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Tendenze nell’adozione dei veicoli elettrici: evidenze dai Paesi dell’Unione Europea

[En] Electric Vehicles Adoption Trends: Evidence from EU Countries

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Riassunto

L’impegno dell’Unione Europea a raggiungere la neutralità climatica entro il 2050 ha accelerato la transizione verso la mobilità elettrica. Tuttavia, la velocità di adozione varia considerevolmente tra gli Stati membri, riflettendo differenze strutturali ed economiche. Questa tesi analizza l’evoluzione dell’adozione dei veicoli elettrici (EV) in 22 Paesi dell’UE tra il 2013 e il 2023, concentrandosi su come la dipendenza dai veicoli con motore a combustione interna (ICE) influenzi la diffusione delle autovetture elettriche a batteria. Utilizzando dati di Eurostat e della Banca Mondiale, lo studio combina un’analisi delle rotture strutturali di Bai–Perron con un modello di regressione a effetti fissi bidirezionali (Two-Way Fixed Effects, TWFE). Il test di Bai–Perron identifica il 2019 come l’anno mediano di rottura strutturale che segna l’inizio di un’accelerazione dell’adozione dei veicoli elettrici nella maggior parte dei Paesi. I risultati della regressione mostrano che, dopo questo punto di discontinuità, i Paesi maggiormente dipendenti dalla tecnologia ICE registrano una crescita significativamente più lenta della quota di mercato dei veicoli elettrici, confermando l’ipotesi secondo cui una forte dipendenza storica dalla tecnologia a combustione interna agisce come una forma di “carbon lock-in”. Nel 2023, i Paesi che nel 2019 erano più dipendenti dalle autovetture con motore a combustione hanno finito per adottare i veicoli elettrici molto più lentamente, mostrando un passaggio verso gli EV chiaramente più debole rispetto ai Paesi meno dipendenti dalla tecnologia ICE. I risultati supportano il quadro teorico della path dependence e sottolineano che regolamentazioni uniformi a livello dell’UE possono produrre esiti asimmetrici in contesti nazionali eterogenei. Le implicazioni di policy suggeriscono che le strategie di decarbonizzazione debbano tenere conto delle strutture industriali specifiche dei singoli Paesi e del livello di preparazione infrastrutturale, al fine di garantire una transizione equa verso sistemi di trasporto sostenibili.

Abstract

The European Union’s commitment to climate neutrality by 2050 has accelerated the transition toward electric mobility. However, the speed of adoption varies considerably across member states, reflecting structural and economic differences. This thesis investigates the evolution of electric vehicle (EV) adoption among 22 EU countries between 2013 and 2023, focusing on how dependence on internal combustion engine (ICE) vehicles influences the diffusion of battery-electric passenger cars. Using Eurostat and World Bank data, the study combines a Bai–Perron structural break analysis with a Two-Way Fixed Effects (TWFE) regression model. The Bai–Perron test identifies 2019 as the median structural break year marking the onset of accelerated EV adoption across most countries. Regression results reveal that, after this breakpoint, ICE-reliant countries show significantly slower growth in EV market share, confirming the hypothesis that strong historical dependence on ICE technology acts as a form of “carbon lock-in.” In 2023, countries that were more dependent on combustion-engine cars in 2019 ended up adopting electric vehicles much more slowly, showing a clearly weaker shift toward EVs compared with less ICE-reliant countries. The findings support the theoretical framework of path dependence and underscore that uniform EU-wide regulations may yield asymmetric outcomes across heterogeneous national contexts. Policy implications suggest that decarbonization strategies must account for country-specific industrial structures and infrastructure readiness to ensure an equitable transition toward sustainable transport systems.

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List of Abbreviations

EV	Electric Vehicle
BEV	Battery Electric Vehicle
PHEV	Plug in Hybrid Vehicle
ICE	Internal Combustion Engine
TWFE	Two Way Fixed Effect

1 Introduction

The European Union’s climate strategies are aimed at achieving climate neutrality by 2050, shaping an economy that produces no net greenhouse gas emissions by that year (European Commision, 2019). With the aim of fostering this goal, several obligations -including regulations, penalties, and incentives- are being introduced by governments in the form of both market and non-market instruments. Meanwhile, the transportation sector remains one of the largest contributors to greenhouse gas emissions in the European Union. For this reason, many of these policy measures target this specific sector. Notably, it is the only sector that has experienced an increase in greenhouse gas emissions over the past 30 years, with a 33.5% rise between 1990 and 2019 (EEA, 2022). Within transport-related emissions, passenger cars alone represent the leading source, accounting for 61% of total CO_2 emissions from road transport in the EU (CO2 emissions from cars, 2019). With this aim, understanding the evolution of passenger car trends and their fuel type transitions is not only essential for individual household choices and decisions, but also plays a critical role in informing broader policy and industrial decision-making.

In 2023, the number of battery-electric passenger cars in EU countries is approximately 88 times greater than it was in 2013 (eurostat, 2024). This demonstrates how cleaner alternatives are evolving over time. Overall, the global transition from conventional fossil-based energy sources to environmentally sustainable fuels is progressing at uneven rates across different regions. For instance, in 2022, China accounted for nearly half of global low-carbon investment, directing about $546 billion toward areas such as solar and wind power, electric mobility, and battery technologies. The European Union ranked second, channelling approximately $180 billion into clean-energy initiatives, while the United States followed with around $141 billion. (Dahlström, 2025) Among all these categories of low-carbon investments, electric vehicles are perhaps the most visible to the public, with their increasing presence on roads serving as tangible evidence of the transition. In 2023, the European Union recorded 2.36 million new EV registrations. The United States, however, has been narrowing the gap; EV registrations there reached 1.43 million in 2023, representing a 52 percent increase compared to 2022. In contrast, EV uptake in the EU expanded by only 18 percent over the same period (Tamba, 2024). The Rhodium Group -an independent research firm specializing in climate and energy analysis- notes in its report that, on both sides of the world (the US and the EU), consumers have shown a clear preference for pure BEVs over PHEVs. For this reason, our research specifically focuses on BEVs -often referred to simply as EVs. The shifts in fuel types are also not expected to occur uniformly across countries within European Union, as the timing depends on each country's specific characteristics and policy objectives. This variation forms a part of the motivation for this thesis.

1.1 Background

The greenhouse gas emissions produced during the manufacturing phase for both EV and ICE vehicles are almost the same, with an average of 6.0 tCO_2e per vehicle. (International Energy Agency, 2021) Over its lifetime, Nevertheless, an average EV is responsible for approximately 11.7 t CO_2-equivalent emissions, compared to 35.9 t CO_2-equivalent for a conventional ICE vehicle which is roughly three times higher. These facts also highlight the challenges associated with transitioning to electric vehicles, particularly given that such a shift may not yield significant profit differentials for manufacturers to justify altering their production structures.

Environmental considerations alone, as is evident, are insufficient to drive a fundamental transformation in production systems without complementary economic incentives or policy interventions. Economic pressures constitute the primary driving force behind the accelerating shift toward electrification in both transportation and industrial sectors. (Khabur, 2023) Numerous EU-wide regulations, implemented through both market-based and non-market instruments, have been introduced to address this gap. Some examples are:

1.1.1 European Green Deal

In 2019, in response to growing public dissatisfaction and increasing concerns about climate change across Europe, the European Commission introduced the European Green Deal. (European Commision, 2024) This deal represented under the leadership of President Ursula von der Leyen (Publications Office of the European Union, 2024). The initiative sets out an ambitious roadmap for achieving net-zero greenhouse gas emissions in the European Union. This includes comprehensive targets in the energy system, transport sector, industrial activities, and the broader economy. (European Commision, 2024) This deal mainly targets 3 milestones as follows: 1- have at least 30 million zero emission cars on the streets of the Europe, climate natural 100 cities and high-speed rail network by 2030. 2- required infrastructure and technology readiness for the first climate-natural passenger airplane by 2023, and finally 3- zero-emissions technology for all modes of transport, including heavy-duty vehicles by 2050. (Fetting, 2020) Regardless of whether these milestones are fully attainable or not, it is clear that the automotive industry plays a crucial role in this transition. For this reason, the “green deal industrial” plan was presented in February 2023, As a support for green technologies. (Alvarez, 2023) Centrum für Europäische Politic (cepStudy) recently published a detailed report on the role of the road transport in decarbonization. The study stresses that the future European automotive sector must indeed at the same time be decarbonised, globally competitive and resilient. The entire EU green deal will be at stake, if one of these interdependent and mutually reinforcing criteria is not fulfilled. (Menner, 2025)

1.1.2 Emission Performance Standards

Regulation (EU) 2019/631 of the European Parliament and of the Council, adopted on 17 April 2019, establishes CO_2 emission performance standards for new passenger cars (95 g CO2/km for the average emissions of new passenger cars) and light commercial vehicles (147 g CO2/km for the average emissions of new light commercial vehicles) across the European Union. (European Parliament, European Council, 2019) This regulation sets binding targets for manufacturers to reduce the average CO_2 emissions of their fleets, thereby contributing to the EU’s broader climate neutrality objectives. excess emissions incur substantial financial penalties, so that from 2021, the excess emissions premium shall be €95 for each gram of CO_2/km by which the target is exceeded, multiplied by the number of new passenger cars registered.

1.1.3 Alternative Fuels Infrastructure Regulation

The regulation (EU) 2023/1804 was introduced in response to the uneven distribution of publicly accessible recharging infrastructure for EVs across the European Union. (European Parliment, European Council, 2023) The Regulation establishes binding minimum targets to promote the deployment of publicly accessible charging and refuelling facilities for road transport. Accordingly, from 2024 onwards, Member States are required to ensure that, by the end of each calendar year, the following cumulative power output thresholds are met:

(a) for every registered light-duty battery electric vehicle within their territory, a minimum total installed power capacity of 1.3 kW must be available through publicly accessible recharging points; and

(b) for every registered light-duty plug-in hybrid vehicle, a minimum total installed capacity of 0.80 kW must be provided via such recharging points.

1.2 Research Question

This thesis seeks to understand how countries with different levels of reliance on ICE vehicles experience EV adoption in passenger cars, focusing on the 22 member states of the European Union. (EU countries, n.d.) Understanding these differences is essential because the speed of EV adoption has direct implications for the effectiveness of EU-wide climate. It analyses the actual trends over time and firstly investigates whether structural breakpoints in EV adoption occurred in different countries - and if so, when. Then, these breakpoints will be used in the main part of the regression model. By incorporating these breakpoints, the empirical strategy can more accurately detect whether countries followed common transition patterns or diverged substantially due to structural, economic, or policy-related factors.

The central research question is: How have EV adoption trends differed across EU countries with different levels of ICE dependency and in a specific baseline year? We use the share of diesel and petrol vehicles as a proxy for ICE dependency, indicating the extent of a country's reliance on this type of passenger car. This proxy captures long-standing market structures, consumer preferences, and industrial specialisation, all of which may shape how rapidly a country can pivot toward electric mobility. Further details will be provided in the methodology section.

To further guide the empirical analysis and ensure the internal validity of the results, we formulate some sub-questions that address potential methodological and robustness considerations. These sub questions are as follows:

- Do countries with a higher share of internal combustion engine vehicles experience slower changes in EV adoption?
- Is the policy effect robust to alternative EV adoption indicators?

- Were there notable differences in EV trends between before the transition period?

Together, these questions contribute to a comprehensive assessment of whether countries’ historical dependence on ICE continues to shape their progress in adopting cleaner vehicle technologies.

1.3 Theoretical Framework

Several theoretical frameworks have been developed to explain the varying pace at which societies adopt green technologies. One such framework is the carbon lock-in, by Unruh (2016) which offers valuable insight into the structural and behavioural barriers that hinder rapid transitions. Although the concept is broad, it is highly relevant to our study. As highlighted, a combination of existing technologies, institutional arrangements, and behavioural norms tends to constrain both the speed and scale of carbon emission reductions. These interlocking systems can significantly delay the transition toward low-carbon alternatives, reinforcing the persistence of high-emission pathways. Unruh and others suggested that according to the Techno-Institutional Complex (TIC) index, ICE passenger vehicles represent the second most locked-in technology globally, following coal-based power generation. This technological lock-in results from strong interdependencies between industrial structures, institutions, and infrastructures that reinforce the dominance of existing systems. The financial barrier associated with transitioning away from ICE vehicles can be illustrated by the estimated carbon price required for their early retirement and replacement with alternative technologies. In this context, approximately 5,000 USD would be needed per gram of CO_2 to make such a replacement economically viable. This immense cost highlights the depth of the economic and institutional entrenchment of ICE technologies. Combined with the high complexity of the TIC framework, these factors make ICE vehicles among the most entrenched technologies, both economically and politically, characterized by strong lobbying pressures, path dependency, and limited flexibility for structural change.

It is worth mentioning that this study itself adopts the term “Carbon Lock-in” theory as originally introduced by Unruh (2000) in its paper named *Understanding carbon lock-in.* The overall insight of these two papers is that carbon lock-in is a special form of path dependency, where past decisions constrain future options, especially in systems involving fossil fuels. It happens when infrastructure, policies, and behaviours collectively sustain reliance on high-carbon practices.

The study also mentions that there are three different types of lock-in, such as: 1. infrastructural and technological lock-in, which comes from long lived physical infrastructures such as power plants, roads, and buildings. It highlighted that, if prior technologies dominate investment and policies, then a barrier for new low carbon technologies will exist. 2. Institutional lock-in will arise as well, if rules, norms, and decision-making structures support carbon intensive systems. These rules often designed intentionally by governments to protect their interests, resulting in difficult changes over time. The last one is behavioural lock-in. It means that habits become automatic with repetition, making change difficult even with new information.

These concepts stablish the first foundational framework of this thesis. In easier terms, both papers together highlighted that Carbon lock-in is described as a path-dependent process, where early technological and institutional choices determine future trajectories. Once large infrastructures are built and networks of complementary technologies form, switching to cleaner systems becomes progressively costlier and politically difficult. These two papers together shaped the main theory in our thesis too, stressing the fact that how ICE and EV vehicles trends are important and fresh to study on, in these days’ society.

1.4 Hypotheses

Shifting to electric vehicle production is a significant challenge for the automotive industry as it involves higher production costs, substantial changes in existing supply and value chains, and high charging expenses, which pose an obstacle for consumer side adoption. (Dietz, 2025) A study from Pavílnek (2022) shows that, the pace of this transition is slower in eastern Europe compared to Western Europe, as countries in the East are likely continue producing internal combustion engine vehicles for a longer period. This trend appears logical, given that Eastern European countries hold a cost advantage due to reduced manufacturing expenses, particularly lower labour costs.

Based on these considerations, together with the theoretical framework and structural resistance of dependant countries, following hypotheses is proposed:
- **H1.** Countries with a higher dependence on ICE vehicles tend to adopt electric vehicles at a slower pace.

1.5 Structure of the Thesis

This thesis is organized into six chapters as follows:

Chapter 1 -Introduction: Presents the motivation and relevance of the study, the rationale behind its conception, and the background on governmental efforts related to the topic. It also outlines the research question and sub-questions to be addressed, as well as the hypotheses that are expected to be tested and validated through the analysis.

Chapter 2 -Literature Review: Reviews the existing academic literature and papers relevant to the research topic, identifying gaps in them and justifying the unique contribution of this research.

Chapter 3- Data and Methodology: Explains the data sources, variables, and econometric methods, as well as adjustments in data sources.

Chapter 4- Results: resents the empirical findings derived from the empirical analysis. It also highlights the robustness of the results and links them to the hypotheses formulated in Chapter 1.

Chapter 5- Discussion: Provides an in-depth interpretation of the empirical results, compares Implementations and limitations with each other.

Chapter 6- Conclusion: Summarises the main findings of the thesis.

Within each chapter, some sub-sections are used to structure the discussion and provide detailed justification for the theoretical and empirical components of the study.

2 Literature Review

The academic and research focus on EV and sustainability related topics has only gained significant momentum in recent years. As a relatively recent area of interest, most articles and reports on the subject have emerged since around year 2010. This makes the present study particularly valuable, as the field still offers considerable opportunities for future contributions. Existing literature is mostly focused on estimating the effect of various incentives on electronic vehicles adoption. One example is study by Sierzchula (2014) which found that financial incentives, the availability of charging infrastructure, and the domestic presence of electric vehicle manufacturing were all statistically significant and positively linked to a country's electric vehicle market shares in 30 countries and solely in the year 2012.

Another relevant paper by Neves (2018) extended the analysis from 2010 to 2016 and included both PHEV together EV in the scope of the research Using Panel-Corrected Standard Errors (PCSE) method, the study demonstrated that technological advancements such as battery range, cost, and capacity along with charging infrastructure, are key factors for the adoption of both vehicle types. The authors also highlighted that adoption patterns of BHEVs and BEVs respond differently to policy, social, economic, environmental factors.

Some studies have found that introduced policy incentives play a meaningful role in this adoption. For instance, Langbroek (2016) highlight not only the impact of such incentives but also underline the importance of behavioural factors. Their research suggests that individuals who view electric vehicles as an effective solution to the externalities and harms caused by traditional transportation, and whose mobility needs align with the capabilities of EVs, are significantly more likely to opt for them.

A valuable contribution of another paper from Fluchs (2020), lies not only in predicting future growth but also in explaining the differences in diffusion patterns across countries. The diffusion of BEVs follows an S-shaped curve, starting slowly, accelerating during the adoption phase, and eventually slowing as market saturation is approached. This study identifies direct financial incentives that reduce the purchase price as the main driver of faster EV adoption, whereas tax discounts and non-financial incentives are found to be less effective.

The finding of This paper is strongly supported and corroborated by the result of another study, which is a very recent scenario-based analysis conducted in Germany in 2024. It investigated the progress of EU member states in transitioning toward net-zero emissions in new passenger car registrations. (Möring-Martínez, 2024) The study applied a clustering methodology to group EU member states into seven distinct categories, with each cluster represented by a prototypical country. The findings suggest that countries recognized for their leadership in innovation exhibit a higher likelihood of achieving the 2035 target for net-zero emissions in new passenger vehicle registrations. (Directorate-General for Climate Action, 2023) The study also demonstrates that countries such as the Netherlands and Sweden are projected to achieve a 100% share of zero-emission vehicle registrations even before the European Union’s 2035 ban takes effect. key finding of the study which is connected to the study of Fluchs (2020) is that the removal of government subsidies may present a significant barrier to electric vehicle adoption -particularly in countries like Germany and Italy-where such fiscal incentives remain a primary policy instrument for promoting the EV adoption.

Some studies examine motivator and barriers affecting the diffusion of EVs again in Europe from a different perspective. A paper from Biresselioglu (2018), has analysed these motivators and barriers across three different decision-making levels named: 1. formal social unit, 2. collective decision-making unit, and 3. individual unit. Authors performed an extensive review of publications between 2003-2017 and keyword searches. The results showed that regardless of the level of units, barriers outweighed motivators, and this imbalance is a sufficient explanation for slow EV adoption and acceptance rates. The authors main policy recommendation is to expand the charging infrastructure.

This is also a concept which constitutes the core idea of the paper by Peng (2023), in which they examine different factors influencing EV market share. The study conducted a distinguishing analysis of the EU and the US, highlighting that EV adaption factors generally vary by region. Hence, location-based policies and enhancing reliable charging networks are important, while also considering social and demographic variations.

Policy research working paper from the World Bank employed methodologies similar to those we will use to determine past changes in this phase. The authors applied a panel regression model for EV demand, using both Ordinary Least Squares (OLS) and Two-Stage Least Squares (2SLS) instrumental variable (IV) estimation to address endogeneity in prices and charging infrastructure. (Shanjun Li, 2021)The regression covered 13 different countries across the globe over the period 2013–2020, during which EVs were first introduced to the market. The results showed that a $1,000 decrease in the consumer price (without subsidies) increases EV sales by 2.9%, while a 10% increase in the number of available public charging ports increases EV sales by 8.2%. This again underscores that charging infrastructure is more cost-effective than other factors, as discussed earlier. More importantly, this study highlights the significant variation in EV adoption across countries, even among those with similar socio-economic characteristics.

To delve deeper into the relationship between ICE vehicles and EVs, a relevant example is provided by Colombo (2024). This study explores the potential willingness of current ICE vehicle users to make such a shift. The research employs a multi-scenario, data-driven case study, drawing on real GPS-tracking data from 200 private vehicle users. The findings indicate that replacing ICE vehicles with EVs on a global scale could lead to substantial reductions in greenhouse gas emissions. However, the magnitude of these benefits is contingent upon two critical factors: the carbon intensity of the electricity used for charging and the overall efficiency of the EVs themselves. The study highlights that achieving deep decarbonization in the transport sector requires not only a widespread adoption of EVs, but also a parallel decarbonization of the electricity grid. A noteworthy limitation is that the empirical model and data are restricted to the context of northern Italy. It provides localized insights and limits the extent to which the results can be confidently generalized across Europe. Nevertheless, the authors conceptually extend their conclusions, suggesting that similar outcomes could be expected elsewhere under comparable conditions.

In the subject of regional analysis, a paper from Vegini (2025) also claims that the EU should not treat all countries the same, and not all regions either. Authors highlighted that based on their ESTDA empirical approach, carbon emission dropped by 33.6% in the whole EU, but this progress is uneven across regions. Some regions are moving fast and others are stuck, and of course it is aligned with regions form clusters with similar behaviour. But for reaching climate naturality, the EU must use targeted, region specific policies and local conditions.

3 Data and Methodology

3.1 Data

The data utilized in this study were obtained from multiple reliable sources, primarily focusing on member countries of the European Union. The selected time frame spans from 2013 to 2023, allowing for a comprehensive analysis of trends over a particularly transformative decade. In particular, the scope of the analysis is limited to the 22 Member States of the 27 countries of European Union (EU-27), as officially defined by the European Commission following the United Kingdom's withdrawal from the Union in 2020 (EU countries, 2018). The selection of the study's time frame is justified by market data reported by the International Energy Agency (IEA).

According to the IEA's chart provided below in figure 1, the introduction of electric vehicles into the European market began in the early 2020s decade, with a notable milestone of approximately 0.1 million EVs registered in 2013. (IEA, 2024) This figure increased substantially, reaching 6.7 million units by 2023. This growth trajectory underscores the relevance of the chosen period in our study, as years beyond 2023 are too recent to provide sufficient post-trend data for robust analysis, and years prior to 2013 are less suitable because many European countries had little to no EV presence during that time.

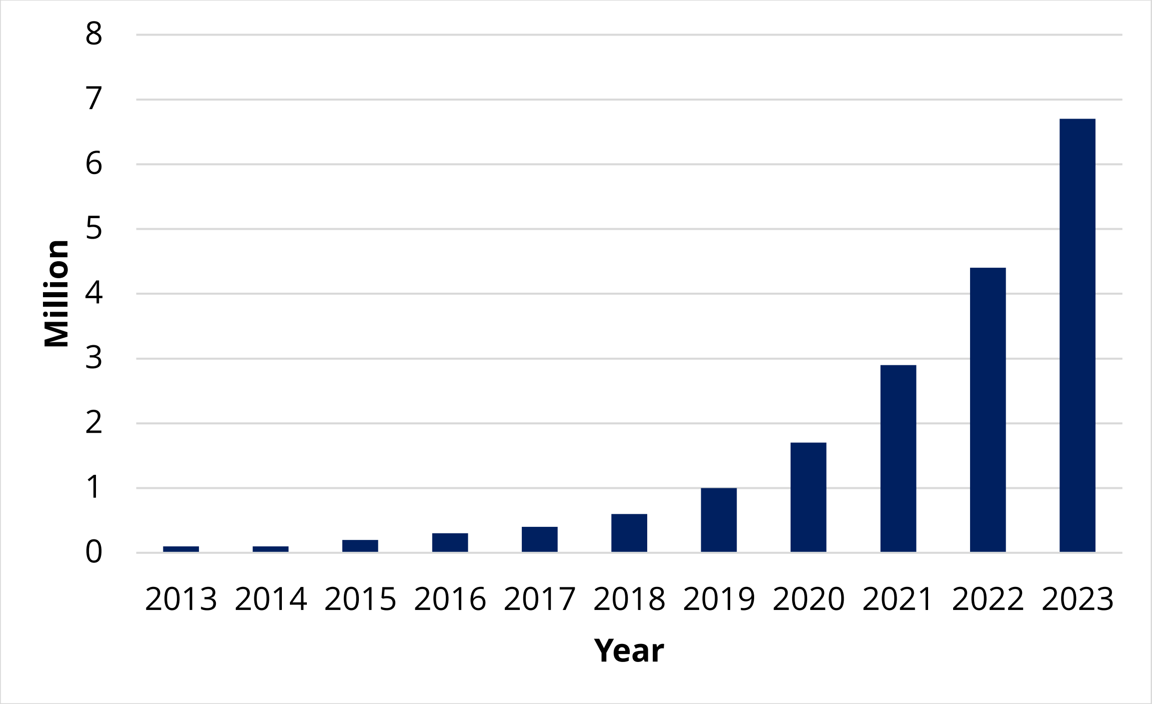

Figure 1- Global Electric Car Stock in Europe, 2013-2023 - *All values are expressed as Millions.*

3.1.1 Electric Passenger Car Registration Share

The first key component of the dataset was sourced from Eurostat -the Statistical Office of the European Union- which provides annual figures on the net number of newly registered electric passenger cars in each EU country from 2013 to 2023. (Eurostat, 2025) To construct the share of electric passenger cars for each country and year -since this variable was not directly available- following data sets are used:

- Number of newly registered electric passenger cars
- Number of totals newly registered passenger cars

Hence, The EV share was calculated through equation 1:

$$EV\ Share_{i,t} = \left(\frac{EV\ Cars_{i,t}}{Total\ Cars_{i,t}}\right) \times 100 \tag{1}$$

where i indicates the country and t the year. The resulting variable is expressed as a percentage and captures the degree of EV market penetration in each EU-27 country from 2013 to 2023.

A sample of the calculated electric vehicle share as a percentage of total passenger car registrations is provided in table 1. While this table shows a limited selection of countries and years for illustrative purposes, the full results are provided in Appendix 1. The values were computed in RStudio and represent the final panel dataset that will be used in the regression analysis.

Table 1- Electric Passenger Car Registration Share - *All values are expressed as percentages (%).*

	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Germany	0.2	0.28	0.39	0.35	0.73	1.05	1.75	6.65	13.58	17.75	18.43
Spain	0.13	0.11	0.25	0.17	0.3	0.43	0.76	1.96	2.66	3.73	5.63
France	0.5	0.6	0.92	1.1	1.18	1.43	1.93	6.64	9.69	13.14	16.49
Netherlands	0.63	0.75	0.71	1.04	1.92	5.41	13.82	20.5	19.75	23.47	30.83
Denmark	0.3	0.83	0.61	0.57	0.31	0.71	2.44	7.15	13.33	20.63	36.09
Belgium	0.1	0.24	0.27	0.38	0.49	0.67	1.59	3.43	5.8	10.08	19.29

3.1.2 Petrol and Diesel Passenger Car Registration

To assess each country's dependence on internal combustion engine vehicles, this study employs a proxy measure based on the number of registered passenger cars with petrol and diesel engines. (Eurostat, 2025) This proxy provides insight into the structural differences in ICE vehicle reliance across countries. It is employed as a time-invariant variable to capture baseline dependence on internal combustion engine technologies. During the data preparation process, we identified missing values in the diesel and petrol registration data for five EU member states: Bulgaria, Czechia, Greece, Croatia, and Slovakia. Because these gaps occur in key explanatory variables, including them would lead to varying sample sizes across models and introduce potential bias. To maintain a consistent and reliable regression sample, these five countries were excluded from the analysis. Consequently, while our study initially covered the EU-27, the final regression sample comprises 22 EU member states with complete data for all variables. Further methodological details -including the rationale for selecting a specific reference year to compare ICE dependency across countries- are presented separately in the methodology section. The ICE dependency variable is calculated based on equation 2 as followes:

$$ICE\ Dependency_i^{2019} = \left(\frac{Petrol\ Cars_i^{2019} + \ Diesel\ Cars_i^{2019}}{Total\ Cars_i^{2019}} \times 100\right) \qquad \textbf{(2)}$$

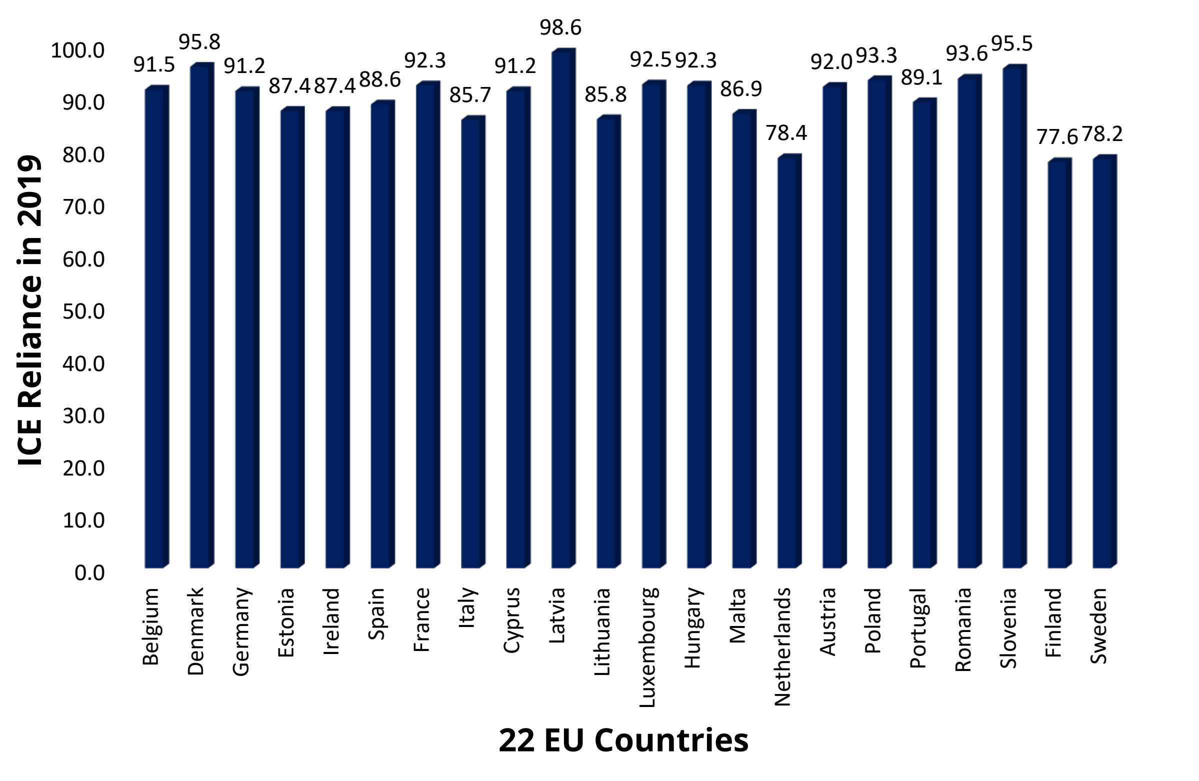

Figure 2- Cross-Country Comparison of ICE Reliance in 2019- *All values are expressed as percentages (%).*

Another noteworthy aspect of this ICE reliance Comparison (Figure 2) shows striking systematic differences across Europe, which align closely with the broader macro-regional patterns described by Poliscanova (2021). In particular, this report groups European countries into four blocks: Nordics+ , Western, Southern, and Eastern, based on factors such as existing EV uptake, income levels, and the policy environment. These regional groupings correspond very clearly to the variation visible in the ICE reliance data in figure 2. Countries belonging to the Nordics+ and Western Europe bloc (for instance Germany, France, the Netherlands) are characterized in the report as “early adopters” or “early majority” , with stronger EV policies, higher GDP per capita, and faster diffusion of electric mobility. Consistent with this, many of these countries display comparatively lower ICE dependence in 2019 in our figure. In contrast, the Southern (Italy, Spain, Portugal) and especially Eastern European countries (Poland, Romania, Lithuania) are identified in the report as “late-majority” or “late adopters” where BEV diffusion begins from a low base and purchasing patterns remain strongly dominated by conventional engine technologies.

3.1.3 Diesel Fuel Price

Weekly retail diesel fuel were obtained from the European Commission’s Oil Bulletin database for all 22 out of EU-27 countries from 2013 to 2023. (European Commission, 2024) The Oil Bulletin provides harmonized data across Member States, collected according to Council Decision 1999/280/EC and published on a weekly basis. The original dataset contains weekly diesel price data for EU Member States from 2005 onwards, of which only the years 2013 to 2023 were retained to ensure consistency with the other variables. Prices are reported both with and without taxes; the version including taxes was selected, as it reflects the final retail prices faced by consumers and is therefore more representative of the price signals that influence consumer preferences. For the purposes of this study, weekly prices were converted into annual averages for each country and year, to align with the panel data structure of the other variables. In the original dataset, prices are reported in euros per 1,000 liters. For consistency and ease of interpretation in the regression, these values were converted to euros per 1 liter by dividing by 1,000. All prices are expressed in nominal EUR/liter.

3.1.4 GDP per Capita

Annual GDP per capita data for the EU-27 countries is available from the World Bank's World Development Indicators database, offering the period from 1960 to 2024. (World Bank, 2015) We extract data for the years 2013 to 2023 for these 22 EU member states. According to the metadata provided by the World Bank, GDP per capita is defined as gross domestic product (GDP) divided by the mid-year population. GDP represents the sum of gross value added by all resident producers in the economy, plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without deductions for the depreciation of fabricated assets or for the depletion and degradation of natural resources. All figures are reported in constant 2015 U.S. dollars to ensure comparability over time.

3.1.5 Urban Population Share

The percentage share of the total population for each country is obtained from the World Bank for our relevant scope (World Bank) . According to the metadata available in the dataset (as provided within the Excel file and not from a separately citable source), urban population share represents the proportion of a country's population living in areas classified as urban by the respective national statistical authorities. The indicator provides a snapshot of the degree of urbanization in a country at a specific point in time, reflecting long-term demographic, economic, and social transformations. According to the World Bank, the data are largely derived from the United Nations' World Urbanization Prospects and provided to users through the World Bank's DataBank platform (United Nations). The measurement unit is percentage (% of total population). The meta data also indicates that explosive growth of cities globally signifies the demographic transition from rural to urban and is associated with shifts from an agriculture-based economy to mass industry, technology, and service. That's what makes this data particularly valuable in our model.

3.1.6 Correlation Matrix

We calculated the Correlation matrix with the aim of 1. Show basic relationship between variables, 2. Detect multicollinearity problems, and 3. Improve transparency and readability. (Bock, 2025) The correlation matrix reports Pearson coefficients based on the pooled panel of 22 EU countries from 2013 to 2023 (N = 242). EV_share refers to the share of battery-electric vehicle registrations in total passenger car registrations, ICE_reliance measures baseline ICE dependence in 2019, GDP_per_cap is GDP per capita (constant 2015 USD), Urban_pop represents the share of urban population, and Diesel_price is the average annual retail diesel price. As shown in table 2, the results show a moderate negative relationship between EV adoption and ICE reliance (r = –0.20), meaning that countries with higher ICE dependence tend to have lower EV shares. EV adoption is positively correlated with GDP per capita (r = 0.29) and urbanization (r = 0.26), which aligns with the expectation that wealthier and more urbanized countries adopt new technologies more quickly. The strongest correlation appears between EV_share and Diesel_price (r = 0.63), suggesting that higher fuel prices are associated with faster EV uptake.

Importantly, none of the correlations among the explanatory variables themselves exceeds 0.5 in absolute value, indicating that multicollinearity is not a concern and that including these variables together in the TWFE model does not pose statistical problems.

Table 2 - Correlation Matrix of main variables

	EV_share	**ICE_reliance**	**GDP_per_cap**	**Urban_pop**	**Diesel_price**
EV_share	1.00	-0.20	0.29	0.26	0.63
ICE_reliance	-0.20	1.00	-0.18	-0.39	-0.26
GDP_per_cap	0.29	-0.18	1.00	0.48	0.15
Urban_pop	0.26	-0.39	0.48	1.00	0.18
Diesel_price	0.63	-0.26	0.15	0.18	1.00

3.2 Methodology

In the model, we aim to examine how the share of electronic vehicles evolves across countries and in each year. Beyond analysing the absolute values of EV share, we also seek to explain the underlying trends. To this end, we utilize an interaction term that explain how EV adoption patterns differ depending on a country's reliance on internal combustion engine. An interaction tells us whether the effect of one variable depends on another variable. As mentioned earlier, we use this approach as a proxy, since determining the exact dependency on ICE is not easily feasible due to unavailable data. For the interaction term to be meaningful, we require a consistent reference year that marks the beginning of EV transition across countries. To identify this year, we will conduct a structural break test for each country, determining when a significant change in EV adoption began. Since this breakpoint is expected to vary across countries, we will take the median of these break years to obtain a unified reference year that represents the point at which EV adoption started in most countries. This reference year will then be used in the main regression to interact with ICE dependency, enabling us to capture how reliance on ICE vehicles influences EV adoption trends.

3.2.1 Bai-Perron Test

Time series models often assume that the relationship between variables remains stable over time. For this reason, structural break models address situations where external factors cause sudden and lasting changes in these relationships by allowing any model parameter to shift permanently. (Aptech Systems, 2024)

There are different types of tests, each suitable for a specific approach, such as The Chow Test, The Quandt likelihood Ratio Test, The SUSUM Test etc. The Bai-Perron test is a structural break analysis method designed for linear regression models, originally introduced in a joint paper by Jushan Bai and Pierre Perron. (Jushan Bai, 1998) This methodology is particularly well suited for identifying multiple structural breaks at unknown points in time within a regression framework. It finds the location and number of breaks with efficient dynamic programming algorithm (Aptech Systems, 2024).

Nowadays, the test is widely implemented in statistical software packages, enabling users to detect and estimate structural changes in time series data through algorithms (Doan, 2025). We applied the Bai–Perron multiple structural break algorithm in Rstudio software, to identify potential break years in the EV market share series -which we have already obtain previously and visualized a sample of that in data section- for each country. The dataset was first reshaped into a long format, filtered to remove invalid entries, and then analysed separately by country using the *breakpoints()* function from the *strucchange* package with a minimum segment size of three observations. The resulting break years were compiled into a summary table, which was subsequently visualised as a country-by-year timeline using ggplot2 to facilitate cross-country comparison of structural shifts.

3.2.2 Two Way Fixed Effect

The equation 3 will be employed to analyse the share of newly registered electric vehicles. This approach controls for both country specific and time invariant factors and year specific shocks that could otherwise bias the results.

$$EV\ Share_{it} = \alpha + \sum_{t=2013}^{2023} \beta_t (ICE_i \times D_t) + \gamma_i + \delta_t + X'_{it}\theta + \varepsilon_{it} \tag{3}$$

Where $EV\ Share_{it}$ poses as the dependent variable and share of newly registered EVs in country i at time t. $ICE_i \times D_t$ is written as Interaction term indicating how EV adoption trends differ depending on a country's ICE dependence. The coefficients β_t show whether ICE heavy countries transition slower or faster toward EVs. γ_i show the Country fixed effects and captures unobserved, time invariant country specific characteristics. δ are year fixed effects, and try to capture EU wide shocks or trends, such as regulations or macroeconomic changes and isolate them in the model. X'_{it} is the control variables representative, such as GDP per capita, Real diesel prices, Urbanization rate.

3.2.3 Justification of the TWFE

Whenever an empirical analysis is conducted, numerous uncertainties emerge concerning which methodological approach is most appropriate among the available alternatives. In our context, the TWFE model have chosen. (Cameron, 2005) This empirical strategy is particularly suitable for the purposes of this thesis because it enables the analysis to focus on within-country changes in EV adoption over time, net of any country-specific characteristics that do not vary across years. By including country fixed effects, the model absorbs all structural, institutional, and cultural factors that are constant within each country. At the same time, year fixed effects control for EU-wide shocks and common trends, such as macroeconomic fluctuations, regulatory developments, or technological progress in the automotive sector. Together, these features ensure that the estimated coefficients capture changes in EV adoption that are driven by temporal variation within countries, rather than by static cross-country differences.

Difference-in-Differences (DiD) is also a similar approach that might also be suitable for policy evaluation. Despite that it is widely used in econometrics studies, it is not suitable for the empirical setting of this thesis. A standard DiD design requires the identification of a treatment and control group, which is clear and justified. It also requires a discrete policy intervention occurring at a specific point in time. In contrast, environmental policy stringency and EV adoption evolve gradually and heterogeneously across European countries, without a single unified policy shock that would allow for a conventional treatment–control comparison. Moreover,in DiD the parallel-trends assumption must met, which requires some untreated samples to provide a valid counterfactual for treated units. Given the strong cross-country heterogeneity in economic structure, policy preferences, and market development, this assumption would be difficult to justify in our context. For these reasons, a TWFE specification provides a more conceptually appropriate framework for the analysis.

4 Results

4.1 Bai-Perron result

The initial stage of the empirical analysis was conducted as illustrated in Figure 3. The results confirm that, for several countries, structural breakpoints occurred at varying points in time, broadly aligning with prior expectations. The range of identified break years begins in 2017, suggesting that the transformation process is relatively recent and that no substantial shifts occurred during the early part of the observation period (2013-2016). Specifically, 2016 emerged as the break year for four countries -Bulgaria, France, Hungary, Lithuania- while 2017 marked the break for nine countries -Austria, Croatia, Denmark, Germany, Ireland, Italy, Malta, Netherlands, Slovenia- 2018 for Spain only, and the combined period of 2019–2020 for thirteen other countries. Countries such as Austria, Bulgaria, Croatia, Denmark, France, Germany, Hungary, Ireland, Italy, Lithuania, Malta, Netherlands and Slovenia observed 2 break years. Nevertheless, since the objective of this test was to determine a suitable reference year for the two-way fixed effects regression, the year 2019 was selected among them. This choice reflects the largest cluster of structural breaks identified across the sample. 2019-2020 group representing approximately 65 % of all cases. By choosing 2019, we capture the earliest point of the majority transition, ensuring that the regression framework aligns with the most representative structural change across countries.

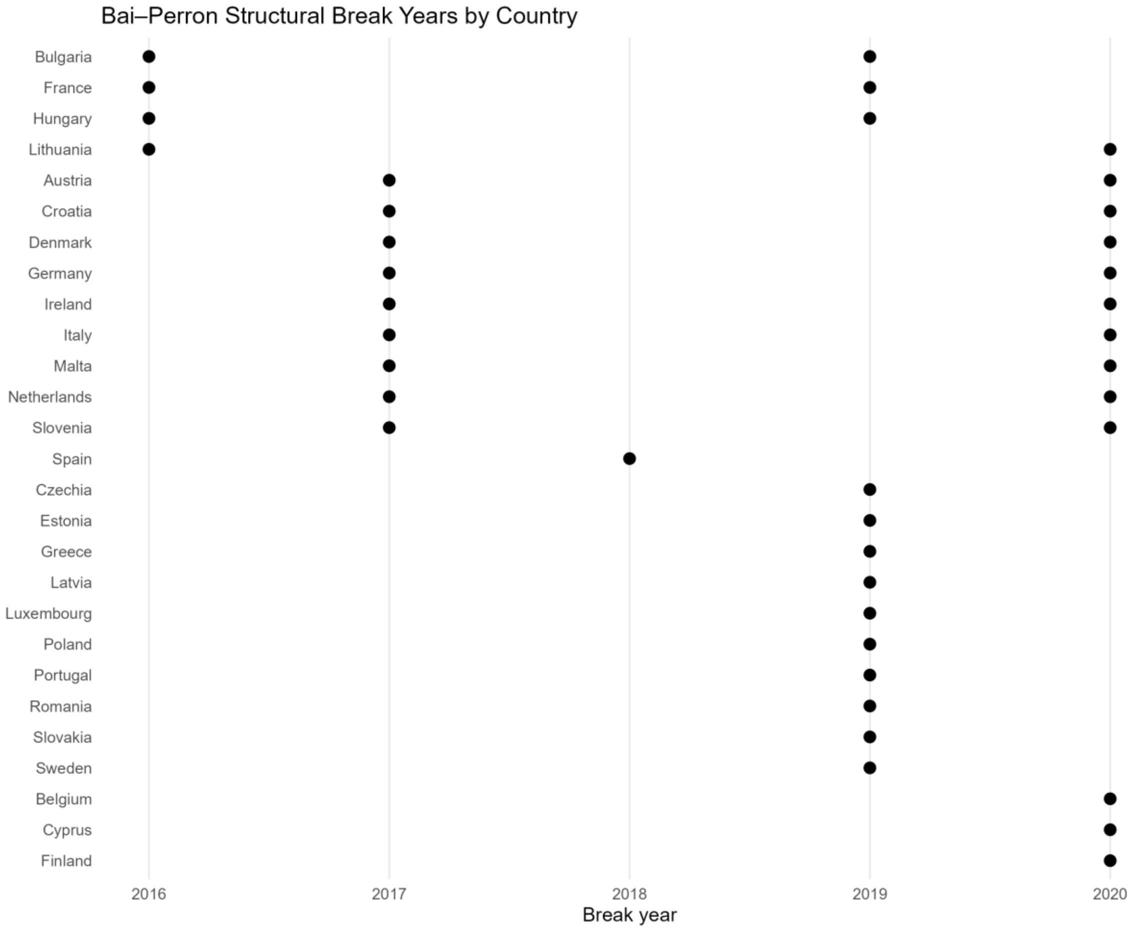

Figure 3- Bai-Perron Structural Break Years by Country

4.2 Two Way Fixed Effect Result

After conducting the Bai–Perron structural break test and determining the appropriate reference year, a unified panel dataset was compiled in Excel. A panel of data consists of a group of cross-sectional units that are observed over time. (Adkins, 2010) The dataset follows a country–year panel structure, where each cross-sectional unit (country) is observed repeatedly over time. The final panel consists of 22 European countries observed annually over the period 2013–2023 as mentioned, yielding a total of 242 country–year observations. For each country and year, the dataset records the share of electric vehicle registrations (EV_share), GDP per capita, urban population share, diesel fuel prices, and a measure of baseline ICE reliance as shown in the data section. The structure of the data ensures that each variable exhibits meaningful time variation within countries, which is essential for identifying how EV adoption evolves relative to economic and demographic conditions.

The panel is balanced by design and is available for every country in every year. The overall completeness of the dataset is sufficient to estimate the TWFE regression models. The main regression analyses were also conducted in RStudio using custom R scripts, exactly same as the previous empirical task. RStudio is particularly well suited for these types of analysis, offering a flexible environment for panel-data econometrics and specialised packages. (Wickham, 2016) In our analysis, the main estimation used the *feols()* function from the *fixest* package to run a TWFE model, including country and year fixed effects and clustering standard errors at the country level. (Berge, 2025) Model summaries were printed in the console and exported as text files, and finally, all three models were combined into a publication-ready LaTeX table using the *modelsummary* package. (Vincent, 2022)

Table 3- Comparison of Regression Models

	Baseline model	Log-transformed (Robustness 1)	Placebo (Robustness 2)
GDP_per_cap	0.000	0.000*	-0.000
	(0.000)	(0.000)	(0.000)
Urban_pop	0.373	0.072	0.555***
	(0.717)	(0.078)	(0.191)
Diesel_price	13.571	0.721	-2.403
	(9.355)	(0.708)	(1.887)
Year = 2014 × ICE_base2019	0.006	0.009	0.023
	(0.033)	(0.011)	(0.016)

	Baseline model	Log-transformed (Robustness 1)	Placebo (Robustness 2)
Year = 2015 × ICE_base2019	-0.002	-0.002	0.008
	(0.036)	(0.008)	(0.012)
Year = 2016 × ICE_base2019	0.013	-0.000	0.011
	(0.032)	(0.006)	(0.012)
Year = 2017 × ICE_base2019	0.011	-0.004	-0.000
	(0.034)	(0.008)	(0.010)
Year = 2018 × ICE_base2019	-0.092*	-0.024**	-0.066
	(0.046)	(0.011)	(0.044)
Year = 2019 × ICE_base2019	-0.238*	-0.039**	
	(0.134)	(0.017)	
Year = 2020 × ICE_base2019	-0.287	-0.026	
	(0.193)	(0.018)	
Year = 2021 × ICE_base2019	-0.369**	-0.033*	
	(0.168)	(0.016)	
Year = 2022 × ICE_base2019	-0.551*	-0.027	
	(0.275)	(0.020)	
Year = 2023 × ICE_base2019	-0.815**	-0.030	

	Baseline model	Log-transformed (Robustness 1)	Placebo (Robustness 2)
	(0.375)	(0.023)	
Num.Obs.	242	242	132
R2	0.804	0.931	0.689
R2 Adj.	0.760	0.915	0.580
R2 Within	0.277	0.174	0.304
R2 Within Adj.	0.229	0.120	0.246
RMSE	3.08	0.26	0.37
Std.Errors	by: Country	by: Country	by: Country

- p < 0.1, ** p < 0.05, *** p < 0.01

As shown in the table 3, The results indicate that among the economic control variables, GDP per capita and urban population show positive but statistically insignificant effects (except for Urban_pop in the placebo model). Diesel price also has a positive yet insignificant coefficient, suggesting that price effects are relatively weak within this sample.

In the baseline model, the coefficients before 2018 are small and mostly insignificant, implying no clear difference in EV share growth between ICE-heavy and less ICE-heavy countries during the early years. However, starting from 2018, the coefficients turn negative and gradually increase in magnitude, indicating that ICE-reliant countries begin to lag behind others in EV adoption after this point. Each yearly coefficient (β_t) from the interaction term represents the difference in EV adoption growth between high-ICE and low-ICE countries relative to the base year (2013). Thus, negative coefficients indicate that ICE-dependent countries experienced weaker growth in EV market share during those years compared to the reference group. The first statistically significant negative coefficient appears in 2018 (-0.092*), becoming even stronger in 2023 (-0.81*), confirming that after 2019, ICE-dependent countries experienced a noticeably slower EV transition. These patterns also align closely with the Bai–Perron test outcome, which identified 2018-2019 as the main structural break year for most countries. In other words, in 2023, countries with 10 percentage points higher ICE reliance in 2019 have, on average, about 8 percentage points lower EV share, conditional on country and year fixed effects and the included control variables. similarly, in 2018, a 1-percentage-point higher ICE reliance in 2019 is associated with a 0.092-percentage-point lower EV share. For a 10-percentage-point difference in ICE reliance, the EV share gap is about 0.92 percentage points.

Regarding model fit, the R^2 (0.80) and Within R^2 (0.27) suggest a reasonable explanatory power, indicating that the two-way fixed effects model captures a meaningful share of the within-country variation over time. Equation 4 is representing adjusted R^2 reported in Table 3. It follows the standard definition provided in Econometrics models. (Kammen, 2019)

$$R_{adj}^2 = 1 - \frac{SSR}{SST} \times \frac{p-1}{p-k-1} \tag{4}$$

The inclusion of both country and year fixed effects ensures that the estimated relationships are not driven by unobserved heterogeneity, such as persistent industrial structures or EU-wide policy shocks. Thereby isolating the within-country temporal dynamics of EV adoption.

When employing the log-transformed model as a first robustness check, the results remain qualitatively consistent. The negative relationship reappears after 2018, with significant coefficients in 2018 (-0.024*) and 2019 (-0.038*), confirming that even after scaling adjustments, ICE-heavy countries continue to exhibit slower EV adoption following the 2018–2019 transition period. In the placebo model we employed, the regression is intentionally restricted to the pre 2019 period to test whether similar differences existed before the main transition began. Since no significant or systematic negative coefficients are observed, this hopefully confirms that the divergence identified in the main models truly emerges after 2019 and is not driven by random fluctuations or data artifacts.

To make the interpretation of the results clearer, percentage changes were calculated using the exponential transformation formula as stated in equation 5: (Wooldridge, 2016)

$$\%\Delta Y \ = \left(e^{\beta} - 1\right) \times 100 \tag{5}$$

This approach allows the regression coefficients to be expressed in percentage terms, which are easier to understand than logarithmic units. Since the model uses a log-transformed dependent variable in the first robustness check, we use the coefficient from this column, not the baseline model, since the baseline model doesn’t contain log units. This conversion helps translate the statistical results into meaningful economic insights. Applying the transformation to each coefficient yields the following year-specific results. For 2018, inserting $\beta_{2018} = -0.024$ into Equation 5 gives:

$$\%\Delta Y \ = (e^{-0.024} - 1) \times 100 = -2.37 \approx \ -2.4\ \%.$$

For 2019, using $\beta_{2019} = -0.039$ results in

$$\%\Delta Y \ = (e^{-0.039} - 1) \times 100 = -3.83 \approx \ -3.8\ \%$$

For 2020,

$$\%\Delta Y \ = (e^{-0.026} - 1) \times 100 = -2.57\% \approx \ -2.6\%$$

For 2021,

$$\%\Delta Y \ = (e^{-0.033} - 1) \times 100 = -3.25\% \ \approx \ -3.2\%$$

For 2022,

$$\%\Delta Y \ = (e^{-0.027} - 1) \times 100 = -2.66\% \ \approx \ -2.7\ \%$$

For 2023,

$$\%\Delta Y \ = (e^{-0.030} - 1) \times 100 = -2.96 \ \approx \ -3.0\ \%$$

Taken together, these estimates indicate that the EV share in ICE-heavy countries is consistently about 2.5 – 4% lower than in countries with lower ICE dependence over the observed period. The magnitudes fluctuate slightly from year to year but do not display a clear upward or downward trend. The negative sign in each case points to a persistent disadvantage for ICE-heavy countries, while the similar size of the coefficients suggests that this gap remains relatively stable rather than systematically widening or narrowing over time. Therefore, we observe a modest, roughly stable negative gap, not a widening one.

5 Discussion

Beyond its empirical findings, this thesis offers several novel contributions to the existing literature on electric vehicle adoption. While most prior studies have focused on the effects of policy incentives, infrastructure availability, or consumer characteristics at a single point in time, this research introduces a dynamic perspective by applying a structural break analysis combined with a TWFE framework. The use of the Bai–Perron test allows the identification of turning points in EV adoption trends across individual EU countries, highlighting when the transition toward electric mobility began to accelerate. By integrating these break years into the regression design, this study captures not only cross-sectional but also temporal heterogeneity in adoption patterns. This is an aspect largely neglected in earlier work. Furthermore, by interacting ICE dependency with the post-break period, the analysis reveals the structural divergence between ICE-heavy and less ICE-dependent economies after 2019. This approach contributes to the literature by linking the concept of carbon lock-in to observable empirical trends, demonstrating how historical industrial dependence can translate into measurable delays in technology diffusion. Overall, the study provides a methodological framework that future research can replicate or extend to other clean-technology transitions, such as hydrogen vehicles or renewable energy systems.

5.1 Theoretical Implications

The findings support our Hypothesis (H1), which posits that countries with higher dependence on ICE vehicles tends to go more slowly toward electric mobility. This is particularly more obvious, after the 2019 structural break. The increasingly negative coefficients observed after 2019 illustrate a growing divergence, indicating that ICE-oriented countries are progressively falling behind others in the shift toward electric mobility. This also supports the findings by

Unruh (2016) where he explains about ICE passenger vehicles being the second very high lock-in risk (after the coal power plants being the worst case), since billions are already in use and even short-lived assets create massive inertia. Our results align with the theoretical background very well, since from an economic perspective, this delayed adjustment can be interpreted through the lens of path dependence and carbon lock-in exactly as said: nations with strong historical reliance on ICE technology face higher transition costs, both in terms of infrastructure adaptation and workforce reskilling. The persistence of the effect even after accounting for year and country fixed effects implies that the slower diffusion of EVs is structurally embedded rather than driven by short-term policy fluctuations. Overall, the global economy is relying on type of an expensive assets which have long live time cycle, not easily replaceable, political lobbying and as the result, that people are reluctant to retire early.

5.2 Policy Implications

The finding that ICE-dependent countries are slower in adopting EVs, even after EU-wide policies, implies that uniform regulations (like CO_2 emission standards as mentioned) may not yield uniform results. This supports the idea that the design of multiple policies should be more country specific, because each country has different characteristics and one policy may not lead to the same result even within EU countries. Referring to the table on IC reliance across countries in 2019, it is notable that most of the highly ICE-dependent countries are in Southern and Central Europe. For instance, Germany, Latvia, Poland, Slovenia, Romania, and Cyprus each exhibit an ICE reliance exceeding 90 percent, whereas countries such as Sweden, the Netherlands, and Finland demonstrate the lowest levels of ICE dependence. However, since this observation is based solely on data from one year, it should not be generalized or interpreted as a definitive trend.

5.3 Limitations

As with all academic studies, this thesis also contains some limitations regarding data, methodology and scope. Regarding the data limitations, this thesis uses only 22 countries due to missing values in 5 counties. Timeline starts at 2010 and ends in 2023, which is a short range for observing phase out trends. It only reflects the early to mid-transition phase, not the long-term equilibrium of full electrification. Another limitation of this study concerns the availability of data for control variables. Ideally, it would have been beneficial to include direct EV charging infrastructure, such as the total number of public charging points or stations in each country. Such data would provide a more accurate representation of the infrastructural readiness that supports EV adoption and, consequently, may influence employment or investment patterns in environmentally related sectors. However, due to the lack of consistent and comparable data across countries and years, this variable could not be incorporated. Instead, a proxy variable for urbanization was used, based on the assumption that countries with a higher share of urbanized areas are more likely to have better-developed charging infrastructure and easier access to EV charging points. While this proxy captures part of the underlying variation, it may not fully reflect the actual differences in charging infrastructure across countries.

As for the methodology and scope, the EV adoption variable relies on aggregate registration data. It does not capture household income differences or other influencing factors for instance. Additionally, the empirical task relies on TWFE, which does not examine causality, but only implies a proxy to see whether factors have correlation with each other or not. For the reason of simplifying reality, we demonstrate ICE dependency as a proxy, which might ignore gradual structural changes, since it assumes that this country reliance is time-invariant. These limitations open a door however, for future studies and contributions on this topic, which is still a fresh and up to date area of study and poses a highly important topic -especially in these days of economic fluctuations. This is a concern not only in Germany’s automative industry, but across the whole world. Future studies might focus on more regional heterogeneities, for example urban vs rural adoption patterns with the help of micro level data. Unobserved policies and cultural variables might be useful for overseeing, to finding exact reasons influencing both ICE dependency and EV adoption at the same time.

6 Conclusion

Overall, this thesis examined how electric vehicle adoption has evolved across 22 EU countries. The range is between 2013 and 2023, and the main subject is to see whether a country's dependence on internal combustion engine vehicles influences this transition. The structural break analysis showed that most countries experienced a clear turning point around 2019, marking the start of a faster shift toward electric mobility. Using this break year as a reference point, the TWFE model revealed that ICE dependent countries move more slowly toward EV adoption after this transition period. The results indicate that before 2018, differences between countries were small. After 2019, however, the gap widened steadily. By 2023, countries with 10 percentage points higher ICE reliance in 2019 have, on average, about 8 percentage points lower EV share. This simply means If a country depended 10% more on ICE in 2019, then in 2023 that country usually has an 8% smaller share of EVs. This pattern aligns with the idea of carbon lock-in, where existing infrastructures, market structures, and consumer habits limit the speed of technological change. The findings also suggest that EU-wide policies do not produce uniform outcomes. Even under shared regulations and common targets, countries follow different transition paths depending on their starting conditions. This highlights the need for policy approaches that account for national characteristics, especially in countries with strong automotive traditions and legacy ICE production. As with any empirical analysis, the study has limitations related to data availability, the short time horizon, and the use of proxies. EV adoption is still in an early phase, and long-term behaviour cannot yet be observed. Despite these limits, the thesis provides clear evidence that differences in ICE dependence matter for understanding current EV trends. It also offers a basis for future work that could incorporate more detailed infrastructure data, regional differences, or micro-level user behaviour to further enrich the analysis of Europe’s path toward cleaner transport.

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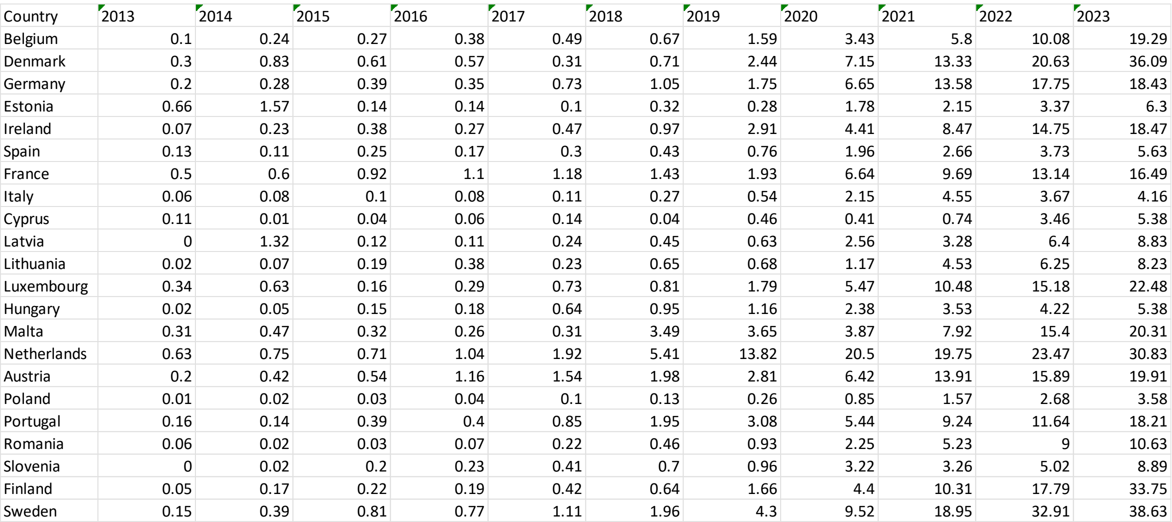
Appendix

1. EV share across EU countries in different year obtained from the Electronic Vehicle registration data and divided to total number of registrations



Country	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Belgium	0.1	0.24	0.27	0.38	0.49	0.67	1.59	3.43	5.8	10.08	19.29
Denmark	0.3	0.83	0.61	0.57	0.31	0.71	2.44	7.15	13.33	20.63	36.09
Germany	0.2	0.28	0.39	0.35	0.73	1.05	1.75	6.65	13.58	17.75	18.43
Estonia	0.66	1.57	0.14	0.14	0.1	0.32	0.28	1.78	2.15	3.37	6.3
Ireland	0.07	0.23	0.38	0.27	0.47	0.97	2.91	4.41	8.47	14.75	18.47
Spain	0.13	0.11	0.25	0.17	0.3	0.43	0.76	1.96	2.66	3.73	5.63
France	0.5	0.6	0.92	1.1	1.18	1.43	1.93	6.64	9.69	13.14	16.49
Italy	0.06	0.08	0.1	0.08	0.11	0.27	0.54	2.15	4.55	3.67	4.16
Cyprus	0.11	0.01	0.04	0.06	0.14	0.04	0.46	0.41	0.74	3.46	5.38
Latvia	0	1.32	0.12	0.11	0.24	0.45	0.63	2.56	3.28	6.4	8.83
Lithuania	0.02	0.07	0.19	0.38	0.23	0.65	0.68	1.17	4.53	6.25	8.23
Luxembourg	0.34	0.63	0.16	0.29	0.73	0.81	1.79	5.47	10.48	15.18	22.48
Hungary	0.02	0.05	0.15	0.18	0.64	0.95	1.16	2.38	3.53	4.22	5.38
Malta	0.31	0.47	0.32	0.26	0.31	3.49	3.65	3.87	7.92	15.4	20.31
Netherlands	0.63	0.75	0.71	1.04	1.92	5.41	13.82	20.5	19.75	23.47	30.83
Austria	0.2	0.42	0.54	1.16	1.54	1.98	2.81	6.42	13.91	15.89	19.91
Poland	0.01	0.02	0.03	0.04	0.1	0.13	0.26	0.85	1.57	2.68	3.58
Portugal	0.16	0.14	0.39	0.4	0.85	1.95	3.08	5.44	9.24	11.64	18.21
Romania	0.06	0.02	0.03	0.07	0.22	0.46	0.93	2.25	5.23	9	10.63
Slovenia	0	0.02	0.2	0.23	0.41	0.7	0.96	3.22	3.26	5.02	8.89
Finland	0.05	0.17	0.22	0.19	0.42	0.64	1.66	4.4	10.31	17.79	33.75
Sweden	0.15	0.39	0.81	0.77	1.11	1.96	4.3	9.52	18.95	32.91	38.63

2. R scripts used for the empirical TWFE analysis are provided below:

```
# 1. Set working directory
setwd("C:/Forouzan/Technische Universitat Dresden/Thesis/Regression")

# 2. Read data
df <- read.csv("unified_panel_2013_2023.csv")

# 3. Create baseline ICE variable (2019 or mean)
df <- df %>%
  group_by(Country) %>%
  mutate(
    ICE_base2019 = ICE.Reliance[Year == 2019][1],
    ICE_base2019 = ifelse(
      is.na(ICE_base2019),
      mean(ICE.Reliance, na.rm = TRUE),
      ICE_base2019
    )
  ) %>%
  ungroup()

# 4. Run TWFE regression (no plotting)
model <- feols(
  EV_share ~ GDP_per_cap + Urban_pop + Diesel_price +
    i(Year, ICE_base2019, ref = 2013) | Country + Year,
  data = df,
  cluster = ~Country
)

# Helper function to add stars based on your rule
add_stars <- function(p) {
  ifelse(p < 0.01, "***",
         ifelse(p < 0.05, "**",
                ifelse(p < 0.10, "*", "")))
}

# 5. Save regression summary with custom significance levels
capture.output({
  cat("TWFE Baseline Regression — Custom Significance Levels\n")
  cat("Significance levels — * p < 0.10; ** p < 0.05; *** p < 0.01\n\n")
  s <- summary(model)
  coef_table <- data.frame(s$coeftable)

  # detect p-value column automatically
```

```
  pcol <- grep("Pr|p.value", names(coef_table), value = TRUE)[1]
  coef_table$Stars <- add_stars(coef_table[[pcol]])

  print(coef_table)
}, file = "TWFE_regression_star.txt")

# Robustness 1: Log transformation
df$log_EV_share <- log(df$EV_share + 1)

model_log <- feols(
  log_EV_share ~ GDP_per_cap + Urban_pop + Diesel_price +
    i(Year, ICE_base2019, ref = 2013) | Country + Year,
  data = df,
  cluster = ~Country
)

capture.output({
  cat("Log-transformed Model — Custom Significance Levels\n")
  cat("Significance levels — * p < 0.10; ** p < 0.05; *** p < 0.01\n\n")
  s <- summary(model_log)
  coef_table <- data.frame(s$coeftable)

  # detect the correct p-value column automatically
  pcol <- grep("Pr|p.value", names(coef_table), value = TRUE)[1]
  coef_table$Stars <- add_stars(coef_table[[pcol]])

  print(coef_table)
}, file = "TWFE_regression_log_star.txt")

# Robustness 2: Placebo (pre-2019 only)
df_pre <- subset(df, Year <= 2018)

model_placebo <- feols(
  EV_share ~ GDP_per_cap + Urban_pop + Diesel_price +
    i(Year, ICE_base2019, ref = 2013) | Country + Year,
  data = df_pre,
  cluster = ~Country
)

capture.output({
  cat("Placebo Model — Custom Significance Levels\n")
  cat("Significance levels — * p < 0.10; ** p < 0.05; *** p < 0.01\n\n")
  s <- summary(model_placebo)
  coef_table <- data.frame(s$coeftable)

  # detect the correct p-value column automatically
  pcol <- grep("Pr|p.value", names(coef_table), value = TRUE)[1]
  coef_table$Stars <- add_stars(coef_table[[pcol]])

  print(coef_table)
}, file = "TWFE_regression_placebo_star.txt")

# Compare models in console
etable(
  list(
    "Baseline" = model,
    "Log model" = model_log,
    "Placebo" = model_placebo
  ),
  tex = FALSE,
  se.below = TRUE
)

# Save all models with custom significance levels to a Word file
models <- list(
  "Baseline model" = model,
  "Log-transformed (Robustness 1)" = model_log,
  "Placebo (Robustness 2)" = model_placebo
)

modelsummary(
  models,
  stars = c('*' = 0.10, '**' = 0.05, '***' = 0.01),
  gof_omit = 'AIC|BIC|Log.Lik|F',
  title = "Comparison of Regression Models — Custom Significance Levels",
  output = "TWFE_regression_star.docx"
)
```

3. R scripts used for the Bai-Perron analysis are provided below:

```
# Create a function to get break years for one country
get_breaks <- function(country_name) {
  df <- data_long %>% filter(Country == country_name, !is.na(EV_share))

  # Skip if not enough data points
  if (nrow(df) < 5) return(NA)

  bp <- breakpoints(EV_share ~ Year, data = df, h = 3)

  # Get break years
  years <- df$Year[breakpoints(bp)$breakpoints]
  years <- years[!is.na(years)]

  if (length(years) == 0) return(NA)

  paste(years, collapse = ", ")
}

# Apply to all countries
breaks_table <- data.frame(
  Country = unique(data_long$Country),
  Break_Years = sapply(unique(data_long$Country), get_breaks)
)

breaks_table
```

Statement of Authorship

"I hereby confirm that I have completed the submitted work on my own without inadmissible tools or without help that is not expressly mentioned in this work. All material that is directly or indirectly taken from other sources is properly referenced."

Dresden, 23/02/2026 Signature