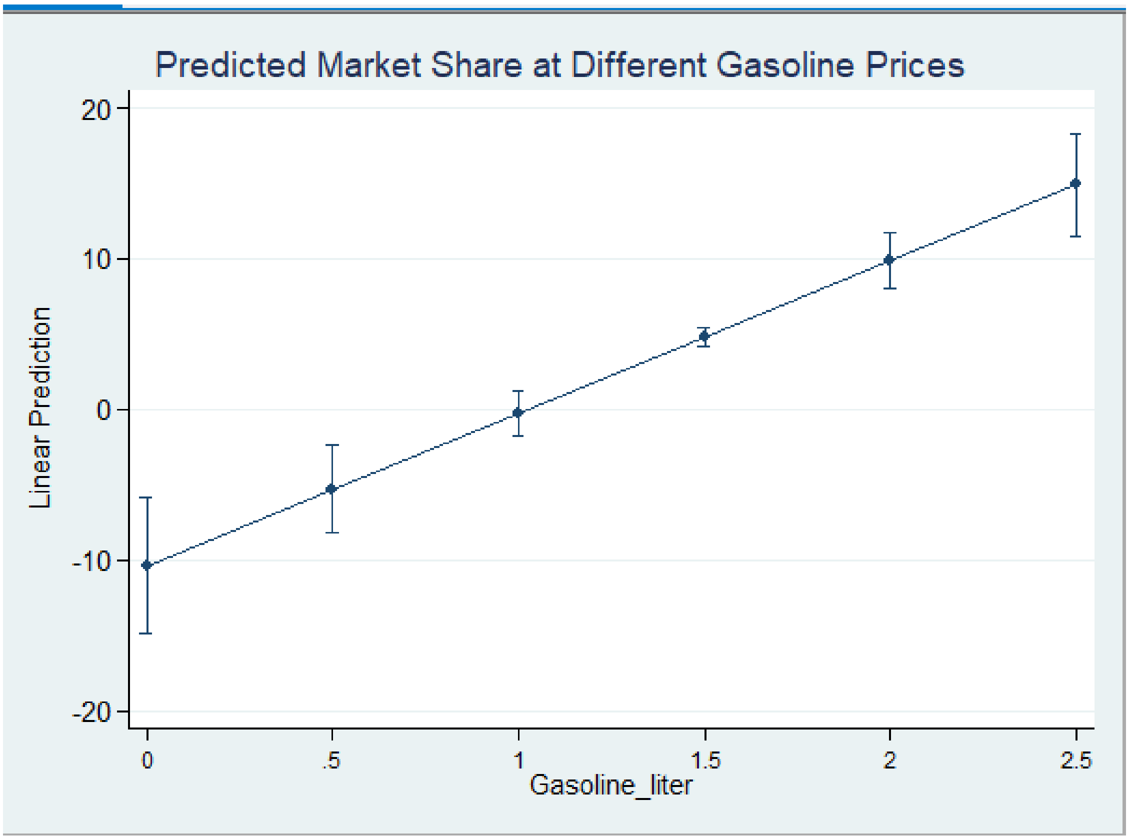


Figure 6:Predictive Margins of GasolineLiter for General Regression with Infrastructure Model

3.1.3 Regression with Policy Model for High-Income Countries

$$MarketShare_{it} = 4.31 \cdot PolicyPositive_{it} - 0.70 \cdot GiniCoef_{it} + 23.48 \cdot GasolineLiter_{it} - 11.8 + \alpha_i + \epsilon_{it} \; (4)$$

Table 5: High-Income Policy Regression Results

Variable	Coef.	Std. Err.	t	P > |t|	95% Conf. Interval
PolicyPositive	4.31	2.19	1.97	0.05	[-0.06; 8.68]
GiniCoef	-0.70	1.25	-0.57	0.57	[-3.20; 1.78]
GasolineLiter	23.48	3.11	7.53	0.00	[17.28; 29.69]
Cons	-11.80	37.63	-0.31	0.75	[-86.79; 63.19]

After conducting two general regressions using the panel data from all countries chosen for this study, further investigation is performed by categorizing regions based on their incomes. This division has been performed separately for each year from 2013 to 2023. As an example, for 2023, Austria is classified as "High-Income" while Bulgaria belongs to "Low-Income" category. Furthermore, a country classified as low-income can shift to high-income or vice versa according to next year's median income level. Just like Croatia, being labeled as "Low-Income" from 2013 until 2022, shifts to "High-Income" in 2023. The first specific regression considers the wealthier group and focuses on the Policy Presence along with Gini Coefficient and Gasoline Price.

Similarly to the first general regression, the coefficient for the variable PolicyPositive is positive and only marginally significant with p=0.053 (compared to 0.073 in the first regression). When an active policy is in place, the adoption of EV increases 4.31 percentage points. This is more than double the 2-percentage point increase of general regression observed before. Also having a lower p-value addresses a more significant relationship. The comparison between two regressions makes it possible to prove that the effectiveness of EV-supportive policies varies with the country's net average earning. Just like Sierzchula et al. (2014, p. 183) observed, "*Financial incentives and* *income levels significantly affect electric vehicle adoption*." and that wealthier countries are more prone to utilize the benefits of policies offered. Similarly, Gnann et al. (2018, p. 360) emphasize that "*Income levels and well-enforced policies jointly drive EV adoption*." Both the literature and results of the regressions point out the importance of tailoring EV policies based on the economic situation of country.

Once again, the Gini Coefficient has a higher p-value (p=0.573) than the expected threshold for statistical significance at the 95% confidence level. The inequality is not direct driver, also at high-income countries, when policy and gasoline prices are accounted for.

The Gasoline Price has a coefficient of 23.48, with a high statistical significance (p=0.00). This result means that for every one-euro price increase, the EV Market Share has 23.48 percentage point increase. This is even higher than the increase in the first general regression which had a coefficient of 15.83. In wealthier regions, the effect of higher fuel prices for ICE vehicles motivates drivers to consider alternative fuel options even more. This can be explained by lower financial barriers to EV ownership due to average higher income. As Li et al. (2017, p. 109) state, "*Higher income levels reduce the relative burden of the higher upfront costs of electric vehicles, enabling wealthier consumers to respond more effectively to incentives and price signals*."

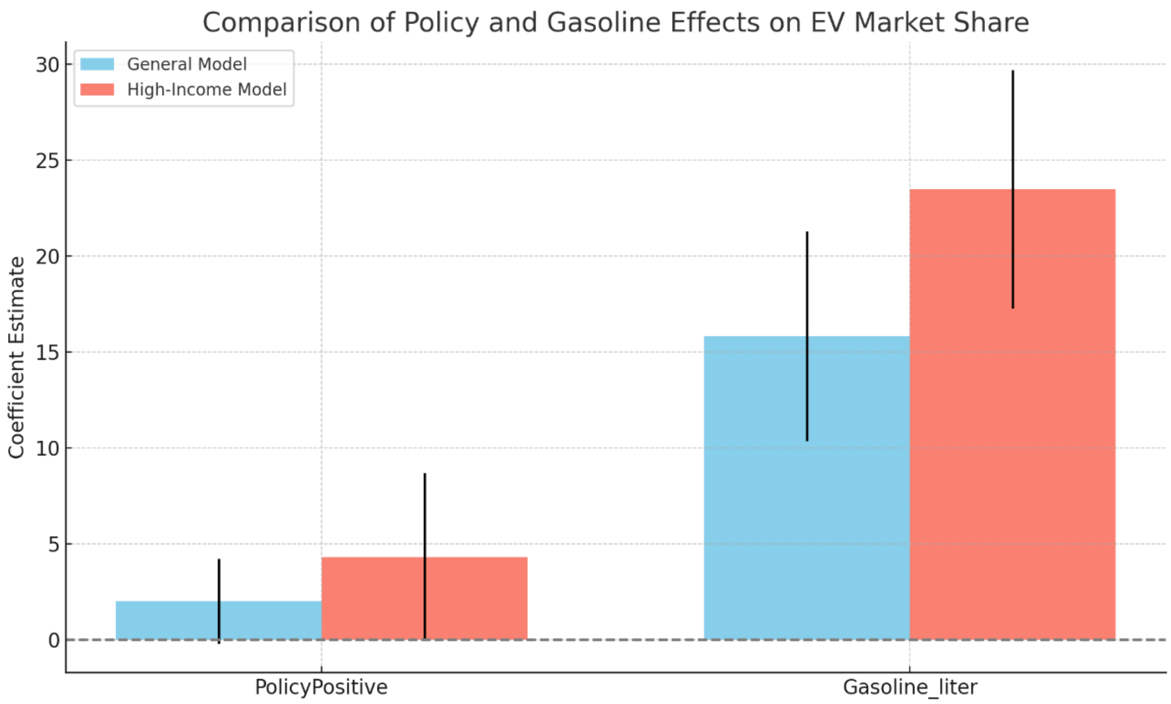


Figure 7:Coefficient Comparison of Policy Support and Gasoline Price in General vs. High-Income Models

As a summary, the regression focused on high-income countries reveals that the most important driver is the fuel prices. The effect of Policy Presence is also positive and more significant with respect to general regression, however it is still only marginally significant. This suggests that in wealthier contexts, people are more responsive to direct economic incentives, like savings from fuel costs, than to policies. It can be the case that EV-supportive policies are already established and relatively uniform in these countries. As a result, the impact of policy may be less noticeable in the data. It is also possible that policy may help establish trust for government in long term but not immediate. Overall, the findings point that expected TCO and purchasing power play a noteworthy role than Policy Presence alone in EV Market Share trend within high-income regions.

3.1.4 Regression with Policy Model for Low-Income Countries

$$MarketShare_{it} = 0.35 \cdot PolicyPositive_{it} - 0.32 \cdot GiniCoef_{it} + 6.24 \cdot GasolineLiter_{it} + 3.22 + \alpha_i + \epsilon_{it} \quad (5)$$

Table 6: Low-Income Policy Regression Results

Variable	Coef.	Std. Err.	t	P > |t|	95% Conf. Interval
PolicyPositive	0.35	0.67	0.52	0.60	[-0.98; 1.69]
GiniCoef	-0.32	0.26	-1.24	0.22	[-0.84; 0.19]
GasolineLiter	6.24	1.13	5.53	0.00	[3.99; 8.48]
Cons	3.22	8.72	0.37	0.71	[-14.09; 20.53]

As the second step of income-based analysis, the focus is now on lower-income countries. Same as before, the independent variables are Policy Presence, Gini Coefficient, and Gasoline Price investigating the impact on EV Market Share.

The coefficient of PolicyPositive is 0.35, with a p-value higher than 0.05 (p=0.60), exceeding the accepted threshold for statistical significance. This outcome points out that, in low-income countries, the presence of policy is not sufficient on its own to increase EV adoption. It is probably due to the limited financial capacity of customers. The higher purchasing costs create a strong barrier to entry, which seems to cancel out any positive effect that incentives may create. This observation is consistent with Vyas and Kushwah (2023), who emphasize that despite the overall effectiveness of government purchasing incentives, lower-income households still face significant challenges in terms of affordability and access.

Even though it has a negative coefficient of -0.32, the Gini Coefficient is not statistically significant with p=0.22. This outcome is consistent across all regressions performed until now, and a direct relationship between inequality and EV Market Share has yet to be observed.

When we take a look at the effect of Gasoline Price, the variable is statistically significant (p=0.00) and addresses 6.24 percentage point increase in EV Market Share for every one-euro increase in fuel prices. Although the coefficient is remarkably lower than high-income regression (which was 23.48), still it reveals that in any income level the cost sensitivity is undeniable and shows a positive relationship with dependent variable. For the lower income group, the structural and economic barriers may be hindering the positive effect of rising gasoline prices.

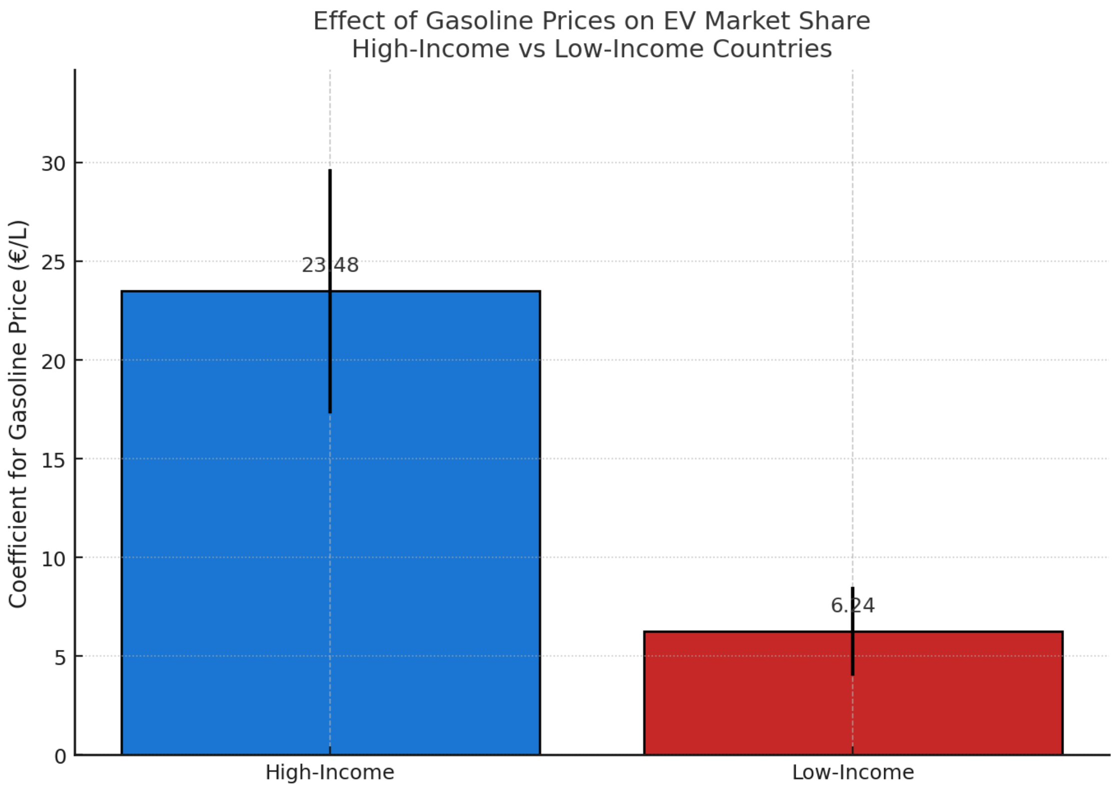


Figure 8: Gasoline Price Coefficient Comparison by Income Group

3.1.5 Regression with Infrastructure Model for High-Income Countries

$$MarketShare_{it} = 0.178 \cdot Infra1000_{it} + 0.79 \cdot GiniCoef_{it} + 15.04 \cdot GasolineLiter_{it} - 43.41 + \alpha_i + \epsilon_{it} \ (6)$$

Table 7: High-Income Infrastructure Regression Results

Variable	Coef.	Std. Err.	t	P > |t|	95% Conf. Interval
Infra1000	0.17	0.03	5.28	0.00	[0.11; 0.25]
GiniCoef	0.79	1.13	0.70	0.48	[-1.46; 3.04]
GasolineLiter	15.04	3.21	4.69	0.00	[8.64; 21.43]
Cons	-43.41	33.50	-1.30	0.19	[-110.17; 23.34]

To explore the effect of income on infrastructure regression model, the regression is performed on the high-income group, using Infrastructure, Gini Coefficient, and Gasoline Price as the independent variables.

The impact of charging infrastructure is statistically significant (p=0.00) and indicates that for every 1000 chargers, the EV Market Share increases by 0.178 percentage point. This finding is remarkably close to coefficient observed in general regression, which was equal to 0.196. As highlighted by Faraj and Basir (2016), the lack of a comprehensive charging network can discourage potential adopters by reinforcing concerns over travel reliability and route planning. The range-anxiety is a genuine concern also in high-income countries and Infrastructure is a key determinant of EV adoption.

For Gini Coefficient, the coefficient is positive and equal to 0.79 but having p=0.484, the result is not statistically significant. Inequality does not directly influence the EV Market Share also in high-income groups.

When it comes to Gasoline Prices, for a one-euro increase in fuel prices, the EV Market Share moves up by 15.04 percentage point. This is a greater influence when compared to general infrastructure regression having 10.11 as coefficient, indicating that cost-driven decision-making is particularly powerful in wealthier scenario. But at the same time, the coefficient 15.09 is lower than the policy regression specifically performed for high income countries which had 23.48 percentage point increase. These changing dynamics and comparisons highlight the complex nature of the factors affecting EV Market Share.

3.1.6 Regression with Infrastructure Model for Low-Income Countries

$$MarketShare_{it} = 0.766 \cdot Infra1000_{it} - 0.24 \cdot GiniCoef_{it} + 4.2 \cdot GasolineLiter_{it} + 2.85 + \alpha_i + \epsilon_{it} \quad (7)$$

Table 8: Low-Income Infrastructure Regression Results

Variable	Coef.	Std. Err.	t	P > |t|	95% Conf. Interval
Infra1000	0.76	0.13	5.92	0.00	[0.51; 1.02]
GiniCoef	-0.24	0.20	-1.21	0.23	[-0.64; 0.15]
GasolineLiter	4.21	1.02	4.11	0.00	[2.17; 6.24]
Cons	2.85	6.67	0.43	0.67	[-10.39; 16.09]

As the ultimate step in the detailed analysis based on incomes, the regression is now performed for low-income country group, using Infrastructure, Gini Coefficient, and Gasoline Price as the three independent variables.

The Infrastructure variable has a coefficient of 0.76, signifying that for every 1000 new public charging points, the EV Market Share increases by 0.76 percentage points. This is nearly four times higher than the other coefficients observed in the general regression with coefficient 0.19 and the high-income group with 0.18 regarding the independent variable Infrastructure. They both show a less steep trend with respect to low-income customers. This can be explained by wealthier countries having reached the base threshold of accessibility, each additional charger is less impactful when compared with the beginning. On the other hand, for poor regions there is still a lack of infrastructural foundation and every new public charger plays a more critical role in EV Market Share. This finding denotes how infrastructural investments are important for increasing the EV adoption specifically in regions where the number of available charging stations is still not sufficient, and how it can create a marginal effect for the desired increase of Market Share.

The indicator of income inequality shows a negative relationship with EV Market Share (-0.24). However, the p-value of 0.23 is higher than the commonly accepted threshold, thus the effect is not statistically significant for this model. This suggests that inequality does not significantly affect EV adoption in this sample as well. Nevertheless, the negative coefficient can still be a sign of a weak potential dampening effect of income inequality on EV adoption.

The third variable, Gasoline Price, shows a strong statistical significance with a p-value of 0.00, and corresponds to a 4.21 percentage point increase in EV Market Share for every one-euro increase in gasoline prices. The results still point out the cost sensitivity of customers, even if the magnitude of the coefficient is way smaller than the general regression (where it was 10.11) and the specific regression with only high-income countries (15.04). Even when the purchasing power is limited due to possible financial constraints, like in this regression group, rising traditional fuel cost can still alter consumers' decision-making process.

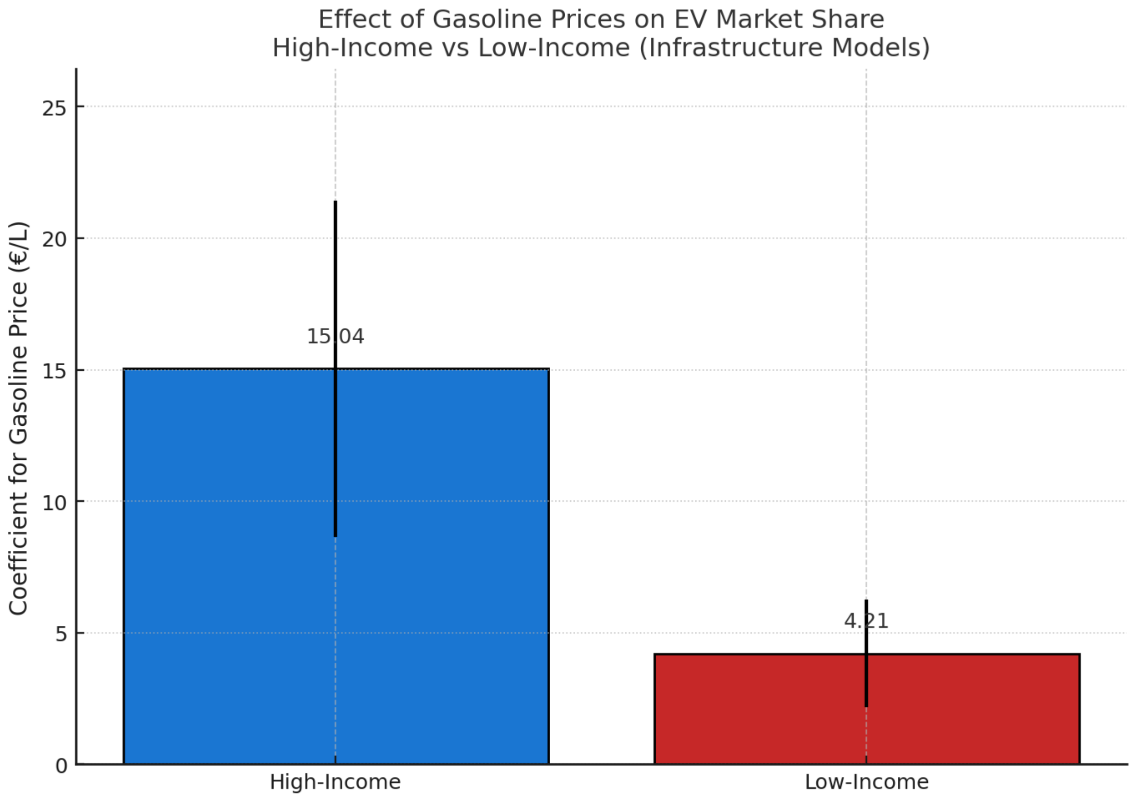


Figure 9: Coefficient Comparison by Income Group for Gasoline Price

When comparing the Figure 9 above with the Figure 8 which was exploring the regression with PolicyPositive as independent variable, the coefficient of GasolinePrice shows an obvious distinction between two models. In both models, the coefficient is way higher for high-income households (23.5 in the policy model, 15.0 in the infrastructure model) than in low-income group (6.2 and 4.2 respectively). This reinforces the idea that the probable financial flexibility in wealthier regions leads to a quicker reaction to fuel price changes and investing on EV rather than traditional ICE. Furthermore, in the policy model, the contrast between the coefficients of two income groups is way sharper. As discussed before, the possible explanation is that in high-income settings, the number of public charging points has reached the baseline threshold and has a less motivational role, while policy is might still be an important enabler when it comes to EV Market Share. As a result, also the visual comparisons support the previous interpretations, analyzing how the relationship between economic conditions can shape EV market dynamics.

3.2 Interaction Effects on EV Market Share: Policy, Infrastructure, and Inequality

3.2.1 Regression with Policy and Infrastructure Interaction

$$MarketShare_{it} = 2.45 \cdot PolicyPositive_{it} + 0.41 \cdot Infra1000_{it} - 0.17 \cdot (PolicyPositive_{it} \; x \; Infra1000_{it}) - 0.28 + \alpha_i + \epsilon_{it} \quad (8)$$

Table 9: Policy and Infrastructure Regression Results

Variable	Coef.	Std. Err.	t	P > |t|	95% Conf. Interval
PolicyPositive	2.45	1.03	2.38	0.02	[0.42; 4.48]
Infra1000	0.41	0.94	4.36	0.00	[0.22; 0.59]
PolicyPositive #Infra1000	-0.17	0.96	-1.75	0.08	[-0.35; 0.02]
Cons	-0.28	0.85	-0.33	0.74	[-1.97; 1.40]

In the second subsection, the first interaction model aims to investigate whether the results of having EV-supportive policies are influenced by the number of public charger stations in a country. Policy Presence and Infrastructure are two independent variables with the third term showing the interaction between these two.

PolicyPositive shows a statistically significant result (p=0.02) with a coefficient of 2.45. Similarly, also Infra1000 is statistically significant (p=0.00) and has a positive coefficient which is equal to 0.41. Both independent variables are relevant and contribute positively to EV Market Share.

However, when the interaction term PolicyPositive#Infra1000 is analyzed, the coefficient becomes negative with -0.17 and p-value is higher than the 0.05 conventional significance threshold (p=0.08). This suggests that the influence of EV-supportive policies might be reduced if the infrastructure is already well-established and developed. The combined effect of Policy Presence and Infrastructure can even be dampening.

These findings obtained in the first interaction regression justify the decision taken to investigate the two variables independently in the first subsection because the effects are not additive and hinder each other. The effectiveness of the EV-supportive policies depends on also the structural development of public charger points.

In countries without any supportive policy in action, which mainly belong to low-income group, the installation of each new public charger has a stronger marginal effect due to the fact that the structure is still under-developed.

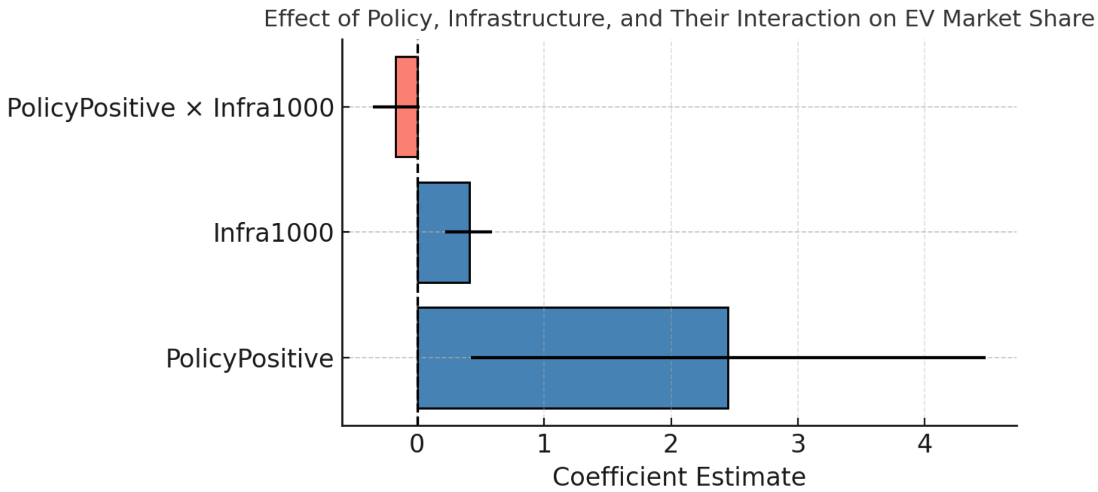


Figure 10: Coefficient Estimation of Policy Presence, Infrastructure, and Interaction Term

3.2.2 Regression with Policy and Gini Coefficient Interaction

$$MarketShare_{it} = 4.52 \cdot PolicyPositive_{it} - 0.45 \cdot GiniCoef_{it} - 0.05 \cdot (PolicyPositive_{it}\ x\ GiniCoef_{it}) + 15.39 + \alpha_i + \epsilon_{it} \quad (9)$$

Table 10: Policy and Gini Coefficient Regression Results

Variable	Coef.	Std. Err.	t	P > |t|	95% Conf. Interval
PolicyPositive	4.52	11.08	0.41	0.68	[-17.34; 26.39]
GiniCoef	-0.45	0.64	-0.70	0.49	[-1.71; 0.82]
PolicyPositive #GiniCoef	-0.05	0.36	-0.13	0.90	[-0.76; 0.67]
Cons	15.39	19.84	0.78	0.44	[-23.76; 54.55]

The second interaction regression focuses on the relationship between PolicyPositive and GiniCoef, with the aim of exploring if the positive influence of EV-supportive policies on Market Share is affected by the income inequality coefficient. For all the regression models performed at the first subsection, Gini Coefficient always remained as not being statistically significant, indicating that there is no direct association between income inequality and EV Market Share.

In this model, PolicyPositive, despite having a positive coefficient equal to 4.52, does not show a statistical significance with a p-value much higher than the expected threshold (p=0.68).

The second independent variable GiniCoef is also not statistically significant, having p=0.49. The coefficient -0.45 shows a negative trend just like the interaction term with -0.05. The negative signs hint at a probable, but statistically unproven, dampening effects. When inequality increases, the positive influence of policy presence might weaken. This interpretation is mentioned by Sheldon (2022), who defends that higher-income households disproportionately benefit from Plug-In Electric Vehicles (PEV) incentives, highlighting income inequality creating an unbalanced distribution. However, according to the regression result, this interaction PolicyPositive#GiniCoef is far from being significant due to the high p-value of 0.90.

3.2.3 Regression with Infrastructure and Gini Coefficient Interaction

$$MarketShare_{it} = 0.62 \cdot Infra1000_{it} + 0.07 \cdot GiniCoef_{it} - 0.01 \cdot (Infra1000_{it}\ x\ GiniCoef_{it}) - 0.68 + \alpha_i + \epsilon_{it} \quad (10)$$

Table 11: Infrastructure and Gini Coefficient Regression Results

Variable	Coef.	Std. Err.	t	P > |t|	95% Conf. Interval
Infra1000	0.62	0.19	3.18	0.002	[0.23; 1.00]
GiniCoef	0.07	0.006	0.17	0.87	[-0.79; 0.94]
Infra1000 #GiniCoef	-0.01	0.006	-1.88	0.06	[-0.02; 0.00]
Cons	-0.68	13.47	-0.05	0.96	[-27.27; 25.91]

This time, the third interaction regression deep dives if the role of charging infrastructure as a catalyst for EV Market Share is impacted by income inequality, measured by the Gini Coefficient.

The coefficient for Infrastructure is positive (0.62) and statistically significant with p-value being equal to 0.002. This confirms that the increasing number of available charging points has a positive outcome on EV adoption, consistent with previous findings discussed for general and income-specific regression model results in the first subsection.

Investigating the second independent variable, Gini Coefficient, with p-value (p=0.87) higher than commonly accepted threshold, remains being not statistically significant, again in line with all previous models. The influence of income inequality is not directly linked to EV Market Share. It may be creating an impact on other independent variables like Policy Presence or Infrastructure, which are significant drivers for EV adoption. However, on its own, this variable is not significant.

The interaction term Infra1000#GiniCoef shows a negative coefficient (-0.01) and a p-value which is marginally significant ($p=0.06$). Even though it misses the conventional significance threshold $p<0.05$, it still provides information about the effectiveness of new public charger points weakening if the income inequality is high. As mentioned many times before, the financial barrier may limit the probable benefits of a strong infrastructure to promote EV adoption.

This outcome reflects a deeper infrastructural problem in real-world examples for public charging points. In order to escape the possible hindering relationship of Gini Coefficient and Infrastructure, governments may prioritize wealthier neighborhoods to install new charging stations, with the goal of seeing faster adoption rates for EV. As Khan et al. (2021) demonstrate in their article about New York City, "*the distribution of EV charging stations is heavily skewed against low-income, Black-identifying, and disinvested neighborhoods*,", similar with Colandré (n.d.) pointing out that charging stations are more heavily concentrated in non-disadvantaged areas (non-DACs) when compared with DACs, further confirming that access remains uneven. While these strategic placements can be successful at the initial phase of increasing EV Market Share, for the long-term targets, it risks limiting the growth, especially in areas with lower income.

3.3 Infrastructure Trends and Density Effects on EV Market Share

3.3.1 Lagged Infrastructure and Delayed Impact as a Supporting Analysis

$$MarketShare_{it} = 0.34 \cdot Infrastructure_{lag_{it}} + 1.73 + \alpha_i + \epsilon_{it} \quad (11)$$

Table 12: Lagged Infrastructure Regression Results

Variable	Coef.	Std. Err.	t	P > |t|	95% Conf. Interval
Infrastructure_lag	0.34	0.03	11.33	0.00	[0.28; 0.40]
Cons	1.73	0.41	4.21	0.00	[0.92; 2.54]

The aim of this additional regression with the new variable called Infrastructure_lag is to analyze whether the investments made for increasing public charger points can show their positive impacts, as demonstrated in the first subsection, immediately or with a time delay. This regression is included in this study as a robustness check and aims to make the complex dynamics of EV Market Share phenomenon more transparent and easier to understand for policymakers and stakeholders.

The variable Infrastructure_lag indicates a positive and statistically significant relationship ($p=0.00$) with the dependent variable Market Share. This outcome suggests that the public charging points installed last year can contribute positively to increasing EV adoption in the current year. The result supports the occurrence of delays between charger installation and their actual usage by drivers, pointing out the period needed for full integration.

$$MarketShare_{it} = 0.29 \cdot Infra1000_{it} - 0.05 \cdot Infrastructure_{lag_{it}} + 1.53 + \alpha_i + \epsilon_{it} \ (12)$$

Table 13: Current and Lagged Infrastructure Regression Results

Variable	Coef.	Std. Err.	t	P > |t|	95% Conf. Interval
Infra1000	0.29	0.10	2.81	0.006	[0.09; 0.50]
Infrastructure_lag	-0.05	0.14	-0.38	0.70	[-0.34; 0.23
Cons	1.53	0.41	3.73	0.00	[0.72; 2.34]

On the other hand, when another regression including both Infra1000 and Infrastructure_lag as independent variables is performed, the results reveal a different scenario.

The coefficient of Infra1000 is positive and statistically significant (p=0.006), while the Infrastructure_lag loses its statistical significance and even turns slightly negative with the coefficient of -0.05. This shift of behavior shows that the previously observed lagged effect (Table 12) is likely a statistical artifact because of the correlation between past and current charging point structures. Once the current infrastructure is well explained by Infra1000, the Infrastructure_lag no longer adds any explanatory value to the model.

It implies that the effect of new public charging points can be seen immediately, without any delay. EV users seem to notice and respond positively to this type of governmental investment rather quickly. A very important psychological barrier defined as range-anxiety can be reduced with simple moves and in a small timeframe with some government interventions.

3.3.2 General Regression with Infrastructure Density Model

$$MarketShare_{it} = 27059.24 \cdot ChargerDensity_{it} - 4843913 \cdot ChargerDensity\_sq_{it} + 1.82 + \alpha_i + \epsilon_{it} \quad (13)$$

Table 14: General Infrastructure Density Regression Results

Variable	Coef.	Std. Err.	t	P > |t|	95% Conf. Interval
ChargerDensity	27059.24	3520.10	7.69	0.00	[20112.74; 34005.75]
ChargerDensity_sq	-4843913	1091239	-4.44	0.00	[-6997344; -2690482]
Cons	1.82	0.44	4.10	0.00	[0.95; 2.70]

The first regression including ChargerDensity and ChargerDensity_sq as independent variables aims to understand the trend between public charging points and EV adoption, and explore if there exists a saturation point, a level which going beyond this number no longer yields substantial gains.

Between the ChargerDensity and EV Market Share, there is a statistically significant relationship (p=0.00) with a coefficient of 27,059.24. At first glance, the coefficient magnitudes may appear extremely large. This scale is due to the nature of the corresponding variable. As explained before, ChargerDensity is defined as the number of public chargers divided by the total land area of a country (in km²). Therefore, the resulting values are typically less than 0.005. As a result, larger coefficients become necessary to demonstrate meaningful changes in the ChargerDensity. For example, a charger density of 0.001 corresponds to approximately 27 percentage points increase in EV Market Share.

Observing the ChargerDensity_sq, the coefficient is -4,843,913, and it is statistically significant (p=0.00). The effect of increasing charger numbers eventually declines after reaching the saturation point.

$$SaturationPoint = -\frac{\gamma_1}{2\cdot\gamma_2} = -\frac{27{,}059.24}{2\cdot(-4{,}843{,}913)} = 0.00279 \text{ chargers/km}^2 \quad (14)$$

The calculation of the SaturationPoint is made by dividing γ_1 (the coefficient of ChargerDensity) to 2 times γ_2 (the coefficient of ChargerDensity_sq) and the result is 0.00279 chargers per km² or 2.79 chargers per 1,000 km². Beyond this threshold, further installation of public chargers corresponds to slower growth or even a decline of EV Market Share, having an inverted-U shape. These results support the idea that there exists a saturation point for number of public charging points and further investments from government is not any more as effective as early phases. Therefore, policymakers should focus on optimizing the location and accessibility to ensure an efficient distribution among the cities and countries.

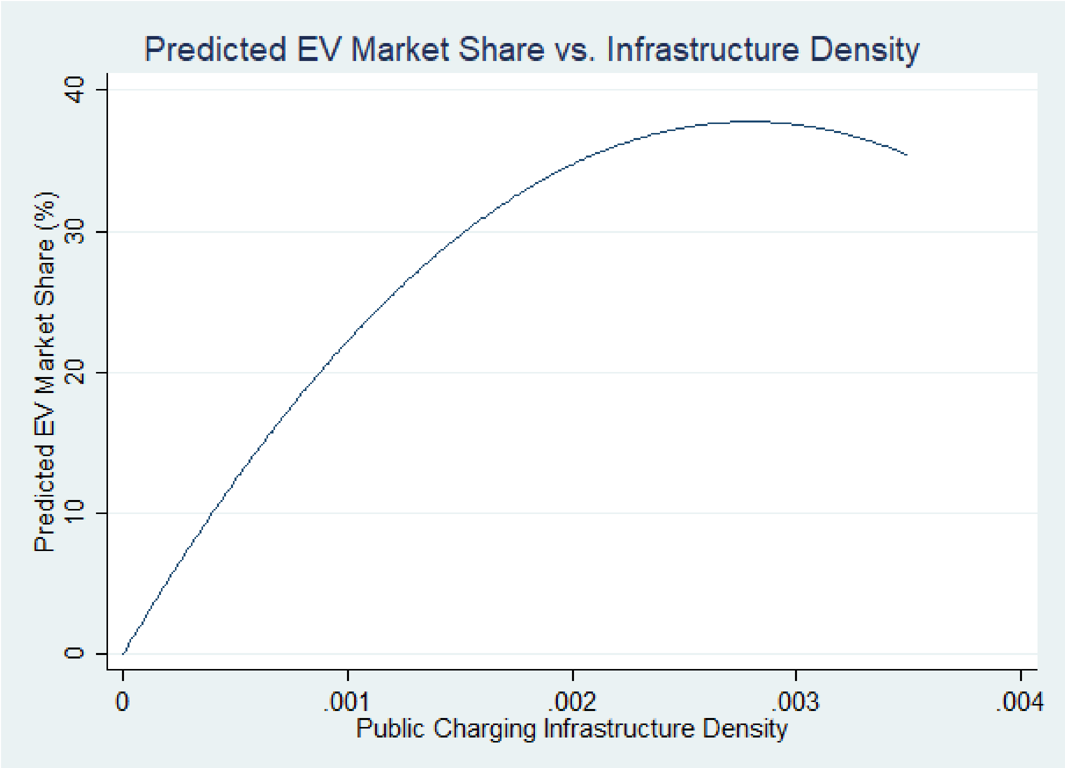


Figure 11: Inverted-U Relationship Between Infrastructure Density and EV Market Share

3.3.3 Regression with Infrastructure Density Model for High-Income Countries

$$MarketShare_{it} = 258557.29 \cdot ChargerDensity_{it} - 4504285 \cdot ChargerDensity\_sq_{it} + 2.55 + \alpha_i + \epsilon_{it} \ (15)$$

Table 15: High-Income Infrastructure Density Regression Results

Variable	Coef.	Std. Err.	t	P > |t|	95% Conf. Interval
ChargerDensity	258557.29	5154.395	5.02	0.00	[15589.21; 36125.37]
ChargerDensity_sq	-4504285	1595423	-2.82	0.006	[-7682530; -1326041]
Cons	2.55	1.09	2.33	0.02	[0.37; 4.73]

Just like subsection 3.1, the panel data is again divided into 2 groups according to their income levels. The independent variables ChargerDensity and ChargerDensity_sq aim to investigate if the non-linear relationship can also be observed for the wealthier regions, where the public charger infrastructure is more developed and EV adoption is more advanced.

Really similar to the general regression performed at 3.3.2, both independent variables are statistically significant. ChargerDensity has a coefficient of 25,857.29, while ChargerDensity_sq has a negative coefficient equal to -4,504,285. The negative squared term proves the diminishing return as density increases.

$$SaturationPoint = -\frac{\gamma_1}{2\cdot\gamma_2} = -\frac{25{,}857.28}{2\cdot(-4{,}504{,}285)} = 0.00287 \text{ chargers/km}^2 \quad (15)$$

With the same reasoning and calculation applied in Formula (14), the threshold for high-income countries results as 0.00287 chargers per km^2, or 2.87 chargers per 1,000 km^2. The saturation points for general regression and for high-income countries closely align with each other. This consistency supports the hypothesis that after a sufficient baseline level of infrastructure is developed, expanding the number of charging points becomes less rewarding for EV Market Share growth. Wealthier regions, typically having already more developed infrastructure, show the same inverted-U trend with the general regression, emphasizing the necessity of strategic planning instead of uniform expansion.

3.3.4 Regression with Infrastructure Density Model for Low-Income Countries

$$MarketShare_{it} = 97043.42 \cdot ChargerDensity_{it} + 6.03e_{+}08 \cdot ChargerDensity\_sq_{it} + 0.38 + \alpha_i + \epsilon_{it} \quad (16)$$

Table 16: Low-Income Infrastructure Density Regression Results

Variable	Coef.	Std. Err.	t	P > |t|	95% Conf. Interval
ChargerDensity	97043.42	30207.08	3.21	0.002	[37090.73; 156996.1]
ChargerDensity_sq	6.03e+08	4.37e+08	1.38	0.17	[-2.65e+08; 1.47e+0.9]
Cons	0.38	0.24	1.60	0.11	[-0.91; 0.85]

As a final step, a separate regression with only low-income countries is performed to observe if the trend of ChargerDensity is consistent with the previous models. The independent variables ChargerDensity and ChargerDensity_sq as the other regression for correct comparison.

The coefficient of ChargerDensity is 97,043.42, and it is statistically significant (p = 0.002), indicating a strong positive relationship between number of public chargers and EV Market Share. This positive effect is notably larger in magnitude compared to both the general model

(27,059.24) and the high-income model (25,857.29), further demonstrating that in low-income countries, the reaction for increased number of public charging points is more remarkable according to the results. In these regions, where public charger networks are often still in their early stages, each additional unit leads to a much greater marginal increase in EV adoption.

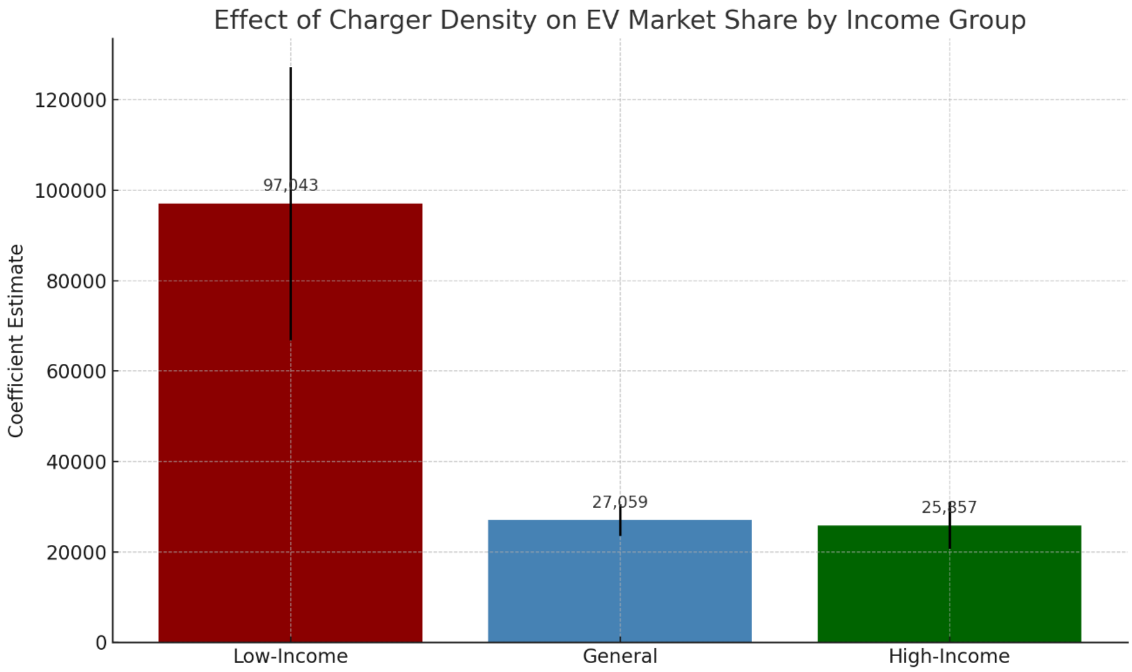


Figure 12: Charger Density Effects on EV Market Share by Income Group

On the other hand, the coefficient for ChargerDensity_sq is still positive with 6.03e+08, but the p-value is way higher than commonly accepted threshold, therefore it is not statistically significant ($p = 0.17$). This suggests that the inverted-U trend observed in the general and high-income regressions does not hold for low-income countries. Not having a negative and significant coefficient proves that the saturation point has not yet been reached for these countries. In other words, charger infrastructure is still far from the saturation point where additional investments would yield decreasing returns.

These results strengthen the idea that, for developing, low-income regions, the authorities should focus more on increasing the number of charger points and making sure the infrastructure is widespread, easily accessible, and reliable for drivers. In comparison to high-income countries, where the focus should be strategical planning for efficiency and optimization, low-income regions are still in the growth phase regarding EV adoption. In these contexts, providing a baseline infrastructure is not only impactful, but also essential for increasing the Market Share.

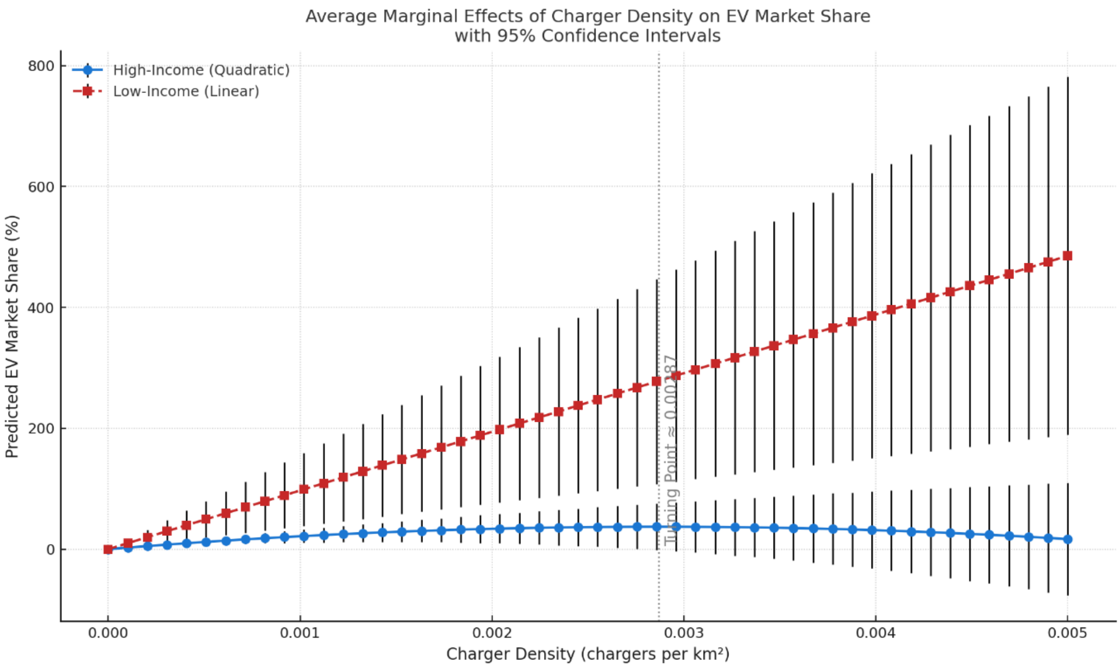


Figure 13: Inverted-U Relationship in High-Income Countries vs. Linear Growth in Low-Income Countries

Chapter 4

Conclusion of Empirical Results

The regression results discussed in Chapter 3 provide a profound understanding of the various factors determining EV Market Share across 38 countries from 2013 to 2023, for a ten-year period.

By addressing (i) individual effects, (ii) interaction effects, and (iii) long term and non-linear infrastructure trends in 3 subsections, this study gained some important insights both in line with the reviewed literature and distinctive with cross-country, income specific analyses.

4.1 Individual Effects of Policy and Infrastructure

4.1.1 General Regressions

In order to observe the individual effects of Policy Presence and Infrastructure separately, two general regressions have been performed. Both of these regressions were controlling for Gini Coefficient and Gasoline Price:

Table 17: Main Predictors of General Regressions Performed

Model	Main predictors	Coefficient	P > |t|	Significance
Policy	PolicyPositive	2.00	0.07	Marginal
	GasolineLiter	15.83	0.00	Strong
Infrastructure	Infra1000	0.19	0.00	Strong
	GasolineLiter	10.11	0.00	Strong

Table 17 summarizes the results obtained from two general regressions that serve as the starting point for this study. The Policy model tests the effect of policy presence, while the Infrastructure model replaces policy with number of public charging points as the key variable.

In the Policy model, the coefficient for PolicyPositive (2.00) shows a positive relationship, but it is only marginally significant ($p = 0.07$). This suggests that, for the 38 countries selected and during the 2013-2023 period, having at least one type of EV-supportive policy correlates with a non-negligible but modest increase in EV Market Share. However, having the p-value higher than the threshold suggests that having an EV supportive policy alone does not create a strong effect. In contrast, GasolineLiter has a strongly significant positive effect (+15.82, $p=0.00$). This result confirms the idea of cost-driven substitution: if having a traditional ICE vehicle becomes more expensive in the long run with all the associated expenses, owning an EV becomes more attractive for customers.

In the Infrastructure model, Infra1000 has as a statistically strong significance and a positive effect on EV Market Share (0.196, p=0.00), pointing out the role of well-developed charging infrastructure in reducing range anxiety, thus increasing EV adoption rates. Gasoline prices again remain significant (+10.11, $p < 0.001$), though the effect is smaller when compared with the Policy model.

Analyzing both models reveals an important nuance: while both policy presence and infrastructure expansion contribute positively to EV market share, infrastructure has a statistically stronger relationship, and gasoline prices per liter remain the most consistent predictor in each situation. This reinforces a topic commonly discussed in the literature, which is the Total Cost of Ownership (TCO) and its influence when deciding which type of vehicle to get. In none of the cases, Gini Coefficient shows a significant effect on EV Market Share. This implies that inequality does not have a direct measurable effect on the adoption of EV.

4.1.2 High- vs. Low-Income Contrasts

Table 18: Main Predictors of Income-Specific Regressions Performed

Model	Income Group	Main predictors	Coefficient	P > |t|	Significance
Policy	High	PolicyPositive	4.31	0.05	Marginal
		GasolineLiter	23.48	0.00	Strong
	Low	PolicyPositive	0.35	0.60	Not significant
		GasolineLiter	6.24	0.00	Strong
Infrastructure	High	Infra1000	0.17	0.00	Strong
		GasolineLiter	15.04	0.00	Strong
	Low	Infra1000	0.76	0.00	Strong
		GasolineLiter	4.21	0.00	Strong

When the policy model regression is broken down by the income levels, the results show an obvious distinction between two groups. In high-income countries, having an EV-supportive policy has a positive effect more than twice the general model's (4.31 vs. 2.00 before), again with a marginal significance (p=0.05 vs. p=0.07 before). This suggests that in wealthier contexts, having lower financial barriers to EV ownership, incentives are more likely to translate into EV purchases. Also from the same regression, one-euro increase in gasoline prices leads to 23.48 percentage point jump in EV Market Share, amplifying the cost-driven substitution even more dramatically for drivers with higher incomes.

Focusing on the low-income level, the results paint a different picture. For this group, existence of an incentive both has a smaller coefficient (0.35) and it is not statistically significant (p=0.60). EV-supportive policies are not enough to overcome the higher upfront costs of EVs. While gasoline prices still exert a positive and statistically significant effect, the impact is limited with respect to high-income settings (6.24 vs. 23.48). It reflects that, without adequate purchasing power, the EV adoption stays limited even with rising fuel costs.

Analyzing the infrastructure model regression divided by income levels, the contrasts between the two levels become even sharper. In high-income countries, the coefficient for Infra1000 is 0.178 percentage points and statistically significant (p=0.00), a value closely matching the general model (0.196). The coefficients suggest that in such situations, where the infrastructure is already in the developing stage, each additional public charger has a smaller effect on increasing EV adoption. Gasoline prices in the same high-income model have a strong and significant effect (15.04, p=0.00), even though this is lower than the 23.48 percentage point increase recorded in the high-income policy model. This reduction may be due to infrastructure and fuel price partially substituting for each other in during decision-making process. If the number of available charging points is already reliable, the effect of rising fuel prices may be slightly less pronounced.

In low-income countries, the infrastructure effect rises remarkably. The coefficient reaches 0.76 percentage points, which is more than four times that in high-income countries, and remains highly significant (p=0.00). This finding is consistent with the idea that in early-stage EV markets, each new charging point has a remarkable influence on adoption, addressing the range anxiety effectively. Infrastructure development emerges as an essential factor for meaningful Market Share growth in these countries. Gasoline prices in low-income contexts have a smaller, yet still statistically significant, effect (4.21, p=0.00), much lower than in high-income markets. This reduced effect reflects the financial constraints faced by many drivers who have less income. Without lower purchasing prices, owning an EV remains out of reach even with higher fuel prices.

Overall, the income-specific regressions prove that the effects of independent variables depend strongly on the economic situation of that country. In high-income markets, EV-supportive policies and gasoline price dynamics are important enablers of EV Market Share growth, while infrastructure has a reinforcing, but less impactful role given that a developed baseline network is already in place. In low-income regions, as opposite, the role of every additional public charging point is remarkably high, whereas incentives alone are not enough to overcome the financial barriers. For both groups the fuel prices influence adoption, but the scale is much lower in low-income countries since they have less purchasing power. Across all models, the Gini coefficient remained statistically insignificant, suggesting that income inequality does not exert a direct, measurable influence on EV adoption in this dataset. Its influence may instead shape other independent variables, thus having only an indirect relationship with EV Market Share.

4.2 Interaction Effects

Building on the general and income-specific results, it is also important to explore whether the impact of the key drivers changes when they interact with each other. While the previous models treated Policy Presence, Infrastructure, and Gini Coefficient as independent influences, real-world conditions often involve overlaps where these factors reinforce or offset each other. To capture these dynamics, 3 interaction regressions were introduced, allowing the analysis to have a deeper understanding.

For the first interaction between PolicyPositive and Infra1000, the outcomes revealed both variables having a positive coefficient, statistically significant (2.45, $p=0.02$; 0.41, $p=0.00$ respectively). However, the interaction term being negative (–0.17) and not statistically significant ($p=0.08$), suggest that the combined impact of policy and infrastructure is weaker than the sum of their separate effects. The result highlights the need to tailor combined policy–infrastructure strategies attentively to prevent the hindering effect.

At the interaction between PolicyPositive and GiniCoef, none of the variables showed a statistical significance (4.52, p=0.68 ; -0.45, p=0.49 respectively). Also the interaction term had a p-value higher than the threshold (p=0.90), with a negative coefficient (-0.05). Even though the negative coefficients of inequality refer to a possible dampening effect on policy, there exists no statistical evidence to confirm. With the chosen panel dataset, income inequality does not directly influence the effectiveness of EV-supportive policies on EV adoption.

From the interaction regression of Infra1000 and GiniCoef, Infrastructure retains a significant positive effect (0.62, p=0.002), while Gini Coefficient remains insignificant (0.07, p=0.87). The interaction term is negative (–0.01) and only marginally significant (p = 0.06). This result proposes the idea that the benefits of infrastructure expansion may weaken in more unequal contexts. However, without statistical significance, there is no conclusive evidence of a direct effect from inequality on availability of public charger points.

4.3 Infrastructure Trends and Saturation Points

All the previous models have focused on the immediate, direct effects of infrastructure on EV adoption. While it is also important to investigate if the impact of available charging points is immediate or occurs with a time delay, and whether there is a Saturation Point beyond which returns start to diminish. To address these questions, the analysis introduced three additional variables: Infrastructure_lag, ChargerDensity, and ChargerDensity_sq. These robustness checks aim to provide a more nuanced view of how infrastructure influences EV adoption over time and across different contexts.

When Infrastructure_lag is tested alone, it shows a positive and statistically significant effect (0.34, p=0.00), suggesting that chargers installed in the previous year contribute positively to current year's EV Market Share. However, when both Infra1000 and Infrastructure_lag is included in the regression, lagged term becomes slightly negative and not statistically significant (-0.05, p=0.70). This outcome tells that the effect of charging point installation is actually mainly immediate, and a delayed response is unlikely.

Table 19: Calculated Saturation Points for Infrastructure Density by Income Group

Income Group	Saturation Point	Interpretation
General	0.00279	2.79 chargers per 1,000 km²
High	0.00287	2.87 chargers per 1,000 km²
Low		No saturation detected

At the general regression for finding the possible Saturation Points, ChargerDensity shows a positive and statistically significant effect on EV adoption (27,059, p=0.00), while the squared term is negative (-4,843,913, p=0.00), indicating an inverted-U trend. The calculated Saturation Point is 2.79 charging points per 1000 km^2 and beyond this number additional chargers display a reduced effectiveness.

Also for high-income countries, the findings show a similar approach. ChargerDensity has a positive coefficient and statistically significant (25,857, p=0.00), meanwhile the ChargerDenisty_sq is negative and significant (-4,504,285, p=0.006). The inverted-U shape is observed just like the general model and Saturation Point is 2.87 charging points per 1000 km^2. Once the structure reaches this threshold, further expansion yields diminishing returns.

The situation changes when it comes to low-income contexts, ChargerDensity has a large positive and significant effect (97,043, p=0.002), much higher in magnitude than in the other models, while ChargerDensity_sq is positive but not statistically significant (p=0.17). The absence of a significant and negative squared term indicates that no Saturation Point has yet been reached. This supports the view that these markets remain in the growth phase, where expanding public charging networks continues to deliver substantial gains in EV adoption. These results underline the need for strategical planning: optimizing charger placement in mature, high-income markets to avoid overcapacity, while prioritizing rapid and equitable network expansion in developing markets to maximize EV adoption potential.

Chapter 5

Limitations

While the results of this study provide valuable insights into the determinants of EV Market Share across different contexts, several limitations should be acknowledged.

First, even though the panel dataset covers 38 countries, full data availability for all variables was not available for every case throughout the 2013–2023 period. In practice, the panel was unbalanced, with most of the observations concentrated around 20 countries. This may introduce sample bias if countries with complete data differ from those with limited records.

Second, the set of independent variables chosen for this analysis was constrained by the availability of reliable, international data. Important factors such as EV purchase prices or battery ranges could not be incorporated, even though they are most likely to influence decision-making. Their exclusion means that the models may omit relevant factors of EV adoption.

Third, although the time frame covers a ten-year period from 2013 to 2023, the EV industry is going through new technological changes rapidly. The outcomes may not capture the effects of recent developments like improved battery life or new charging options.

Fourth, the PolicyPositive variable captures only the presence or absence of supportive EV policies, not being able to distinguish between their type, scale, or duration. As a result, countries with fundamentally different incentive structures may appear similar in the dataset and can lead to mistaken interpretations.

Finally, the analysis relies on national-level panel data, which may hide significant regional or city-level variations in infrastructure, income distribution, and policy implementation. These subnational differences, which can strongly influence EV Market Share, are therefore not directly accounted.

Moreover, it is crucial to point out the limitations regarding causal inference. Although the use of fixed-effects regressions across multiple countries and scenarios strengthens internal validity of obtained results, causality in social sciences is not a binary concept but a continuum. The associations identified in this study provide robust evidence of relationships between income, inequality, infrastructure, policies, fuel prices, and EV adoption, yet they cannot entirely rule out omitted variables, feedback effects, or reverse causality. Therefore, the findings should be interpreted as strong empirical indications of these relationships rather than conclusive proof of causation.

Chapter 6

Policy Implications

Despite the limitations discussed, still the findings of this analysis provide essential guidance for policymakers aiming to improve EV adoption rates. The results underscore the relative effectiveness of EV-supportive policies, number of public charging points, and gasoline prices differs between different income contexts, reinforcing the need for strategical planning according to the situation.

For high-income countries, where baseline infrastructure is already developed, policies and gasoline price dynamics are the most effective factors for increasing the EV adoption. Instead of focusing only on increasing the number of charging points, the placements should be chosen attentively, prioritizing the locations with less accessibility. Given the strong fuel price sensitivity observed, policies like carbon-based fuel taxation could be an important complementary tool. Furthermore, introducing low emission, ICE restricted zones, reduced tolls for EVs, or promoting corporate fleet electrifications can be beneficial for achieving higher EV Market Share.

When it comes to low-income countries the most influential factor observed is infrastructural development. The first move should be rapidly increasing the accessibility to public charging points, ensuring enough coverage across all regions. The absence of Saturation Point points out that further infrastructure investments will deliver strong returns. The higher upfront costs of EVs can be addressed through targeted financing solutions, leasing options, or purchase subsidies aiming to lower financial barriers. The effect of fuel prices is moderate with respect to wealthier regions, indicating the price-based strategies will not be enough without improving accessibility and affordability of EVs.

Across all income levels, the interaction term between policy presence and infrastructure highlights that overlapping measures can cause diminishing returns, while carefully coordinated policies and infrastructure investments can amplify their effectiveness. Although the Gini coefficient was not statistically significant in the regressions performed, it may still indirectly shape EV adoption through its influence on income distribution, policy effectiveness, or accessibility to infrastructure, and thus should not be disregarded in long-term strategies.

Finally, while these recommendations are based on robust empirical results, they should not be interpreted as conclusive causal proof. The relationships observed between income, inequality, EV-supportive policies, infrastructure, gasoline prices, and EV adoption strongly suggest patterns that policymakers can take into consideration, but they cannot entirely exclude the influence of omitted variables or reverse dynamics. Hence, the findings should be a guide for choosing effective strategies, while leaving space for flexibility, adaptation, and further evidence-based evaluation over time.

References

1- Singh, V., 2022. Sustainable development and climate change. In: *IGI Global eBooks*, pp.944–964. Available at: https://doi.org/10.4018/978-1-6684-3885-5.ch050 [Accessed 26 July 2025]

2- IEA, 2023. *Global EV Outlook 2023: Catching up with climate ambitions*. International Energy Agency. Available at: https://www.iea.org/reports/global-ev-outlook-2023 [Accessed 26 July 2025].

3- IPCC, 2022. *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. [online] Cambridge University Press. Available at: https://www.ipcc.ch/report/ar6/wg3/ [Accessed 26 July 2025].

4- Cui, S. and Zhao, N., 2024. A study on the current status and future prospects of EV automotive market. *Journal of Smart and Sustainable Cities and Development*, 1(2). Available at: https://doi.org/10.70767/jsscd.v1i2.296 [Accessed 26 July 2025].

5- European Environment Agency (EEA), 2024. *New registrations of electric vehicles*. [online] Available at: https://www.eea.europa.eu/en/analysis/indicators/new-registrations-of-electric-vehicles [Accessed 27 July 2025].

6- UNFCCC, 2024. *The Paris Agreement*. United Nations Framework Convention on Climate Change. Available at: https://unfccc.int/process-and-meetings/the-paris-agreement [Accessed 26 July 2025].

7- European Guanxi, 2023. *The role of electric vehicles in sustainable development*. [online] Available at: https://www.europeanguanxi.com/post/the-role-of-electric-vehicles-in-sustainable-development [Accessed 26 July 2025].

8- Zou, Y., Ji, Q., Han, F. and Zhang, D., 2024. Does income inequality affect green innovation? A non-linear evidence. *Technological and Economic Development of Economy*, 30(1), pp.45–71. [online] Available at: https://doi.org/10.3846/tede.2024.19996 [Accessed 27 July 2025].

9- Sadeghvaziri, E., Rahimi, M., Lee, H. and Lee, S., 2024. A machine learning approach to understanding sociodemographic factors in electric vehicle ownership in the U.S. *Sustainability*, 16(23), p.10202. Available at: https://doi.org/10.3390/su162310202 [Accessed 27 July 2025].

10- Socio-Economic and Demographic Factors Affecting Adoption of Electric Vehicles in India, 2024. Indian Journal of Economics and Finance (IJEF). Available at: https://doi.org/10.54105/ijef.a2561.04010524 [Accessed 27 July 2025].

11- Bajpai, S.M., Abbas, H. and Mishra, V.K., 2024. The influence of socio-economic factors on electric vehicle adoption in Uttar Pradesh. *Lloyd Business Review*, pp.1–17. Available at: https://doi.org/10.56595/lbr.v3i2.27 [Accessed 27 July 2025].

12- Qorbani, D., Korzilius, H. and Fleten, S., 2024. Ownership of battery electric vehicles is uneven in Norwegian households. *Communications Earth & Environment*, 5(1). Available at: https://doi.org/10.1038/s43247-024-01303-z [Accessed 27 July 2025].

13- World Inequality Report, 2022. *World Inequality Report 2022*. [online] World Inequality Lab. Available at: https://knowledge4policy.ec.europa.eu/publication/world-inequality-report-2022_en [Accessed 27 July 2025].

14- Büchs, M. and Schnepf, S.V., 2013. *The impact of income inequality on energy efficiency investments*. Energy Economics, 38, pp.120–130. Available at: https://doi.org/10.1016/j.eneco.2013.03.009 [Accessed 27 July 2025].

15- Aghion, P., Akcigit, U., Bergeaud, A., Blundell, R. and Hemous, D., 2019. *Innovation and top income inequality*. Review of Economic Studies, 86(1), pp.1–45. Available at: https://doi.org/10.1093/restud/rdy039 [Accessed 27 July 2025].

16- EAFO, 2023. *EAFO Consumer Monitor and Survey 2023*. European Alternative Fuels Observatory. [online] Available at: https://www.eafo.eu/ [Accessed 27 July 2025].

17- Rietmann, N. and Lieven, T., 2019. *A comparison of policy measures promoting electric vehicles in 20 countries*. In: *Mobility in a Globalised World 2018*. Springer, Cham, pp.125–145. Available at: https://doi.org/10.1007/978-3-319-96526-0_7 [Accessed 28 July 2025].

18- Patil, G.R., Pode, G., Diouf, B. and Pode, R., 2024. *Sustainable decarbonization of road transport: Policies, current status, and challenges of electric vehicles*. Sustainability, 16(18), p.8058. Available at: https://doi.org/10.3390/su16188058 [Accessed 28 July 2025].

19- Gao, Z., Hu, Y. and Tang, S., 2023. *Investigating the impact of new energy policy on the market for new energy vehicles*. Advances in Economics, Management and Political Sciences. Available at: https://doi.org/10.54254/2754-1169/64/20231534 [Accessed 28 July 2025].

20- Dharmakeerthi, C.H., Mithulananthan, N. and Saha, T.K., 2013. *Planning of electric vehicle charging infrastructure*. In: IEEE Power & Energy Society General Meeting, pp. 1–5. [Accessed 29 July 2025].

21- van Haaren, R., 2011. *Assessment of electric cars' range requirements and usage patterns based on driving behavior recorded in the National Household Travel Survey of 2009*. New York: Solar Journey USA. [Accessed 29 July 2025].

22- Pevec, D., Babic, J., Carvalho, A., Ghiassi-Farrokhfal, Y., Ketter, W. and Podobnik, V., 2019. *Electric vehicle range anxiety: An obstacle for the personal transportation (r)evolution?* In: 2019 International Conference on Smart and Sustainable Technologies (SpliTech), pp. 1–8. Available at: https://doi.org/10.23919/SPLITECH.2019.8783178 [Accessed 29 July 2025].

23- Hou, Q., Zhou, S. and Chi, G., 2024. *The factors affecting electric vehicle adoption in the United States, 2016–2021*. In: S. Yao and X. Feng, eds. *Proceedings of the 2023 International Conference on Energy Economics and Policy*. Singapore: Springer Nature, pp. 299–306. Available at: https://doi.org/10.1007/978-981-97-0523-8_28 [Accessed 29 July 2025].

24- Peterson, A., 2024. *Evaluating the impact of price fluctuations on consumer buying decisions and adaptation strategies in the automotive market*. Law and Economy, 3(4), pp.1–9. Available at: https://doi.org/10.56397/le.2024.04.01 [Accessed 29 July 2025].

25- Bushnell, J., Muehlegger, E. and Rapson, D., 2022. *Energy prices and electric vehicle adoption*. National Bureau of Economic Research. Available at: https://doi.org/10.3386/w29842 [Accessed 29 July 2025].

26- Mutascu, M., Strango, C. and Sokic, A., 2024. *Demand for electric cars and oil prices: A wavelet approach*. Journal of Applied Economic Sciences. Available at: https://doi.org/10.1080/15435075.2024.2385420 [Accessed 29 July 2025].

27- Randall, T., 2022. *US crosses the electric car tipping point for mass adoption*. [online] Bloomberg. Available at: https://www.bloomberg.com/news/articles/2022-07-09/us-electric-car-sales-reach-key-milestone [Accessed 8 July 2025].

28- Ferris, N., 2022. *Have booming EV sales crossed the mass-adoption tipping point?* [online] Energy Monitor. Available at: https://www.energymonitor.ai/sectors/automotive/electric-vehicle-tipping-point/ [Accessed 8 July 2025].

29- International Energy Agency (IEA), 2024. *Global EV Outlook 2024: Changing gears for faster electric mobility*. [online] International Energy Agency. Available at: https://iea.blob.core.windows.net/assets/a9e3544b-0b12-4e15-b407-65f5c8ce1b5f/GlobalEVOutlook2024.pdf [Accessed 8 July 2025].

30- Frost, J., 2019. *Regression analysis: An intuitive guide for using and interpreting linear models*. [online] Statistics By Jim Publishing. Available at: https://statisticsbyjim.com/regression/what-is-regression/ [Accessed 9 July 2025].

31- Field, A., 2013. *Discovering Statistics Using IBM SPSS Statistics*. 4th ed. London: SAGE Publications.

32- Ozili, P.K., 2022. *The acceptable R-square in empirical modelling for social science research*. [online] SSRN. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4128165 [Accessed 9 July 2025].

33- Gnann, T., Plötz, P., Kühn, A. and Wietschel, M., 2018. What drives the market for plug-in electric vehicles? — A review of international PEV market diffusion models. *Transportation Research Part D: Transport and Environment*, 62, pp.347-366. Available at: https://doi.org/10.1016/j.trd.2018.04.002 [Accessed 10 July 2025].

34- Sierzchula, W., Bakker, S., Maat, K. and van Wee, B., 2014. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, 68, pp.183-194. Available at: https://doi.org/10.1016/j.enpol.2014.01.043 [Accessed 10 July 2025].

35- Li, S., Tong, L., Xing, J. and Zhou, Y., 2017. The market for electric vehicles: indirect network effects and policy design. *Journal of the Association of Environmental and Resource Economists*, 4(1), pp.89–133. Available at: https://econpapers.repec.org/RePEc:ucp:jaerec:doi:10.1086/689702 [Accessed 11 July 2025].

36- Vyas, A.M. and Kushwah, G.S., 2023. *Accelerating the Shift to Electric: A Review of Government Purchasing Incentives for E-Vehicles*, pp. 1–6. [online] Available at: https://ieeexplore.ieee.org/document/10236342 [Accessed 13 July 2025].

37- Sheldon, T.L., 2022. *Evaluating electric vehicle policy effectiveness and equity*. Annual Review of Resource Economics, 14(1), pp.669–688. [online] Available at: https://doi.org/10.1146/annurev-resource-111820-031114 [Accessed 25 July 2025].

38- Colandré, C., n.d. *Electric vehicle charging utilization in disadvantaged and non-disadvantaged communities*. [online] Available at: https://doi.org/10.23860/thesis-colandre-camila-2023 [Accessed 25 July 2025].

39- Khan, H.A.U., Price, S., Avraam, C. and Dvorkin, Y., 2021. *Inequitable access to EV charging infrastructure*. [online] arXiv. Available at: https://arxiv.org/abs/2111.05437 [Accessed 26 July 2025].

Appendix

```
Fixed-effects (within) regression               Number of obs     =        136
Group variable: countrycode                     Number of groups  =         20

R-sq:                                           Obs per group:
     within  = 0.6256                                         min =          5
     between = 0.5560                                         avg =        6.8
     overall = 0.3539                                         max =          7

                                                F(7,109)          =      26.01
corr(u_i, Xb)  = -0.9465                        Prob > F          =     0.0000

-------------------------------------------------------------------------------------
       Market_Share |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------------+----------------------------------------------------------------
                GDP |    .000466   .0005217     0.89   0.374     -.000568    .0015001
Net_average_earning |   .0016634   .0003343     4.98   0.000     .0010008    .0023261
       Top_10__share|   78.08588    56.1305     1.39   0.167    -33.16295    189.3347
    Fuel_cost_Index |  -.1814049   .0677928    -2.68   0.009     -.315768   -.0470418
          Gini_Coef |   1.241702   .6748228     1.84   0.068    -.0957746    2.579179
                    |
         policycode |
                  Y |   .7640158   1.541304     0.50   0.621    -2.290799    3.818831
     Infrastructure |   .0001063   .0000323     3.29   0.001     .0000423    .0001704
              _cons |  -104.6834   31.15374    -3.36   0.001    -166.4291   -42.93769
--------------------+----------------------------------------------------------------
            sigma_u |  15.984033
            sigma_e |  4.4257785
                rho |  .92879256   (fraction of variance due to u_i)
-------------------------------------------------------------------------------------
F test that all u_i=0: F(19, 109) = 6.97                     Prob > F = 0.0000
```

. **reg Market_Share GDP Net_average_earning Top_10__share Fuel_cost_Index Gini_Coef**

Source	SS	df	MS			
				Number of obs	=	136
				F(5, 130)	=	16.51
Model	3365.09359	5	673.018717	Prob > F	=	0.0000
Residual	5298.019	130	40.7539923	R-squared	=	0.3884
				Adj R-squared	=	0.3649
Total	8663.11258	135	64.1712043	Root MSE	=	6.3839

Market_Share	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
GDP	-.0000124	.0001008	-0.12	0.902	-.0002119	.000187
Net_average_earning	.0007096	.0001981	3.58	0.000	.0003178	.0011014
Top_10__share	-5.365083	25.55149	-0.21	0.834	-55.91566	45.18549
Fuel_cost_Index	-.1114995	.0672433	-1.66	0.100	-.2445322	.0215333
Gini_Coef	.0036084	.252823	0.01	0.989	-.4965717	.5037884
_cons	-4.905678	5.785587	-0.85	0.398	-16.35177	6.540415

.

. **vif**

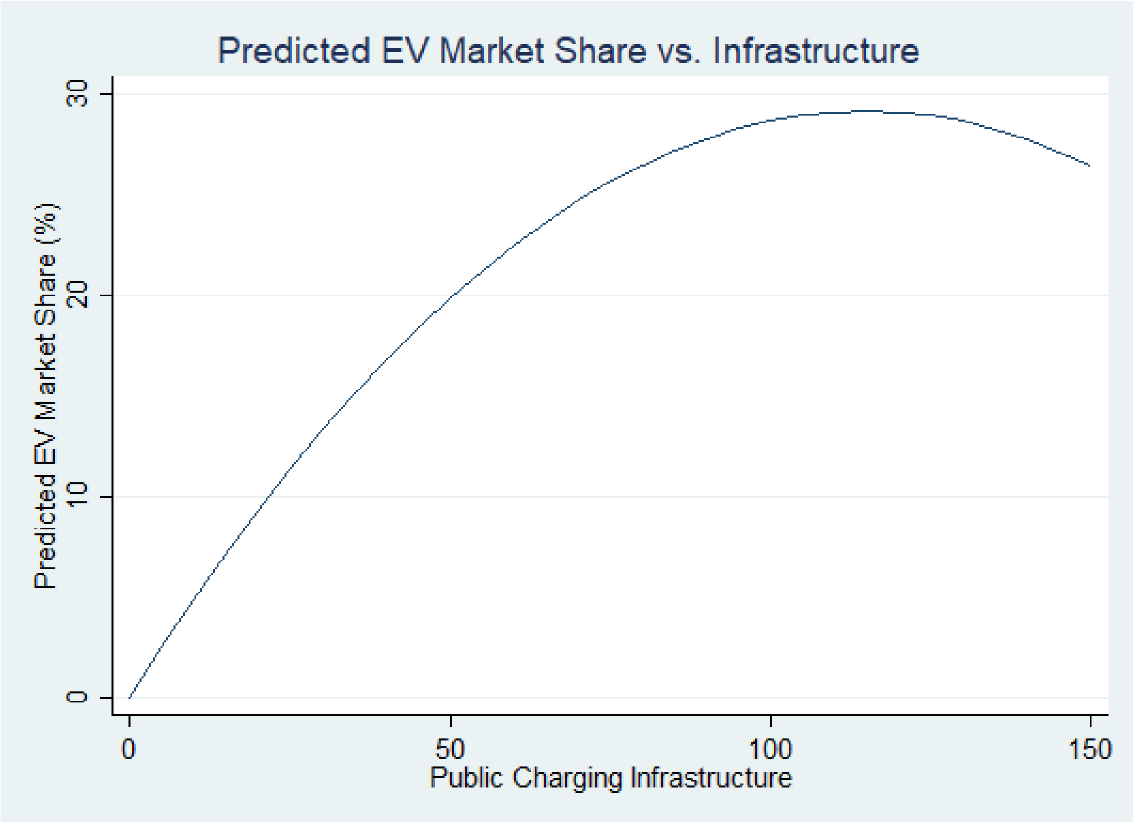
Variable	VIF	1/VIF
GDP	6.44	0.155229
Net_averag~g	6.17	0.161980
Top_10__sh~e	3.48	0.287488
Gini_Coef	3.43	0.291309
Fuel_cost_~x	1.17	0.856470
Mean VIF	4.14	

. **xtreg Market_Share c.Infrastructure c.infra_sq, fe robust**

Fixed-effects (within) regression		Number of obs =	200
Group variable: **countrycode**		Number of groups =	20
R-sq:		Obs per group:	
within =	0.5210	min =	10
between =	0.3842	avg =	10.0
overall =	0.4108	max =	10
		F(1,19) =	.
corr(u_i, Xb) =	-0.5648	Prob > F =	.

(Std. Err. adjusted for **20** clusters in countrycode)

Market_Share	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
Infrastructure	.0005089	.0001529	3.33	0.004	.0001889	.0008289
infra_sq	-2.22e-09	1.14e-09	-1.95	0.067	-4.60e-09	1.67e-10
_cons	.3627503	.8732075	0.42	0.682	-1.464894	2.190395
sigma_u	4.0930766					
sigma_e	4.5743482					
rho	.4446442	(fraction of variance due to u_i)				




```
. xtreg Market_Share ChargerDensity_scaled ChargerDensity_sq_scaled, fe

Fixed-effects (within) regression               Number of obs     =        200
Group variable: countrycode                     Number of groups  =         20

R-sq:                                           Obs per group:
     within  = 0.3610                                         min =         10
     between = 0.3607                                         avg =       10.0
     overall = 0.2970                                         max =         10

                                                F(2,178)          =      50.28
corr(u_i, Xb)  = -0.5946                        Prob > F          =     0.0000

------------------------------------------------------------------------------------------
            Market_Share |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------------------+----------------------------------------------------------------
   ChargerDensity_scaled |   27.05924   3.520104     7.69   0.000     20.11274    34.00575
ChargerDensity_sq_scaled |  -4.843913   1.091239    -4.44   0.000    -6.997344   -2.690482
                   _cons |   1.825925   .4456981     4.10   0.000      .946393    2.705457
-------------------------+----------------------------------------------------------------
                 sigma_u |  4.0970976
                 sigma_e |  5.2836664
                     rho |  .37550234   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
F test that all u_i=0: F(19, 178) = 3.89                     Prob > F = 0.0000
```

```
. xtreg Market_Share ChargerDensity_scaled ChargerDensity_sq_scaled if lowincome_group == 0, fe

Fixed-effects (within) regression               Number of obs     =         89
Group variable: countrycode                     Number of groups  =         12

R-sq:                                           Obs per group:
     within  = 0.3741                                         min =          1
     between = 0.3073                                         avg =        7.4
     overall = 0.2379                                         max =         10

                                                F(2,75)           =      22.41
corr(u_i, Xb)  = -0.7008                        Prob > F          =     0.0000

------------------------------------------------------------------------------
            Market_Share |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------------------+----------------------------------------------------------------
   ChargerDensity_scaled |   25.85729   5.154395     5.02   0.000     15.58921    36.12537
ChargerDensity_sq_scaled |  -4.504285   1.595423    -2.82   0.006     -7.68253   -1.326041
                   _cons |   2.548571   1.095254     2.33   0.023      .366713    4.730429
-------------------------+----------------------------------------------------------------
                 sigma_u |  5.0863417
                 sigma_e |  7.6670808
                     rho |  .30560358   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
F test that all u_i=0: F(11, 75) = 2.20                      Prob > F = 0.0231
```

```
. xtreg Market_Share ChargerDensity_scaled ChargerDensity_sq_scaled if lowincome_group == 1, fe

Fixed-effects (within) regression               Number of obs     =        111
Group variable: countrycode                     Number of groups  =         12

R-sq:                                           Obs per group:
     within  = 0.5870                                         min =          6
     between = 0.4502                                         avg =        9.3
     overall = 0.5434                                         max =         10

                                                F(2,97)           =      68.93
corr(u_i, Xb)  = -0.1976                        Prob > F          =     0.0000

------------------------------------------------------------------------------
            Market_Share |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------------------+----------------------------------------------------------------
   ChargerDensity_scaled |   97.04342   30.20708     3.21   0.002     37.09073    156.9961
ChargerDensity_sq_scaled |   602.8632   437.0735     1.38   0.171    -264.6066    1470.333
                   _cons |   .3821606   .2385622     1.60   0.112    -.0913193    .8556404
-------------------------+----------------------------------------------------------------
                 sigma_u |  1.0583633
                 sigma_e |  1.6984902
                     rho |  .27968348   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
F test that all u_i=0: F(11, 97) = 3.55                      Prob > F = 0.0003
```