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TRABAJO FIN DE MÁSTER

Analysis of the Purchase Drivers of Electric Vehicles from Registration Microdata.

Autor: Arturo Gómez Corbatón

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Madrid

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Analysis of the Purchase Drivers of Electric Vehicles from Registration Microdata.

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ANALYSIS OF THE PURCHASE DRIVERS OF ELECTRIC VEHICLES FROM REGISTRATION MICRODATA.

Autor: Gómez Corbatón, Arturo.
Director: Pérez Bravo, Manuel; Díaz Casado, Andrés.
Entidad Colaboradora: ICAI – Universidad Pontificia Comillas

RESUMEN

INTRODUCCIÓN

La transición hacia los coches eléctricos es crucial para alcanzar los objetivos de sostenibilidad, y muchas naciones están implementando políticas para fomentar su adopción. Sin embargo, comprender la toma de decisiones de los consumidores en la compra de vehículos eléctricos es vital, ya que influye significativamente en el ritmo de esta transición. Este estudio tiene como objetivo identificar y analizar sistemáticamente los principales determinantes que afectan la decisión de compra de coches eléctricos, proporcionando perspectivas valiosas para promover la movilidad eléctrica y formular estrategias de políticas efectivas. Al abordar estos factores, la investigación busca contribuir a la movilidad sostenible, los objetivos ambientales globales y la construcción de un futuro en transporte más sostenible y económicamente eficiente. Para lograr estos objetivos, se ha desarrollado un modelo de decisión discreto que permite un análisis estructurado de las elecciones de los consumidores y ayuda a identificar las variables más impactantes en el proceso de toma de decisiones.

ESTUDIO DE LAS VARIABLES

En la fase preliminar de esta investigación, se realizó un estudio exhaustivo de variables para identificar los factores más significativos que influyen en las decisiones de los consumidores al comprar vehículos eléctricos. Este análisis inicial fue fundamental para refinar el modelo de decisión discreta, asegurando que capture de manera precisa los determinantes clave y mejore la capacidad predictiva y la fiabilidad del modelo.

Las variables que se han tenido en cuenta en el estudio preliminar se muestran en la tabla a continuación. Los resultados del estudio de variables son los siguientes:

Tabla 1: Resumen regresión lineal.

	Coeficiente	P value	Coeficiente de determinación $(R)^2$
Constante	-0,0296	0,031	-
Renta por persona	6.385e-06	0,000	0,627
Disponibilidad de garaje	0,0642	0,014	0,328
Densidad de puntos de recarga	-0,046	0,378	-0,011
Zona de bajas emisiones	0,0401	0,006	-0,041

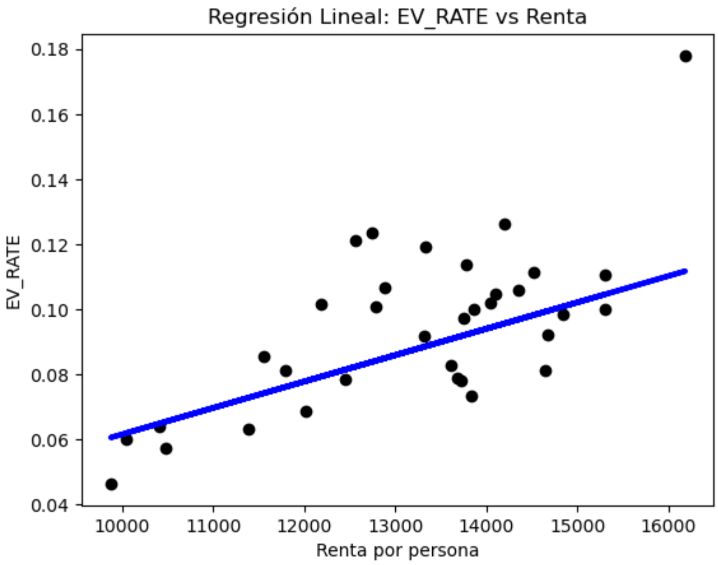

Ilustración 1: EV_RATE vs Renta por persona

Basado en el estudio estadístico previo, se obtienen las conclusiones necesarias para desarrollar un modelo de decisión de compra de vehículos eléctricos.

Variables significativas:

- El ingreso por persona, la disponibilidad de garaje y la existencia de zonas de bajas emisiones son variables significativas en el modelo.
- La densidad de puntos de recarga no es significativa y puede ser excluida del modelo.

Impacto de las variables:

- El ingreso por persona tiene el coeficiente de determinación más alto, lo que indica que contribuye significativamente a explicar la variabilidad en las matriculaciones de vehículos eléctricos.
- La disponibilidad de garaje también tiene un impacto significativo en las matriculaciones de vehículos eléctricos.
- La existencia de zonas de bajas emisiones tiene un impacto positivo significativo en la adopción de vehículos eléctricos.

Consideraciones para el modelo de decisión:

- El ingreso por persona es la variable más significativa en el modelo. Según los resultados obtenidos, se observa que la penetración de vehículos eléctricos es considerablemente mayor en los municipios con ingresos más altos.
- En el proceso de toma de decisiones para promover la adopción de vehículos eléctricos, es crucial considerar políticas que fomenten la disponibilidad de garajes y la creación de zonas de bajas emisiones.
- La infraestructura de recarga, aunque no es significativa en este estudio, sigue siendo importante para la adopción de vehículos eléctricos y debe ser monitoreada y mejorada.

MODELO DE DECISIÓN

1.1.1 Función de utilidad y de probabilidad.

El principio de maximización de la utilidad se basa en el concepto de una función de utilidad, que cuantifica las preferencias de un usuario en función de los atributos de las opciones de viaje y las características del individuo. Esta función indica que, si el valor de utilidad para la opción "a" es mayor que para la opción "b", el usuario preferirá "a" sobre "b". Por el contrario, si un usuario prefiere la opción "b" sobre "a", el valor de la función de utilidad para "b" será mayor que para "a". Esta función de utilidad tiene la siguiente forma:

$$Vi = b_0 + b_1 * x_1 + \cdots + b_k * x_k$$

Siguiendo el principio de maximización de la utilidad, se espera que los individuos elijan la opción "i" si perciben que tiene la mayor utilidad, reflejada por U(i) > U(j) para cualquier otra opción "j" en el conjunto A. Para manejar esta expresión, se necesitan suposiciones sobre la distribución conjunta de probabilidad de los errores e(i), específicamente que son distribuidos de manera independiente e idéntica (IID) y la forma de su distribución de probabilidad. Diferentes distribuciones de probabilidad para las diferen cias e(j) - e(i)producen diferentes modelos: una distribución uniforme conduce a un modelo de probabilidad lineal, mientras que una distribución normal conduce a un modelo Probit. El modelo Logit es comúnmente utilizado, asumiendo que los errores e(i) siguen una distribución Gumbel, lo que resulta en diferencias e(j) – e(i) que tienen una distribución logística. La probabilidad de elegir la opción (i) en el modelo Logit está dada por la densidad logística:

$$P(i) = \frac{e^{Vi}}{e^{Vi} + e^{Vj} + \cdots + e^{Vn}}$$

1.1.2 Modelo LOGIT: segmento de potencia y precio premium BEV

Para clasificar los vehículos según su segmento de potencia, se realizó un estudio breve y rápido. A través de un método de clustering, se asignó a cada vehículo un valor de 0 a 4 basado en su peso en vacío o tara.

Por otro lado, la variable "Precio Premium BEV" representa el costo adicional que un consumidor incurre al comprar un vehículo eléctrico (EV) en comparación con un vehículo de motor de combustión interna (ICE).

Los precios premium asignados a los vehículos BEV y PHEV, dependiendo de la potencia del vehículo, son los siguientes:

Los valores asignados a las variables potencia label y precio premium BEV se muestran en la siguiente tabla:

Tabla 2: Segmento de potencia y precio premium.

Potencia Label	**Segmento 0**	**Segmento 1**	**Segmento 2**	**Segmento 3**	**Segmento 4**
Tara [kg]	[0-1350]	[1350-1700]	[1700-2150]	[2150-2600]	[>2600]
Precio premium [€]	10000	10000	17000	22000	32000

1.1.3 Modelo

Los resultados obtenidos para el modelo son los siguientes:

Tabla 3: Resumen resultados del modelo.

vehicle_type=PHEV	**coef**	**P>|z|**
const	1.0484	<0.05
Potencia_label	0.1944	<0.05
Premium_Price_BEV/Renta	0.7374	<0.05
POB	-1.392e-07	<0.05
Coc_hab	-0.5542	<0.05
IND_NUEVO_USADO	3.6245	<0.05
POBLACION	1.122e-07	<0.05

El coeficiente para "Potencia_label" es 0.1944, con un valor p de <0.05, lo que indica una alta significancia. El coeficiente positivo sugiere que, a medida que aumenta la etiqueta de potencia, también aumenta la probabilidad de que el vehículo sea un PHEV. Para "Precio_Premium_BEV/Renta", el coeficiente es 0.7374, también con un valor p altamente significativo de <0.05. Este coeficiente positivo indica que los precios premium más altos para los BEV o los vehículos de alquiler están asociados con una mayor probabilidad de que el vehículo sea un PHEV. Ambas variables muestran una relación directa con la probabilidad de que el vehículo sea categorizado como un PHEV.

Se obtienen resultados similares para los vehículos ICE. Ambas variables utilizadas en el estudio son altamente significativas en el modelo.

RESULTADOS

Con el desarrollo del modelo predictivo, se pueden determinar las decisiones de los clientes respecto a la compra de nuevos vehículos, evaluando específicamente la probabilidad de que opten por BEVs, PHEVs o vehículos ICE. El modelo aprovecha datos y tendencias actuales del mercado automotriz en España, proporcionando información sobre cómo diversos escenarios podrían impactar las ventas de vehículos.

Para analizar a fondo estos posibles resultados, se han creado tres escenarios distintos. El precio premium de los vehículos eléctricos se ha modificado según diferentes hipótesis sobre el entorno del mercado:

Tabla 4: Resumen de escenarios.

Scenarios	**Net zero emissions**	**Steady progress**	**Lagging behind**
New Premium price of the BEV vehicles	0 % * Premium_Price_BEV	50% * Premium_Price_BEV	150% * Premium_Price_BEV

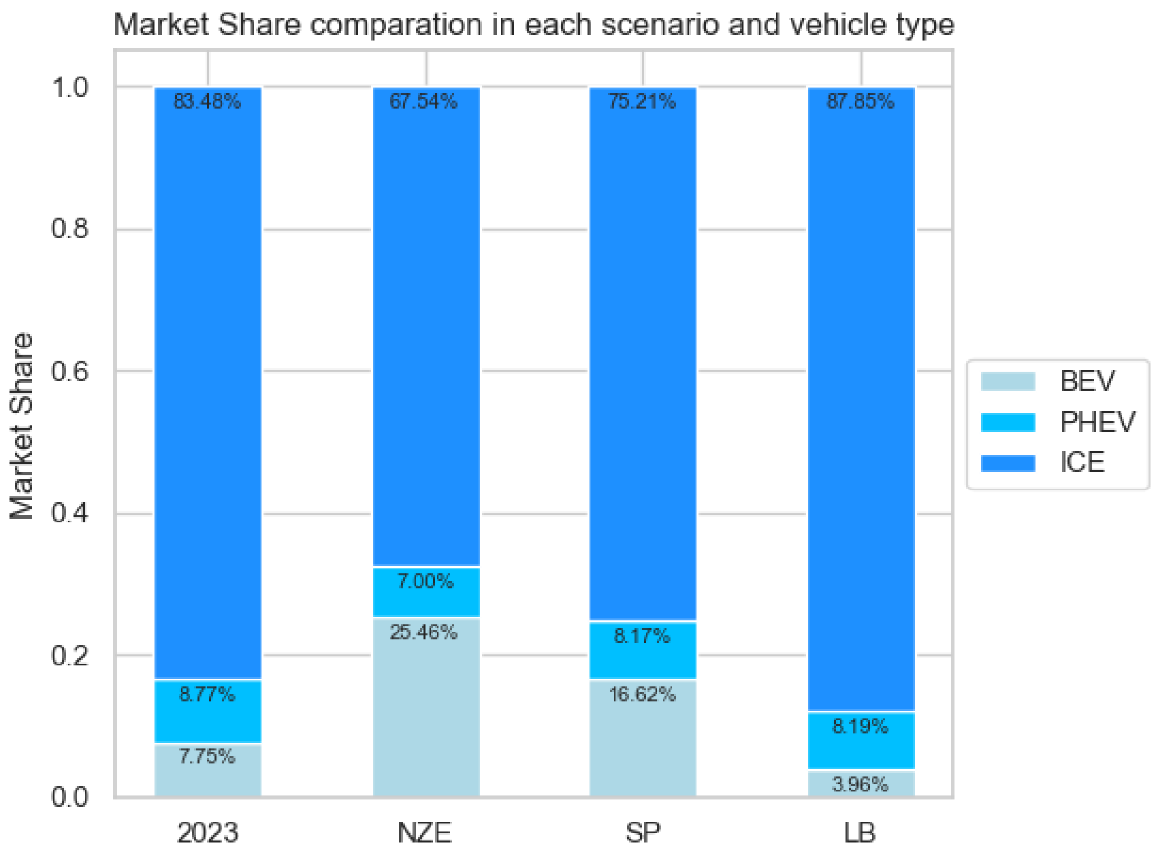

Ilustración 2: Market share por escenario.

En el escenario de referencia, los vehículos ICE dominan el mercado español con una participación del 83.48%, mientras que los PHEV y BEV tienen participaciones menores del 8.77% y 7.75%, respectivamente. En el escenario NZE, que apunta a emisiones netas cero eliminando el precio premium de los BEV, la participación de los vehículos ICE disminuye al 67.54%, y la participación de los BEV aumenta significativamente al 25.46%, aunque los PHEV se mantienen en el 7.00%. El escenario de Transición Económica muestra una disminución moderada de los vehículos ICE al 75.21%, con un aumento de los BEV al 16.62% y de los PHEV al 8.17%. En el escenario de Rezago, la participación de los vehículos ICE aumenta al 87.85%, mientras que los BEV y PHEV disminuyen al 3.96% y 8.19%, respectivamente, destacando el impacto de políticas desfavorables en la adopción de vehículos eléctricos.

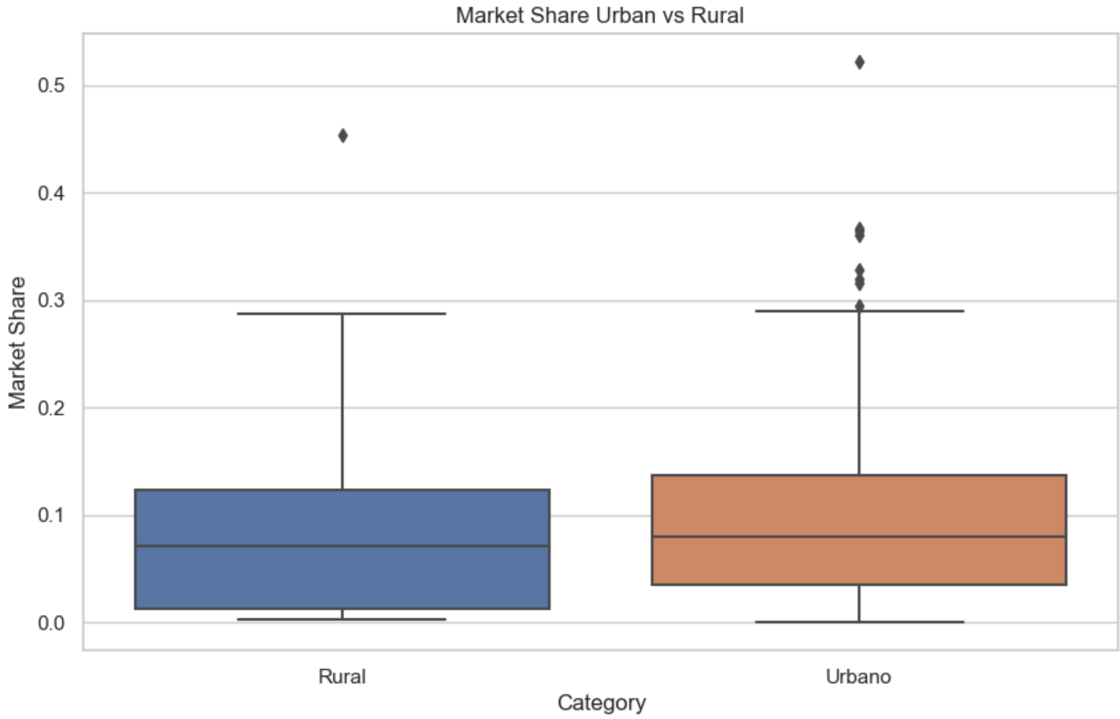

Ilustración 3: Market share urbano vs rural.

Al examinar la adopción de vehículos eléctricos a nivel nacional, se observa una tendencia notable: las áreas urbanas tienden a exhibir una participación de mercado mediana ligeramente mayor en comparación con las regiones rurales. Esto sugiere que, en promedio, los mercados urbanos pueden tener una mayor proporción, lo que implica que los vehículos eléctricos podrían penetrar más efectivamente en los mercados urbanos que en los rurales. Vale la pena señalar que se pueden derivar perspectivas similares al comparar áreas de ingresos altos y bajos, diferentes tamaños de vehículos y otras variables. Esto subraya la aplicabilidad más amplia de estos hallazgos a través de diversas divisiones demográficas y geográficas, aunque los resúmenes suelen proporcionar solo una visión general breve de análisis tan detallados.

CONCLUSIÓN

El modelo predictivo desarrollado para analizar las decisiones de los consumidores en la compra de nuevos vehículos proporciona información sobre la futura adopción de BEV, PHEV y vehículos ICE en España. El análisis de tres escenarios—Emisiones Netas Cero

(NZE), Progreso Estable y Rezago—revela cómo diferentes factores influyen en la dinámica del mercado y las preferencias de los vehículos.

En el escenario NZE, la eliminación del precio premium para los BEV y la implementación de estrictas regulaciones de emisiones aumentan significativamente la adopción de BEV, reduciendo la cuota de mercado de los vehículos ICE. Esto demuestra la efectividad de las fuertes intervenciones gubernamentales y los incentivos para acelerar la transición a los vehículos eléctricos. Por el contrario, el escenario de Rezago, caracterizado por el aumento de los costos de los BEV y regulaciones de emisiones laxas, resulta en una disminución en la adopción de BEV y un ligero aumento en la cuota de mercado de vehículos ICE, destacando la importancia de políticas de apoyo y cadenas de suministro estables.

En el escenario de referencia, los vehículos ICE dominan con una cuota de mercado del 83.48%, mientras que los BEV y PHEV tienen un 7.75% y un 8.77%, respectivamente. El escenario NZE ve la cuota de mercado de los BEV aumentar significativamente al 25.46%, reduciendo los vehículos ICE al 67.54%, demostrando el impacto de fuertes incentivos y regulaciones. El escenario de Progreso Estable muestra una disminución moderada en la cuota de mercado de vehículos ICE al 75.21%, con aumentos en las cuotas de BEV y PHEV, indicando una transición gradual. Por el contrario, el escenario de Rezago resulta en una disminución en la adopción de BEV y un ligero aumento en la cuota de mercado de vehículos ICE, destacando los riesgos de un apoyo político inadecuado y las interrupciones en la cadena de suministro.

Comparando nuestro modelo con BloombergNEF EV Outlook, nuestro escenario más favorable (NZE) estima una cuota de mercado del 32% para vehículos de cero emisiones, en comparación con el 70% estimado por BloombergNEF para vehículos de pasajeros. A pesar de las diferencias, ambos destacan una trayectoria positiva hacia los objetivos de política, aunque se necesitan medidas adicionales para alcanzar la ambiciosa cuota de mercado del 100% para 2050.

El análisis de sensibilidad revela una clara correlación negativa entre los precios de los BEV y su cuota de mercado, enfatizando la importancia de las estrategias de precios y los subsidios. Los valores variables de R^2 a lo largo de los escenarios indican diferentes niveles de sensibilidad del mercado a los precios de los BEV, con el escenario de Rezago mostrando el impacto negativo más fuerte.

Por último, el análisis regional muestra que las áreas urbanas tienen una cuota de mercado mediana ligeramente mayor para los BEV y más valores atípicos con cuotas significativamente más altas, lo que sugiere un mayor potencial para la penetración del mercado de BEV en áreas urbanas en comparación con las áreas rurales. El análisis subraya el papel crítico de las políticas gubernamentales, las estrategias de precios y las cadenas de suministro estables en la configuración del futuro de la adopción de vehículos en España, destacando la necesidad de estrategias específicas para abordar diferentes condiciones de mercado y comportamientos de los consumidores para una transición sostenible hacia los vehículos eléctricos.

ABSTRACT

INTRODUCTION

The transition to electric cars is crucial for achieving sustainability goals, and many nations are implementing policies to encourage their adoption. However, understanding consumer decision-making in EV purchases is vital, as it significantly influences the pace of this transition. This study aims to systematically identify and analyze the key determinants affecting the decision to purchase electric cars, providing valuable insights for promoting electric mobility and formulating effective policy strategies. By addressing these factors, the research seeks to contribute to sustainable mobility, global environmental goals, and the construction of a more sustainable and economically efficient future in transportation. To accomplish these objectives, a discrete decision model has been developed, enabling a structured analysis of consumer choices and aiding in the identification of the most impactful variables in the decision-making process.

VARIABLE STUDY

In the preliminary phase of this research, a comprehensive variable study was conducted to identify the most significant factors influencing consumer decisions in purchasing electric vehicles. This initial analysis was crucial for refining the discrete decision model, ensuring that it accurately captures the key determinants and enhances the model's predictive power and reliability.

The variables taken into account for the preliminary study are shown in the following table. The results of the variables study are as follows:

Table 1: Linear regression summary.

	Coefficient	P value	Coefficient of determination (R^2)
Constant	-0,0296	0,031	-
Rent per person	6.385e-06	0,000	0,627
Garage availability	0,0642	0,014	0,328
Density of recharge points	-0,046	0,378	-0,011
Low emissions	0,0401	0,006	-0,041

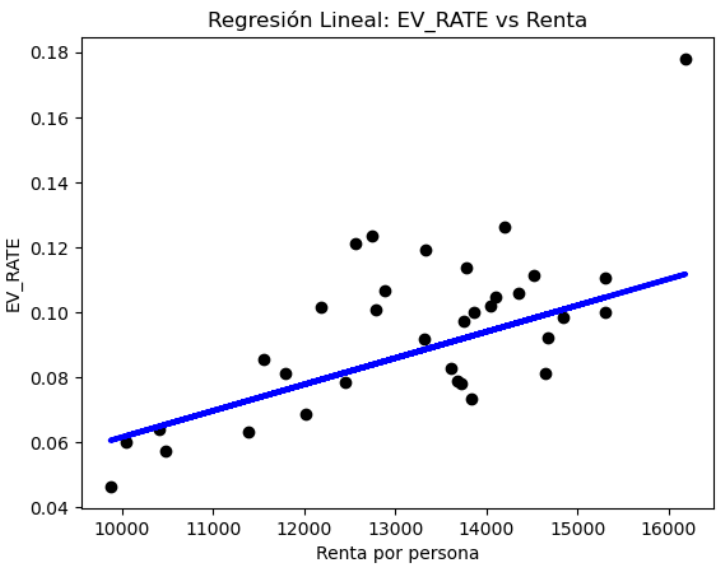

Figure 1: EV_RATE vs Renta

Based on the previous statistical study, the necessary conclusions are drawn to obtain a purchase decision model for electric vehicles.

Significant variables:

- Income per person, garage availability and the existence of low emission zones are significant variables in the model.
- The density of recharge points is not significant and can be excluded from the model.

Impact of variables:

- Income per person has the highest coefficient of determination, indicating that it contributes significantly to explaining the variability in EV registrations.
- Garage availability also has a significant impact on electric vehicle registrations.
- The existence of low-emission zones has a significant positive impact on the adoption of electric vehicles.

Considerations for the decision model:

- Income per person is the most significant variable in the model. According to the results obtained, it is observed that the penetration of electric vehicles is considerably higher in municipalities with a higher income.
- In the decision-making process to promote the adoption of electric vehicles, it is crucial to consider policies that encourage the availability of garages and the creation of low-emission zones.
- The charging infrastructure, although not significant in this study, is still important for the adoption of electric vehicles and should be monitored and improved.

DECISION MODEL

1.1.4 Utility function & Probability function

The principle of utility maximization relies on the concept of a utility function, which quantifies a user's preferences based on the attributes of the travel options and the individual's characteristics. This function indicates that if the utility value for option "a" is higher than for option "b", the user will prefer "a" over "b". Conversely, if a user prefers option "b" over "a", the utility function's value for "b" will be higher than for "a". This utility function has the following form:

$$Vi = b_0 + b_1 * x_1 + \cdots + b_k * x_k$$

Following the principle of utility maximization, individuals are expected to choose option “I” if they perceive it to have the highest utility, reflected by (U(i) > U(j)) for any other option “j” in set A. To handle this expression, assumptions about the joint probability distribution of the errors e(i) are needed, specifically that they are independently and identically distributed (IID) and the form of their probability distribution. Different probability distributions for the differences (e(j) - e(i)) yield different models: a uniform distribution leads to a linear probability model, while a normal distribution leads to a Probit model. The Logit model is commonly used, assuming errors e(i) follow a Gumbel distribution, resulting in differences (e(j) - e(i)) having a Logistic distribution. The probability of choosing option (i) in the Logit model is given by the Logistic density:

$$P(i) = \frac{e^{Vi}}{e^{Vi} + e^{Vj} + \cdots + e^{Vn}}$$

1.1.5 LOGIT Model: Power segment and Premium BEV price

To classify the vehicles based on their power segment, a quick and brief study was conducted. Through clustering, each vehicle was assigned a value from 0 to 4 based on its curb weight.

On the other hand, the variable "Premium Price BEV", represents the additional cost that a consumer incurs when purchasing an electric vehicle (EV) compared to an internal combustion engine (ICE) vehicle.

The premium prices assigned to BEV and PHEV vehicles depending on the power of the vehicle are the following:

Table 2: Weight label & premium price BEV

Label	**Segment 0**	**Segment 1**	**Segment 2**	**Segment 3**	**Segment 4**
Net weight [kg]	[0-1350]	[1350-1700]	[1700-2150]	[2150-2600]	[>2600]
Premiumprice [€]	10000	10000	17000	22000	32000

1.1.6 Model

The results of the logistic model for the hybrid vehicles are the following:

Table 3: Decision model summary.

vehicle_type=PHEV	**coef**	**P>|z|**
const	1.0484	<0.05
Potencia_label	0.1944	<0.05
Premium_Price_BEV/Renta	0.7374	<0.05
POB	-1.392e-07	<0.05
Coc_hab	-0.5542	<0.05
IND_NUEVO_USADO	3.6245	<0.05
POBLACION	1.122e-07	<0.05

The coefficient for Potencia_label is 0.1944, with a p-value of <0.05, indicating high significance. The positive coefficient suggests that as the power label increases, the likelihood of the vehicle being a PHEV also increases. For Premium_Price_BEV/Renta, the coefficient is 0.7374, also with a highly significant p-value of <0.05. This positive coefficient indicates that higher premium prices for BEVs or rental vehicles are associated with an increased likelihood of the vehicle being a PHEV. Both variables show a direct relationship with the probability of the vehicle being categorized as a PHEV.

Similar results are obtained for ICE vehicles. Both variables used for the study are highly significant in the model.

RESULTS

With the development of the predictive model customer decisions can be determined regarding the purchase of new vehicles, specifically evaluating their likelihood of opting for BEVs, PHEVs, or ICE vehicles. The model leverages current data and trends within Spain's automotive market, providing insights into how various scenarios might impact vehicle sales.

To thoroughly analyze these potential outcomes, three distinct scenarios have been created. Premium price of electric vehicles has been modified according to different hypothesis regarding market environment:

Table 4: Scenario summary

Scenarios	**Net zero emissions**	**Steady progress**	**Lagging behind**
New Premium price of the BEV vehicles	0 % * Premium_Price_BEV	50% * Premium_Price_BEV	150% * Premium_Price_BEV

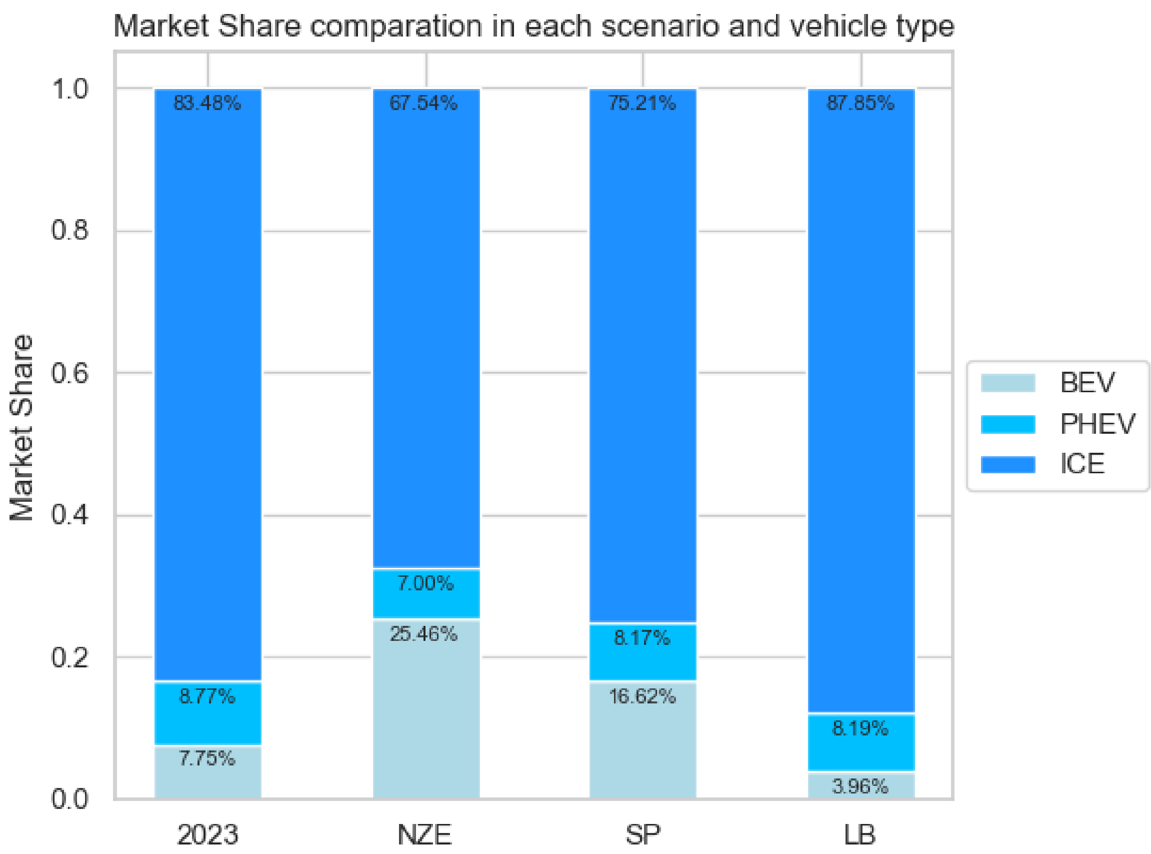

Figure 2: Scenario market share.

In the baseline scenario, ICE vehicles dominate Spain's market with an 83.48% share, while PHEVs and BEVs hold smaller shares at 8.77% and 7.75%, respectively. In the NZE scenario, aiming for net zero emissions by eliminating the BEV price premium, ICE vehicles' share drops to 67.54%, and BEVs' share rises significantly to 25.46%, though PHEVs remain at 7.00%. The Economic Transition Scenario shows a moderate decline in ICE vehicles to

75.21%, with BEVs increasing to 16.62% and PHEVs to 8.17%. In the Lagging Behind scenario, ICE vehicles' share rises to 87.85%, while BEVs and PHEVs drop to 3.96% and 8.19%, respectively, highlighting the impact of unfavorable policies on EV adoption.

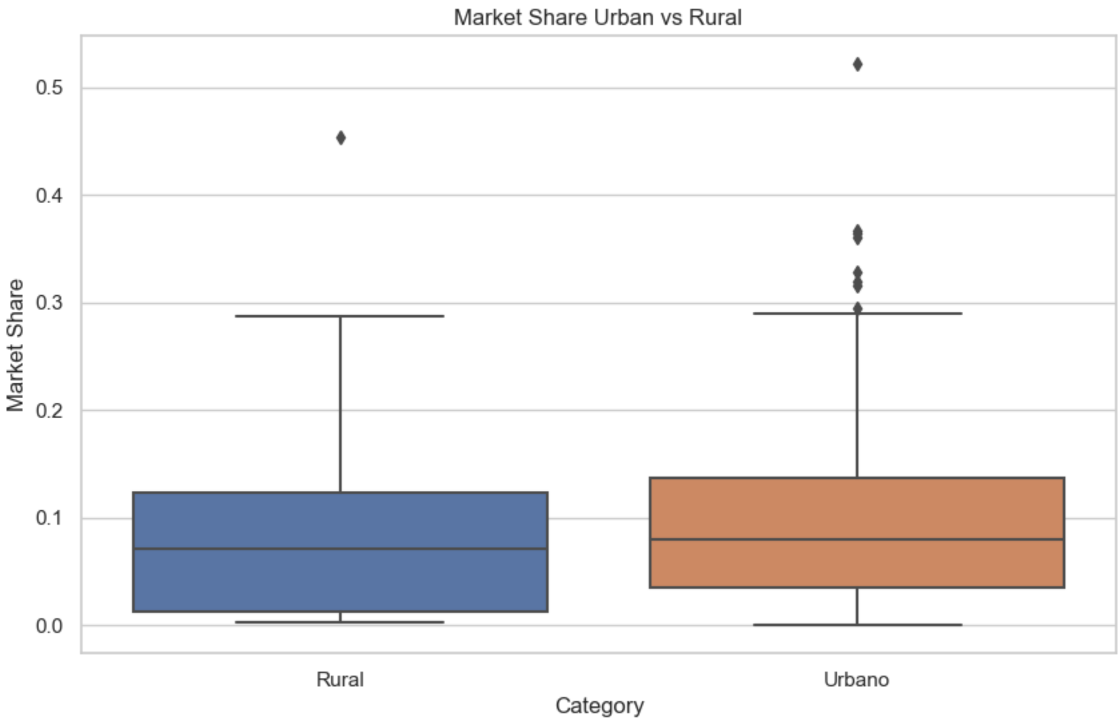

Figure 3: Urban vs Rural box plot.

When examining the adoption of electric vehicles nationwide, there is a noticeable trend: urban areas tend to exhibit a slightly higher median market share compared to rural regions. This suggests that, on average, urban markets may command a larger proportion, implying that electric vehicles could potentially penetrate urban markets more effectively than rural ones. It's worth noting that similar insights can be derived for comparisons between high and low-income areas, different vehicle sizes, and other variables. This underscores the broader applicability of these findings across various demographic and geographic divisions, although abstracts typically provide only a brief overview of such detailed analyses.

CONCLUSION

The predictive model developed for analyzing customer decisions in the purchase of new vehicles provides insights into the future adoption of BEVs, PHEVs, and ICE vehicles in Spain. The analysis of three scenarios—Net Zero Emissions (NZE), Steady Progress, and

Lagging Behind—reveals how different factors influence market dynamics and vehicle preferences.

In the NZE scenario, eliminating the premium price for BEVs and implementing strict emissions regulations significantly boost BEV adoption, reducing the market share of ICE vehicles. This demonstrates the effectiveness of strong government interventions and incentives in accelerating the transition to electric vehicles. Conversely, the Lagging Behind scenario, characterized by increased BEV costs and lax emissions regulations, results in a decline in BEV adoption and a slight increase in ICE vehicle market share, highlighting the importance of supportive policies and stable supply chains.

In the baseline scenario, ICE vehicles dominate with an 83.48% market share, while BEVs and PHEVs hold 7.75% and 8.77%, respectively. The NZE scenario sees BEV market share rise significantly to 25.46%, reducing ICE vehicles to 67.54%, demonstrating the impact of strong incentives and regulations. The Steady Progress scenario shows a moderate decline in ICE vehicle share to 75.21%, with increased shares for BEVs and PHEVs, indicating a gradual transition. Conversely, the Lagging Behind scenario results in decreased BEV adoption and a slight increase in ICE vehicle share, highlighting the risks of inadequate policy support and supply chain disruptions.

Comparing our model with BloombergNEF EV Outlook, our most favorable scenario (NZE) estimates a 32% market share for zero-emission vehicles, compared to BloombergNEF's 70% estimate for passenger vehicles. Despite differences, both highlight a positive trajectory towards policy targets, though further measures are needed to achieve the ambitious 100% market share by 2050.

Sensitivity analysis reveals a clear negative correlation between BEV prices and their market share, emphasizing the importance of pricing strategies and subsidies. Varying R^2 values across scenarios indicate different levels of market sensitivity to BEV pricing, with the Lagging Behind scenario showing the strongest negative impact.

Lastly, the regional analysis shows urban areas having a slightly higher median market share for BEVs and more outliers with significantly higher shares, suggesting greater potential for BEV market penetration in urban areas compared to rural areas. The analysis underscores the critical role of government policies, pricing strategies, and stable supply chains in shaping the future of vehicle adoption in Spain, highlighting the need for targeted strategies to address different market conditions and consumer behaviors for a sustainable transition to electric vehicles.

Index

Figure index

Table index

CHAPTER 1. INTRODUCTION

In today's era characterized by a growing environmental consciousness and the need to address climate change, sustainable mobility has become a global priority. In this context, the adoption of electric vehicles (EVs) represents a promising solution to reduce greenhouse gas emissions and decrease dependence on fossil fuels in the transportation sector. The transition to electric cars is a key component of the strategy to achieve sustainability goals, and many nations are implementing policies to encourage their adoption. However, consumer decision-making in the purchase of EVs is a critical element influencing the pace of this transition. Consumer decision-making in the purchase of electric cars is a fundamental component of this transition, and there is still a lack of complete understanding of the factors influencing their choice. This study addresses the problem of systematically identifying and analyzing key determinants affecting the decision to purchase electric cars, with the purpose of providing valuable information for the promotion of electric mobility and the formulation of effective policy strategies for a more sustainable and environmentally friendly future. This study aims to contribute to the advancement of sustainable mobility and the achievement of global environmental goals. Understanding the factors influencing the decision to purchase electric cars is essential for promoting this technology and overcoming barriers that may hinder its adoption. Additionally, this study addresses the problem of systematically identifying and analyzing key determinants affecting the decision to purchase electric cars, with the purpose of providing valuable information for the promotion of electric mobility and the formulation of effective policy strategies for a more sustainable and environmentally friendly future. Thus, this work seeks to contribute to the construction of a more sustainable, environmentally friendly, and economically efficient future in the field of transportation.

1.2 MOTIVATION

My motivation for undertaking this research stems from my profound interest in addressing challenges related to sustainability and the environment. The transition to sustainable mobility and the adoption of electric vehicles present opportunities to apply my knowledge and technical skills, while contributing to the creation of a cleaner and healthier world. My previous experience and collaboration with the Electric Vehicle and Sustainable Mobility Observatory have strengthened my commitment in this area, providing me with the chance to develop meaningful research and development skills. Simultaneously, I contribute to advancing knowledge in the field of sustainable mobility and electric vehicle technology.

1.3 PROJECT OBJECTIVES

1. Analysis of Registrations and Statistical Study:

- Conduct a comprehensive analysis of electric vehicle registrations to identify and understand the determining factors in the purchasing process. This involves carrying out a rigorous statistical study with the aim of assessing the significance and influence of the factors identified in the registration analysis, prioritizing those most relevant to the decision to purchase electric vehicles.

2. Choice Model: Development of a Decision Model to Understand Electric Vehicle Purchase Behavior.

- Utilize the results obtained in the statistical analysis to develop a choice model that accurately and quantitatively describes the buying behavior of electric vehicle consumers, highlighting the most influential factors in their decisions.

3. Energy Integration: Implementation of the Choice Model in the OVEMS Energy Model.

- Integrate the developed choice model within the framework of the energy model of the OVEMS (Electric Vehicle and Sustainable Mobility Observatory) to enhance and improve the representation of consumer preferences in the energy system.

- Using the decision model developed, estimate the rate of fleet renewal in Spain, taking into account sociodemographic factors and the attributes of electric vehicles identified in the previous analysis. This model will contribute to understanding and predicting electric vehicle adoption trends in the national context, aiding in the design of strategies and policies.

1.4 ALIGNMENT WITH SUSTAINABLE DEVELOPMENT GOALS

My master's thesis directly aligns with several United Nations Sustainable Development Goals (SDGs).

Firstly, the work contributes to **SDG 7, "Affordable and Clean Energy,"** by promoting the adoption of electric vehicles. This advancement towards cleaner and sustainable energy aims to reduce dependence on fossil fuels and encourages the use of renewable energy sources for vehicle charging. Addressing the affordability of electric vehicles (EVs) is essential for their widespread adoption, considering the current challenge of high initial costs and the associated infrastructure expenses.

Furthermore, the research is linked to **SDG 11, "Sustainable Cities and Communities."** By influencing the adoption of electric vehicles in urban environments, the study contributes to the reduction of air pollution, thereby enhancing the quality of life in cities. The decrease in pollutant emissions also addresses associated health issues.

The work plays a crucial role in relation to **SDG 12, "Responsible Consumption and Production."** By identifying and analyzing factors influencing the decision to purchase electric vehicles, the study opens the door to a better understanding of consumer choices. This deeper knowledge not only facilitates the promotion of more responsible and sustainable consumption in the transportation sector but also provides an opportunity to encourage more conscious consumer behavior.

Additionally, the research aligns with **SDG 13, "Climate Action,"** by promoting the adoption of electric vehicles, closely associated with the reduction of CO_2 emissions and the mitigation of climate change. This is crucial for limiting global warming.

Finally, the collaboration with the Electric Vehicle and Sustainable Mobility Observatory in your project demonstrates how cooperation between academic institutions and organizations can drive sustainable solutions and promote the Sustainable Development Goals. This aligns particularly with **SDG 17, "Partnerships for the Goals."**

1.5 WORK METHODOLOGY

The process carried out in this work was structured into several stages, starting with a review of the existing literature and continuing with a detailed statistical analysis. Each phase of the process is detailed below:

Statistical Study of Variables:

- A statistical study of each variable separately was conducted, using techniques such as linear regression. This analysis evaluated the relationship between each variable and the decision to purchase electric vehicles. Furthermore, an analysis of the interrelation between variables was carried out to identify possible correlations and determine the relative contribution of each variable to the decision-making process.

- Through statistical analysis, the most representative and significant variables influencing the decision to purchase electric vehicles were identified. This step was crucial to focus the study on key aspects that have a greater impact on consumer behavior.

Decision Model:

- With the identified variables as the most representative, a broader decision model was developed. This model aimed to understand and predict the behavior of electric vehicle buyers by integrating the key variables selected in previous stages.

Validation and Conclusion:

- The results and the proposed model were validated through comparisons with previous studies and the application of additional statistical methods. The work concluded by highlighting key findings and their relevance to understanding consumer decision-making processes in the adoption of electric vehicles. Additionally, practical implications were discussed, and possible areas for future research were suggested. The development of the work will adhere to the Gantt chart shown below:

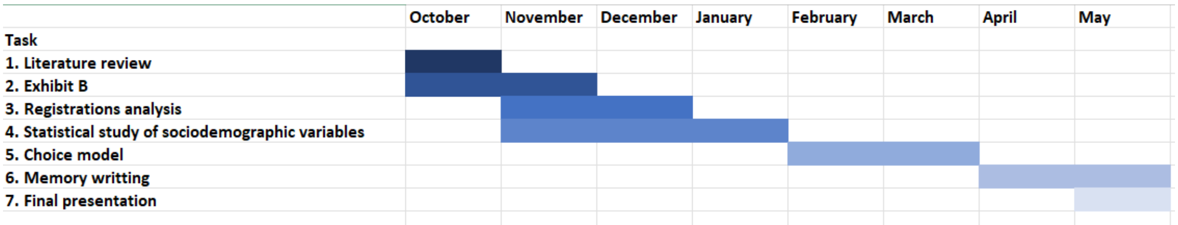

Figure 4: Gantt

1.6 RESOURCES

In my Master's Thesis, I employed a variety of resources to conduct the analysis of factors influencing the decision-making process for electric vehicle purchases.

Firstly, I used Python as the primary tool for processing registration microdata. This enabled me to underpin my research on objective data regarding the factors influencing the choice of electric vehicle purchases. Python is a versatile tool that offers data analysis and statistical modeling capabilities. Additionally, I implemented GitHub as the central platform for version control and collaboration. GitHub facilitated precise tracking of changes made in the code, enabled effective collaboration across different project phases, and ensured integrity and transparency in development. It also served as a centralized repository for Python code and any scripts used in data analysis, strengthening the reproducibility of the study.

Moreover, for writing the thesis, creating tables, and processing data, I used essential Microsoft Office tools such as Word and Excel. These applications were crucial for presenting the results of my research clearly and organized.

When it became necessary to delve deeper into discrete choice analysis or "discomfort choice," I developed a discrete decision model using Python. This approach allowed for a more detailed exploration of how people react to uncomfortable or challenging situations when making purchasing decisions.

CHAPTER 2. STATE OF THE ART

2.1 VARIABLE STUDY LITERATURE

Understanding the sociodemographic factors underlying the choice to acquire an Electric Vehicle (EV) has become a critical research area to promote its adoption and design effective policies that accelerate the transition to more sustainable mobility. The state of the art aims to address current knowledge on EV adoption and the sociodemographic determinants influencing this choice while highlighting areas where existing research has identified gaps and challenges requiring deeper analysis.

According to Tanţău and Gavrilescu, 2019 [1], the decision to purchase an Electric Vehicle (EV) is influenced by crucial factors. These include the acquisition cost (often after applying purchase incentives), battery range, charging autonomy (encompassing the availability of charging stations, charging time, and device compatibility), vehicle dynamic performance, long-term savings, and buyer knowledge in the field. Literature on barriers to electric mobility adoption identifies significant aspects related to potential buyers' anxiety, reducing their willingness to acquire electric vehicles. These aspects include, for example, the fear of running out of battery mid-journey ("range anxiety") to concerns about not finding an available charging station at any time or that the charging cable connector may not be compatible ("charging anxiety"). Additionally, there are fears related to the possibility of unforeseen disruptions to daily routines ("daily routine disruption anxiety"), home electrical grid overload during charging affecting appliances and lighting ("damage anxiety"), as well as fears of charging process problems that could lead to vehicle fires ("risk anxiety"). Lastly, there's concern that freedom of movement may be restricted with an EV ("restricted freedom anxiety"). Addressing these anxieties represents challenges that must be tackled to encourage widespread adoption of electric vehicles and promote sustainable mobility. In addition to this paragraph, Li et al. [2] study the effect of implementing policies favoring the purchase of these vehicles. This study investigates the effect of providing consumers with tax exemptions or facilitating financial assistance to consumers.

Moreover, quoting Yan and Pakir, 2022 [3], a series of hypotheses related to different factors influencing the intention to purchase Electric Vehicles (EVs) are presented. These hypotheses are based on previous research and address various aspects that may influence the decision to acquire an EV. The most important hypotheses studied are as follows:

1. There is a positive correlation between demographic characteristics and the intention to purchase EVs. According to literature, demographic factors such as age, gender, education level, income, and family size are related to environmental behavior.

2. There is a positive correlation between social media influence and the intention to purchase EVs. Social media influence refers to acquiring information about EVs through the media.

3. There is a positive correlation between facilitating conditions and the intention to purchase EVs: Facilitating conditions refers to the perception of infrastructure or technical support for EV use. It is suggested that battery availability, charging infrastructure, and maintenance services influence the intention to purchase EVs.

4. There is a positive correlation between EV features and design and the intention to purchase: EV features and design, such as comfort, efficiency, and ease of use, are considered important factors in the decision to purchase EVs.

5. There is a negative correlation between price and the intention to purchase EVs: Price and financial aids, such as government subsidies, are considered factors that can influence the intention to purchase EVs.

Regarding the decision-making process about which vehicle each user will purchase, there are different models that simulate this situation. Discrete Choice Analysis (DCA) is a statistical and econometric methodology used to model and analyze decisions made by individuals or entities when faced with a set of discrete and mutually exclusive alternatives. It is widely applied in various fields, including economics, transportation, marketing, environmental science, and social sciences. DCA provides a framework for understanding and predicting how people make decisions based on the attributes and characteristics of available options.

According to Ben-Akiva and Lerman, 1985 [4], the fundamental problem faced by discrete choice analysis is modeling choice from a set of alternatives. The discrete choice model is based on the principle of utility maximization. In simple terms, decision-makers are modeled as selecting the alternative with the highest utility among those available when making a decision. An operational model consists of utility functions parameterized in terms of observable independent variables and unknown parameters, and their values are estimated from a sample of observed choices made by decision-makers when faced with a choice situation.

It is essential to recognize that it is impossible to specify and estimate a discrete choice model that always succeeds in predicting the alternatives chosen by all individuals. Therefore, the concept of random utility is adopted. In this approach, the actual utilities of alternatives are considered random variables, implying that the probability of choosing an alternative is defined as the probability of having the highest utility among the available alternatives.

Another approach of interest for the study is the "Discomfort Choice" model. In this situation, decision-making related to discomfort or inconvenience is studied. In this type of analysis, the choices people make when facing uncomfortable or challenging situations are explored. The context may vary depending on the specific application but generally involves understanding the circumstances and factors influencing the choices people make when experiencing discomfort or inconvenience.

In this approach, choices made in uncomfortable situations are explored to understand how people balance their needs, preferences, and limitations in less predictable and more emotional contexts than conventional discrete choice analysis. An example of the mentioned model is the MA3T. [5]

2.2 DECISION MODEL LITERATURE REVIEW

In the realm of transportation demand modeling, the foundational premise is that passenger flows within a transportation system arise from the decisions made by its users. This concept is extensively discussed by renowned experts such as Ortúzar and Willumsen [6], as well as Ben-Akiva and Lerman. These experts emphasize that travelers' choices—such as selecting a transportation mode, deciding on a route, choosing a destination, and determining travel timing—are influenced by a complex interplay of factors.

Discrete choice models are a fundamental tool in transportation research and demand modeling, extensively explored by experts like Ben-Akiva and Lerman [4]. These models are used to understand and predict the decisions individuals or groups make when faced with discrete alternatives. In transportation, these alternatives can include different travel modes (such as car, bus, train), routes, departure times, or destinations.

The core premise of discrete choice models is that individuals choose the alternative that provides them with the highest utility or satisfaction, given their preferences and the constraints they face (such as cost, travel time, comfort, and reliability). These models are based on the economic theory of consumer choice, adapted to the context of transportation and mobility.

There are several types of discrete choice models, including:

1. **Binary Choice Models:** These models involve choices between two alternatives, such as choosing between driving a car or using public transit.
2. **Multinomial Logit Models (MNL):** This is one of the most common types of discrete choice models, where individuals choose among several distinct alternatives. MNL assumes that the utility of each alternative is a linear function of its attributes and individual-specific parameters.

3. **Nested Logit Models:** These models accommodate the hierarchical structure of choices, where alternatives can be grouped into nested sets. For example, choosing between driving alone, carpooling, or using public transit, where public transit itself consists of various modes (bus, subway).
4. **Mixed Logit Models:** Unlike MNL, mixed logit models relax the assumption that individuals have identical preferences. They allow for heterogeneity in preferences across individuals by modeling parameters as random variables.

These models are used for various purposes in transportation planning and policy analysis, including:

- **Forecasting Travel Demand:** Predicting how changes in transportation infrastructure, policies, or demographics will affect mode choice, route selection, and overall travel behavior.
- **Evaluating Transportation Policies:** Assessing the impact of policy interventions (such as tolls, subsidies, or new transit services) on travelers' choices and system performance.
- **Designing Transportation Systems:** Informing decisions about the design and expansion of transportation networks to meet the needs and preferences of users efficiently.
- **Understanding Travel Behavior:** Providing insights into why individuals make specific travel choices, which helps in designing more effective transportation interventions and investments.

In essence, discrete choice models are powerful tools that enable researchers and policymakers to simulate and understand the decision-making processes of travelers within transportation systems, thereby facilitating more informed and effective transportation planning and management.

2.2.1 Discrete choice model

According to the "*Instituto mexicano de transporte*" in "Métodos de elección discreta en la estimación de la demanda de transporte" [7][8] and the citations mentioned above, transportation demand modeling begins with the principle that the movement of passengers within the transport network stems from the decisions taken by its users. whether as individuals or collective decision-making groups (families, school students, employees of a company, etc.). These choices may include the mode of transportation to use, the route, the destination, or the time of travel. Additionally, it is assumed that users of the transportation system make rational decisions and express their travel preferences by seeking to maximize the utility provided by the trip (or, alternatively, minimizing the inconveniences of making the trip).

The application of the principle of utility maximization in user decision-making relies on the concept of a utility function. This function is a mathematical representation whose value depends on both the attributes of the travel option being considered and the characteristics of the individual making the choice. The utility function effectively captures the user's preferences: if the utility value for travel option "a" is higher than for option "b", the individual will prefer "a" over "b". Conversely, if the individual prefers option "b" over "a", the utility function will yield a higher value for "b" than for "a".

Therefore, the utility function aligns with the user's preferences, and when presented with a finite number of options, the individual will select the one with the highest utility value.

To work with a utility function, the following elements need to be defined:

a) The set of available options, denoted as A, which includes all known travel choices accessible to the user (such as private car, taxi, bus, etc.). Each option "j" in set A is characterized by a set of attributes Xj (such as travel time, cost, comfort, etc.).
b) The set of attributes S of the individual making the decision, which are relevant for the decision-making process. These attributes typically encompass factors like age, gender, annual income, number of owned cars, and so forth.

Following the principle of utility maximization, we seek a function U that depends on both the attributes of the alternatives in set A and the attributes S of the individual making the travel decision. This function should have the property that for any pair of options j, k in set A, the relationship: $U(X_j, S) > U(X_k, S)$ indicates that the user prefers option j over option k and will therefore choose j if given the choice between them. When the individual must choose among several options in A, they will choose option j whenever the relationship: $U(X_j, S) > U(X_k, S)$ holds for all options k in A.

2.2.2 Probabilistic approach

As a continuation of what the "*Instituto mexicano de transporte*" in "Métodos de elección discreta en la estimación de la demanda de transporte" [7] [9], it has been observed that it is common to find two travelers identified with exactly the same travel attributes, classified with the same socioeconomic characteristics, and facing a decision among the same set of options, yet they choose differently. Furthermore, it also happens that the same individual, when faced with the same travel options on different occasions, chooses differently each time. Several reasons explain this behavior:

A) individuals apparently identical in socioeconomic characteristics and facing the same travel option attributes have different tastes or perceive the attributes differently.
B) the model of travel options constructed may not have all the necessary information about the travel options.
C) the model may not know all the socioeconomic characteristics of the travelers that are relevant for the choice.

Deterministic choice models fall short in accurately forecasting under these conditions. As a result, choice modeling expands into a probabilistic framework, which accommodates the uncertainty and incomplete information about the attributes of options or the socioeconomic characteristics of travelers. Consequently, random utility models are developed to represent travelers' preferences probabilistically. These models do not predict the specific option a traveler will choose; instead, they estimate the probabilities of each available option being chosen. The general form of a probabilistic utility model, U, is composed of two parts: a deterministic utility component, V (also known as systematic), which is calculated using the attributes of the options and the characteristics of travelers, and an error term, e. This error term is a random variable that accounts for variations not captured by the deterministic component. Therefore, the model can be expressed as follows:

$$U(i) = V(i) + e(i)$$

2.2.3 LOGIT model

Assuming rational behavior by the individual, the function V(i) can be specified by selecting variables that represent the attributes of the alternatives important to the traveler. A simple and commonly used form is the linear form, where coefficients indicate the significance of each attribute. This can be expressed as follows:

$$V(i) = b_0 + b_1 * x_1 + \cdots + b_k * x_k$$

Following the principle of utility maximization, an individual is expected to choose option i if they perceive it as having the highest utility. This is indicated by U(i) being greater than U(j) for any other option j available in the set A. Thus, the probability, P(i), of option i to be chosen is defined by the following equation:

$$P(i) = P[U(j) < U(i)] \; for \; al \; i \neq j$$

As a continuation of the previous equation:

$$P(i) = P[e(j) - e(i) < V(i) - V(j)] \; for \; al \; i \neq j$$

Developing the previous equation:

$$P(i) = P[e(j) < V(i) - V(j) + e(i)] \; for \; al \; i \neq j$$

And considering the joint probability distribution F(.) of the random components e(1), e(2), … , e(i), … , e(N) , for N available options, as well as the marginal density function of the random component ‘i’, f_i (.), the aforementioned probability can be calculated as:

$$P(i) = \int F\left[e(j) < V(i) - V(j) + e(i)\right] f_i(\theta) d\theta \ \ for\ al\ i \neq j$$

To make the previous expression manageable, it is necessary to make assumptions about the joint probability distribution of the error terms e(i). The first assumption is that these errors are independently and identically distributed (IID). The second assumption involves specifying the form of their probability distribution.

Different probability distributions for the differences e(j) − e(i) lead to different models. For example, a uniform distribution results in a linear probability model, while a normal distribution results in a Probit model. The Logit model is widely used. In the Logit model, assuming the errors e(i) follow a Gumbel distribution (also known as extreme value distribution), it can be shown that the differences e(j) − e(i) follow a Logistic distribution (Ben-Akiva & Lerman, 1985). The second term in equation is the cumulative distribution function (CDF) of the differences e(j) − e(i), so the probability of choosing option "i" in the Logit model is given by the Logistic density.

$$P(i) = \frac{e^{Vi}}{e^{Vi} + e^{Vj}}$$

The binomial Logit model described earlier can be naturally extended to account for more than two user choice options. If there are N options with systematic utilities V_1, V_2, … , V_n, the basic form of the model for the probability of choosing option "i" is given by:

$$P(i) = \frac{e^{Vi}}{e^{Vi} + e^{Vj} + \cdots + e^{Vn}}$$

2.2.4 Parameters estimation

To estimate the parameters β_k of the Logit model, given the mentioned characteristics, it is not possible to use the ordinary least squares method, particularly due to the condition of non-constant variance (known as heteroscedasticity). The procedure commonly used in practice is the maximum likelihood method, which is detailed next.

Like other parameter estimation methods in statistical literature, maximum likelihood utilizes information from a sample of the studied population to estimate parameters of the proposed Logit model. The fundamental idea of this method is to find numerical values of the parameters β_k that maximize the likelihood of observing the values obtained in the sample under the proposed model.

Maximum likelihood estimation is a widely used method to fit discrete choice models, such as logit and probit models, to observed data. The objective is to find parameter values θ that maximize the likelihood function, which represents the joint probability of observing the data given the estimated parameters.

- **Likelihood Function**: The likelihood function L(θ|y,X) for a discrete choice model depends on the parameters θ, the observed choices y, and the explanatory variables X. For example, in a multinomial logit model, the likelihood function is defined as:

  - $$\mathrm{L}(\beta \mid \mathrm{y}, \mathrm{X}) = \Pi_{i=1}^{N} \Pi_{j=1}^{J} \frac{e^{x_i \beta_j}}{\Sigma_{k=1}^{J} e^{x_i \beta_k}}$$

- where β are the parameters to be estimated, x_i is the vector of characteristics of option i, β_j are the parameters associated with option j, and y_{ij} is an indicator variable that takes the value 1 if option i is chosen and 0 otherwise.

- **Optimization**: To find the optimal values of β that maximize L(β|y,X), numerical optimization methods such as the Newton-Raphson algorithm or stochastic gradient methods are used. These iterative methods adjust the model parameters in each iteration until converging to the solution that maximizes the likelihood function.

Specific details on implementation and simulation techniques for mixed models and other refinements can be found in Kenneth Train's book, "Discrete Choice Methods with Simulation" (2009) [10].

CHAPTER 3. VARIABLE STUDY

3.1 METHODOLOGY

3.1.1 Data Sources

In order to carry out this study, several data sources were used to provide the necessary information to analyze the factors that influence the adoption of electric vehicles in the municipalities of Spain. The data sources used are detailed below:

1) **Microdata from the DGT (Dirección General de Tráfico)** [11]**:**

The data on electric vehicle registrations were obtained by adapting the microdata provided by the Dirección General de Tráfico (DGT). This microdata contain detailed information on the characteristics of the registered vehicles, including their propulsion type and municipality of registration.

2) **INE (National Statistics Institute)** [12]**:**

For variables related to per capita income, garage availability and availability of low emission zones, we used data provided by the National Statistics Institute (INE). These data provide a broad and updated view of the socioeconomic and demographic conditions of Spanish municipalities.

3) **Electromaps data** [13]**:**

The information on the availability of charging points for electric vehicles was obtained from an adaptation of the data provided by Electromaps, a collaborative platform that collects information on charging stations throughout Spain. This data was processed and analyzed to determine the number of charging points available in each municipality.

3.1.2 Data collection

The data collection process was carried out following a structured procedure that allowed obtaining the necessary information to perform the analysis of the factors influencing the adoption of electric vehicles in the municipalities of Spain.

Obtaining Data from the Sources Mentioned:

The previously mentioned databases, including DGT microdata, INE data and Electromaps information, were accessed to compile the relevant data for the study.

Data Structuring with Pandas in Python:

Using the Pandas library in Python, we proceeded to structure the data obtained so that each column represented a variable of interest.

Variables Included in the Data Structure (more on this later):

The variables included in the data structure were as follows:

a) Number of registered electric vehicles.
b) Total vehicle registrations in each municipality.
c) Population of the municipality.
d) Per capita income of the municipality.
e) Proportion of dwellings that have a garage.
f) Number of recharging points available in the municipality.
g) Existence of a low emission zone in the municipality (binary variable).

Normalization and Data Cleansing:

A data standardization and cleaning process was carried out to ensure data consistency and reliability. This included identifying and correcting possible errors, eliminating duplicate or inconsistent data, and making the data formats suitable for further analysis.

Creation of the Final Data Set:

Once the data were structured, normalized and cleaned, the final data set was created to serve as the basis for the statistical analysis and the construction of the multiple linear regression model.

3.1.3 Variables

To carry out the multiple linear regression analysis, a set of variables were selected that were considered important to understand and predict the level of electric vehicle (EV) registrations in Spanish municipalities. The dependent variable (Y) in this model is the "EV_rate", defined as the ratio of EV registrations to total registrations in each municipality.

In a first study at the national level, as the main variable of interest, the average per capita income of the municipalities (in euros) was considered as a measure of their socioeconomic level. This variable is expected to have a significant influence on the purchase of electric vehicles, since it reflects the purchasing power of the inhabitants.[2][14]

Given the considerable variability in the data and in order to focus the study on municipalities with more homogeneous demographic and socioeconomic characteristics, it was decided to limit the analysis to municipalities with a population of more than 50,000 inhabitants.

For these municipalities, in addition to per capita income, the following additional variables were included as predictors in the multiple linear regression model:

1. **Garage availability**: This variable represents the proportion of homes in the municipality that have covered parking space, which may influence the adoption of electric vehicles due to the convenience and security offered by parking.

2. **Charging availability:** Refers to the number of EV charging stations divided by the number of EV registrations in the municipality. The charging infrastructure plays a crucial role in the acceptance and adoption of EVs, as it affects the accessibility and convenience of charging vehicles.

3. Availability of low-emission zones: This binary variable indicates whether the municipality has areas designated as low-emission zones, where restrictions on polluting vehicle traffic apply. The existence of these zones may motivate residents to opt for electric vehicles to avoid possible restrictions or charges associated with conventional vehicles.

3.2 STUDY: INCOME PER PERSON AND EV_RATE AT THE NATIONAL LEVEL

As a first approach to the problem, a regression is proposed between the average income per person and the EV_RATE of that municipality. The results obtained from the statistical study are shown below. It is important to clarify that "national" refers to the inclusion of all municipalities. In reality, the study is conducted at the municipal level, encompassing all municipalities in the country.

The representation of the points and the regression line:

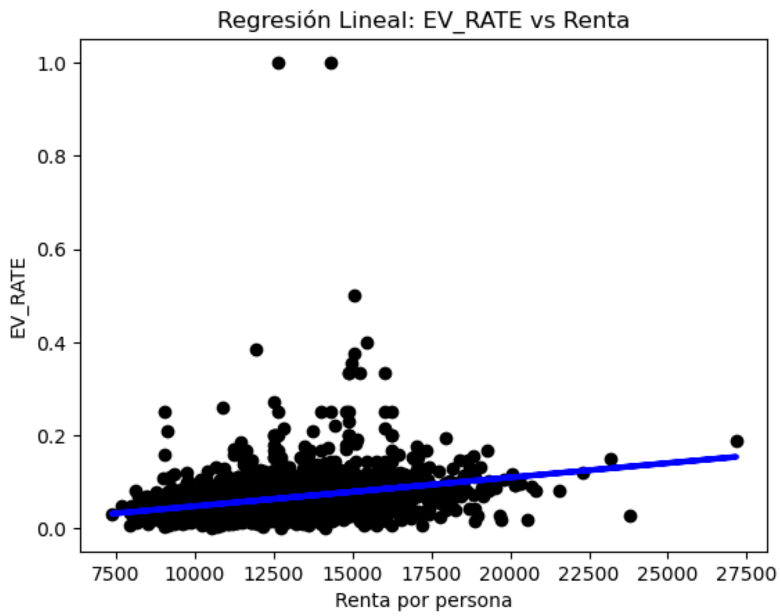

Figure 5: Income vs EV_RATE I

Evaluation of the regression model:

Table 5: Income vs EV_RATE regression evaluation.

Metrics	**Mean absolute error**	**Mean square error**	**Root mean square error**	**Coefficient of determination (R)^2**
Value	0,0269	0,0024	0,0496	0,079

The metric that will be used to determine how well the regression model performs is R^2 .

An R-squared value of approximately 8% suggests that the current regression model is not capturing most of the variability in the data. It can be interpreted that the regression is not very useful for making accurate measurements.

3.3 STUDY: PROVINCIAL CAPITALS AND MUNICIPALITIES > 50,000 INHABITANTS

As a consequence of the previous results, it was decided to carry out a study with a group of municipalities that are considered to have similar characteristics.

The following part of the study takes into account municipalities that contain provincial capitals and those municipalities that contain cities with more than 50,000 inhabitants.

Furthermore, in this case, additional data are available for municipalities with the aforementioned characteristics, therefore, from now on, the variables of garage availability, recharging availability and whether or not low emission zones are available will be taken into account for the study.

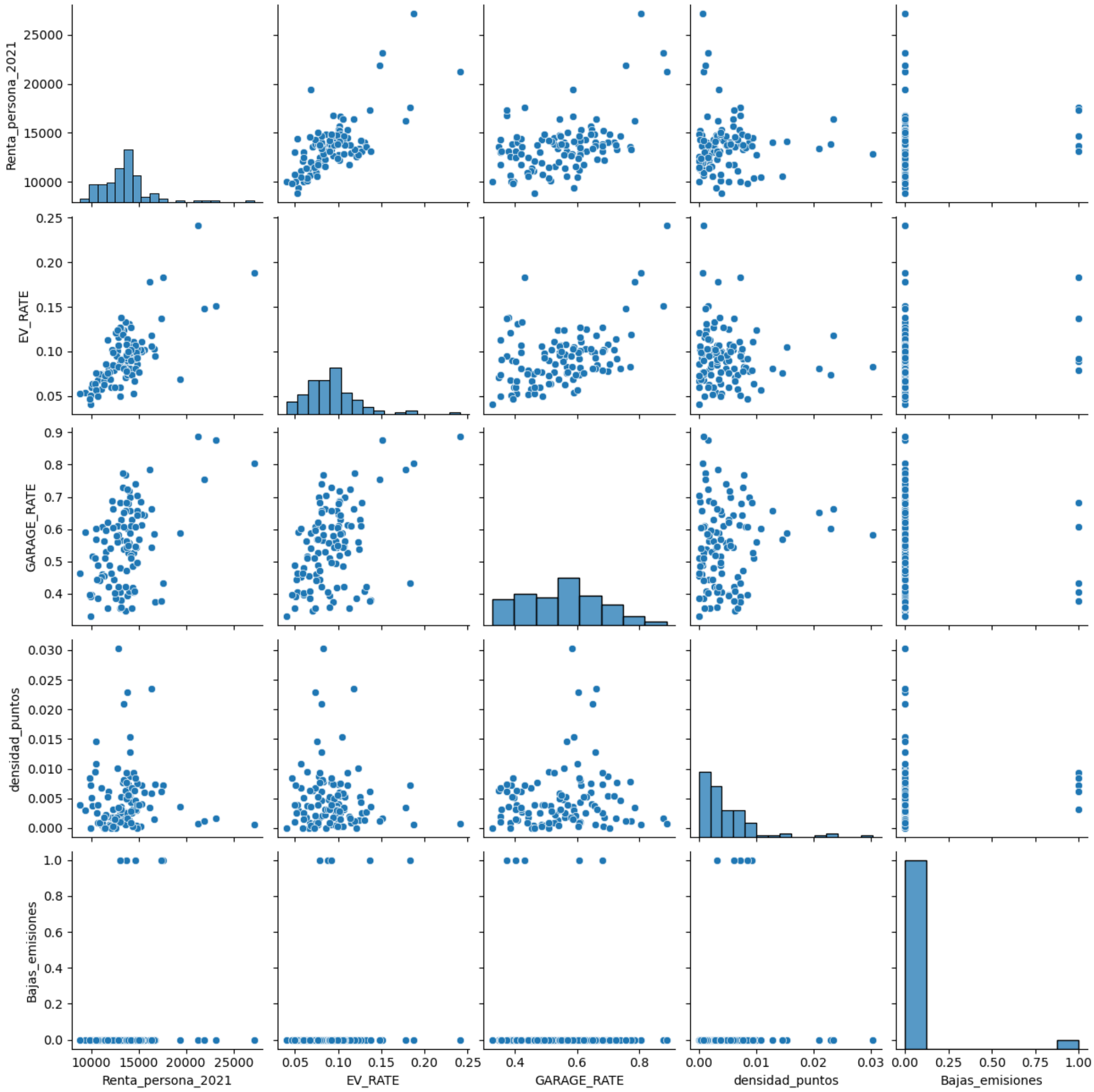

Figure 6: Multivariable regression

From the above graph it can be seen that with respect to the study variable EV_RATE there is apparently a positive linear correlation with rent. In addition, some correlation is intuited with respect to garage availability.

In the first case, it is interesting to study how the performance of the income regression model has improved against EV_RATE.

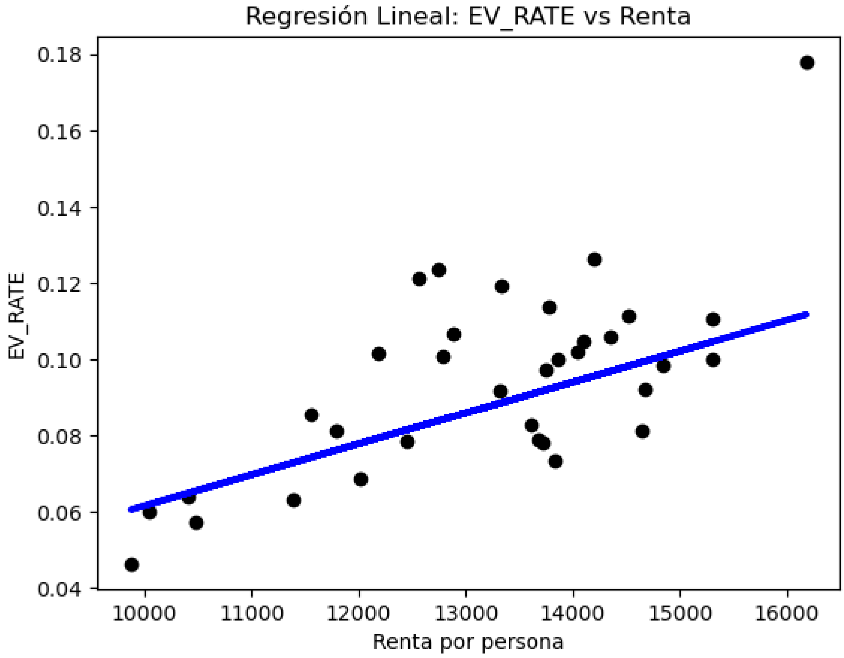

Figure 7: Income vs EV_RATE II

Evaluation of the regression model:

Table 6: Evaluation Income vs EV_RATE II

Metrics	**Mean absolute error**	**Mean square error**	**Root mean square error**	**Coefficient of determination $(R)^2$**
Value	0,0155	0,00053	0,0147	0,36

Although we have previously considered only the coefficient of determination as a metric for determining the usefulness of the regression, it is interesting to mention that the mean absolute, mean square and root mean square errors have been reduced considerably.

It is observed that the model improves significantly following the new criterion. In this case, the model captures a moderate proportion of the variability of the data, approximately 36%. In this case the model can be useful for predictions, although it is advisable to study other metrics and variables.

Analyzing the multivariate regression model, the result is as follows.

Table 7: Linear regression summary.

	Coefficient	**Std. error**	**T student**	**P value**	**Coefficient of determination (R)^2**
Constant	-0,0296	0,013	-2,206	0,031	-
Rent per person	6.385e-06	1.03e-06	6,214	0,000	0,627
Garage availability	0,0642	0,025	2,530	0,014	0,328
Density of recharge points	-0,046	0,502	-0,888	0,378	-0,011
Low emissions	0,0401	0,014	2,846	0,006	-0,041

Regarding the model constant, the negative value indicates that, when all other variables are zero, the response variable is expected to be slightly negative. The P-value suggests that this coefficient is significantly different from zero at the 0.05 significance level.

The income per person variable suggests that an increase in income per person is associated with a very small increase in the response variable. This can be explained by looking at the unit sizes of EV_RATE and income, as EV_RATE takes values between 0 and 1 and income values reach the tens of thousands. The high T-value and very low P-value indicate that this coefficient is highly significant in the model.

On the other hand, garage availability also indicates that an increase in garage availability implies an increase in electric vehicle registrations.

The negative coefficient of the variable "Density of recharge points" suggests that an increase in the density of recharge points is associated with a decrease in the response variable, which, a priori, does not make sense, but since the high P-value indicates that this coefficient is not significant in the model, we should not worry too much.

Finally, the positive coefficient on the variable "Low Emission Zone" indicates that an increase in the number of low emission vehicles is associated with an increase in the response variable. The P-value suggests that this coefficient is significant at the 0.05 significance level.

3.4 CONCLUSIONS

Based on the previous statistical study, the necessary conclusions are drawn to obtain a purchase decision model for electric vehicles.

Significant variables:

- Income per person, garage availability and the existence of low emission zones are significant variables in the model.
- The density of recharge points is not significant and can be excluded from the model.

Impact of variables:

- Income per person has the highest coefficient of determination, indicating that it contributes significantly to explaining the variability in EV registrations.
- Garage availability also has a significant impact on electric vehicle registrations.
- The existence of low-emission zones has a significant positive impact on the adoption of electric vehicles.

Considerations for the decision model:

- Income per person is the most significant variable in the model. According to the results obtained, it is observed that the penetration of electric vehicles is considerably higher in municipalities with a higher income.
- In the decision-making process to promote the adoption of electric vehicles, it is crucial to consider policies that encourage the availability of garages and the creation of low-emission zones.
- The charging infrastructure, although not significant in this study, is still important for the adoption of electric vehicles and should be monitored and improved.

CHAPTER 4. DECISION MODEL

4.1 VARIABLES FOR THE DECISION MODEL

Study	Econometric Model	Attributes Included	Findings
Beggs et al. (1981)	Ranked Logit	Purchase Price, Driving Range, Acceleration, Top Speed, Operating Costs, Fuel Costs, Seating Capacity, Air Conditioning and Warranty	Results indicate considerable dispersion in individual coefficients for the choice model.
Calfee (1985)	Disaggregate MNL	Purchase Price, Driving Range, Top Speed, Operating Costs and Number of Seats	Great diversity in individual trade-offs among attributes, with range and top speed generally being highly valued
Bunch et al. (1993)	MNL and Nested Logit	Purchase price, Driving range, Fuel Costs, Acceleration, Fuel Availability, Pollution, Dedicated versus Multi-Fuel	Range between refueling and fuel costs are important attributes.
Ewing and Sarigöllü (1998)	MNL	Purchase Price, Driving Range, Acceleration, Fuel Costs, Repair and Maintenance Costs, Commuting Costs, Recharging Time and Commuting Time	Differential commuting costs and times for cleaner vehicles have modest effects on vehicle choice.
Brownstone et al. (2000)	Joint Mixed Logit Model of Stated and Revealed Preferences	Purchase Price, Driving Range, Top Speed, Acceleration, Home Refueling Costs, Service Station Fuel Costs, Home Refueling Time, Service Station Availability, Tailpipe Emissions, Vehicle Size, Vehicle Type and Luggage Space	There are advantages of merging SP and revealed preference (RP) data. RP data appear to be critical for obtaining realistic body-type choice.
Potoglou and Kanaroglou (2007)	Nested Logit Model	Purchase Price, Acceleration, Annual Fuel Cost, Annual Maintenance Cost, Fuel Availability, Pollution Level, Vehicle Size and Incentives	Reduced monetary costs, purchase tax relieves and low emissions rates would encourage households to adopt a cleaner vehicle.

Figure 8: " Consumer preferences for electric vehicles in Germany" literature

Based on the literature from the document "*Consumer preferences for electric vehicles in Germany*" [15], along with the linear statistical study conducted in the previous section of this master's thesis, the variables that will be definitively considered for my work are as follows:

- The relation between the purchase price of the vehicle and the average net income of the municipality where it was registered.
- The power of the vehicle. This variable is highly correlated with the driving range and net weight of the vehicle.
- The inhabitants of both the municipality and the postal code.

- Whereas the car is new or not.
- The average amount of car bought in each municipality per person per year.

4.1.1.1 Power segment and Premium BEV price

All the variables mentioned above are considered for each registration done in Spain from 2015 to 2023. [16]. To take into account the price of the vehicle, a variable called "*Premium BEV Price*" was created, in order to be able to introduce it in the model. This variable had a different value depending on the power of the vehicle. *Source: "market prices in Spain, 2024"*

To classify the vehicles based on their power segment, a quick and brief study was conducted. Through clustering, each vehicle was assigned a value from 0 to 4 based on its curb weight. Furthermore, some insights were taken from

The premium prices assigned to BEV and PHEV vehicles depending on the power of the vehicle are the following:

Table 8: Weight labels

Label	**Segment 0**	**Segment 1**	**Segment 2**	**Segment 3**	**Segment 4**
Net weight [kg]	[0-1350]	[1350-1700]	[1700-2150]	[2150-2600]	[>2600]
Premium price [€]	10000	10000	17000	22000	32000

4.2 MULTINOMIAL LOGIT MODEL

4.2.1 Model results

The model results are shown in the following table:

Table 9: Model results summary I

Dep. Variable:	vehicle_type	**No. Observations:**	126708
Model:	MNLogit	**Df Residuals:**	126694
Method:	MLE	**Df Model:**	12
Date:	Sun, 30 Jun 2024	**Pseudo R-squ.:**	0.3206
Time:	11:22:35	**Log-Likelihood:**	-43589.
converged:	True	**LL-Null:**	-64156.
Covariance Type:	nonrobust	**LLR p-value:**	0.000

The model shows a good fit with a Pseudo R-squared value of 0.3206, indicating that approximately 32.06% of the variance in `vehicle_type` is explained by the model. The log-likelihood value of -43,589, compared to the LL-Null value of -64,156, demonstrates a substantial improvement in model fit over the null model, which includes no predictors. Additionally, the likelihood ratio test p-value is 0.000, signifying that the model as a whole is statistically significant and that the predictors significantly enhance the model's explanatory power.

4.2.1.1 ICE results

Table 10: Model results summary II

vehicle_type=ICE	coef	std err	z	P>|z|	[0.025	0.975]
const	3.8288	0.044	86.924	<0.05	3.743	3.915
Potencia_label	-2.7368	0.024	-112.401	<0.05	2.785	-2.689
Premium_Price_BEV/Renta	0.7374	0.047	15.703	<0.05	0.645	0.829
POB	-1.392e-07	5.56e-09	5.56e-09	<0.05	-1.5e-07	1.28e-07
Coc_hab	-0.5542	0.122	-4.530	<0.05	-0.794	-0.314
IND_NUEVO_USADO	3.6245	0.066	55.326	<0.05	3.496	3.753
POBLACION	1.122e-07	1.22e-08	9.202	<0.05	8.83e-08	1.36e-07

In summary, all variables have p-values of 0.000, indicating they are highly significant predictors of whether a vehicle is an ICE. The sign of each coefficient indicates the direction of the relationship between the predictor and the likelihood of the vehicle being an ICE.

According to our study, it is interesting to see how the variables Potencia_label and Premium price BEV affects to the consumer decision of buying an electric vehicle.

- **Potencia_label:**

The coefficient for Potencia_label is -2.7368 with a highly significant p-value of 0.000. The negative sign of the coefficient suggests that as the power label increases, the likelihood of the vehicle being an ICE decreases. This indicates an inverse relationship between vehicle power and the likelihood of it being categorized as an ICE.

- **Premium_Price_BEV/Renta:**

The coefficient for Premium_Price_BEV/Renta is 0.7374, and the p-value is 0.000, indicating high significance. The positive sign of the coefficient implies that higher premium prices for BEVs or rental vehicles are associated with an increased likelihood of the vehicle being an ICE.

4.2.1.2 PHEV results

Table 11: Model resutls summary III.

vehicle_type=PHEV	coef	std err	z	P>|z|	[0.025	0.975]
const	1.0484	0.055	19.180	<0.05	0.941	1.156
Potencia_label	0.1944	0.029	6.606	<0.05	0.137	0.252
Premium_Price_BEV/Renta	0.7374	0.047	15.703	<0.05	0.645	0.829
POB	-1.392e-07	5.56e-09	5.56e-09	<0.05	-1.5e-07	1.28e-07
Coc_hab	-0.5542	0.122	-4.530	<0.05	-0.794	-0.314
IND_NUEVO_USADO	3.6245	0.066	55.326	<0.05	3.496	3.753
POBLACION	1.122e-07	1.22e-08	9.202	<0.05	8.83e-08	1.36e-07

In this case is also interesting to mention how the two variables mentioned before affect the model.

- **Potencia_label:**

The coefficient for Potencia_label is 0.1944, and the p-value is 0.000, indicating that it is highly significant. The positive sign of the coefficient suggests that as the power label increases, the likelihood of the vehicle being a PHEV (Plug-in Hybrid Electric Vehicle) also increases. This shows a direct relationship between the vehicle's power and the probability of it being categorized as a PHEV.

- **Premium_Price_BEV/Renta:**

The coefficient for Premium_Price_BEV/Renta is 0.7374, with a highly significant p-value of 0.000. The positive sign of the coefficient implies that higher premium prices for BEVs or rental vehicles are associated with an increased likelihood of the vehicle being a PHEV. This indicates that premium pricing positively impacts the probability of the vehicle being a PHEV.

4.2.1.3 ICE & PHEV comparison

Comparing these results with the previous table for `vehicle_type = ICE`, we notice the following differences:

- **Potencia_label:**

- For ICE vehicles, the coefficient was -2.7368, indicating a negative relationship, meaning that higher power labels decreased the likelihood of the vehicle being an ICE.

- For PHEV vehicles, the coefficient is 0.1944, indicating a positive relationship, meaning that higher power labels increase the likelihood of the vehicle being a PHEV.

- **Premium_Price_BEV/Renta:**

- The coefficient for Premium_Price_BEV/Renta is the same (0.7374) for both ICE and PHEV vehicles, with a highly significant p-value of 0.000. This suggests that higher premium prices for BEVs or rentals consistently increase the likelihood of the vehicle being either an ICE or a PHEV, though the impact may vary in context.

These differences highlight that the relationship between vehicle power and its type varies significantly between ICE and PHEV vehicles, while premium pricing impacts both types similarly in terms of significance but might reflect different market behaviors or consumer preferences.

4.2.2 Collinearity check

Checking multicollinearity in regression models is crucial for several reasons. Firstly, multicollinearity can inflate the standard errors of the regression coefficients, making some coefficients appear statistically insignificant when they might actually be important. This undermines the reliability of the model's predictive power and the interpretation of individual predictors' effects. Secondly, multicollinearity violates the assumption of independence among predictors, potentially leading to biased estimates of the regression coefficients. Thirdly, it complicates the identification of the true relationship between predictors and the response variable, hindering the model's ability to accurately capture the underlying patterns in the data. Addressing multicollinearity through techniques like VIF calculation helps ensure the robustness and validity of regression analyses, enhancing the trustworthiness of the model's conclusions and predictions.

The Variance Inflation Factor (VIF) serves as a crucial diagnostic tool in regression analysis to assess multicollinearity among predictor variables. It is computed for each predictor by taking the reciprocal of $1-R_j^2$, where R_j^2 represents the coefficient of determination obtained from regressing the variable X_j against all other predictors. A high VIF (typically exceeding 10) indicates significant correlation among predictors, potentially leading to unstable coefficient estimates and reduced prediction accuracy. References such as Douglas C. Montgomery's 'Introduction to Linear Regression Analysis' [17] provide detailed insights into diagnosing multicollinearity and strategies to mitigate it, including variable selection and regularization techniques.

Table 12: Collinearity check

Variable	**Variance inflation factor**
Const	10.98
Potencia_label	1.12
Premium_price_BEV/Renta	1.20
POB	1.73
Coc_hab	1.03
IND_NUEVO_USADO	1.04
POBLACION	1.67

In summary, most variables have a **Variance inflation factor** , VIF values, well below the threshold of 10, indicating that multicollinearity is not a significant issue in this model. The constant term's VIF is at the threshold, which could be a point of concern, but overall, the predictors do not exhibit problematic multicollinearity. This implies that the regression coefficients can be interpreted with greater confidence, as they are not unduly influenced by multicollinearity.

4.2.3 Model accuracy

The accuracy of the model was evaluated by comparing the real share of electric vehicles (EVs) observed in the dataset with the EV market share predicted by the trained model. This comparison is visualized in a graph, where the x-axis represents the actual EV market share and the y-axis represents the predicted EV market share.

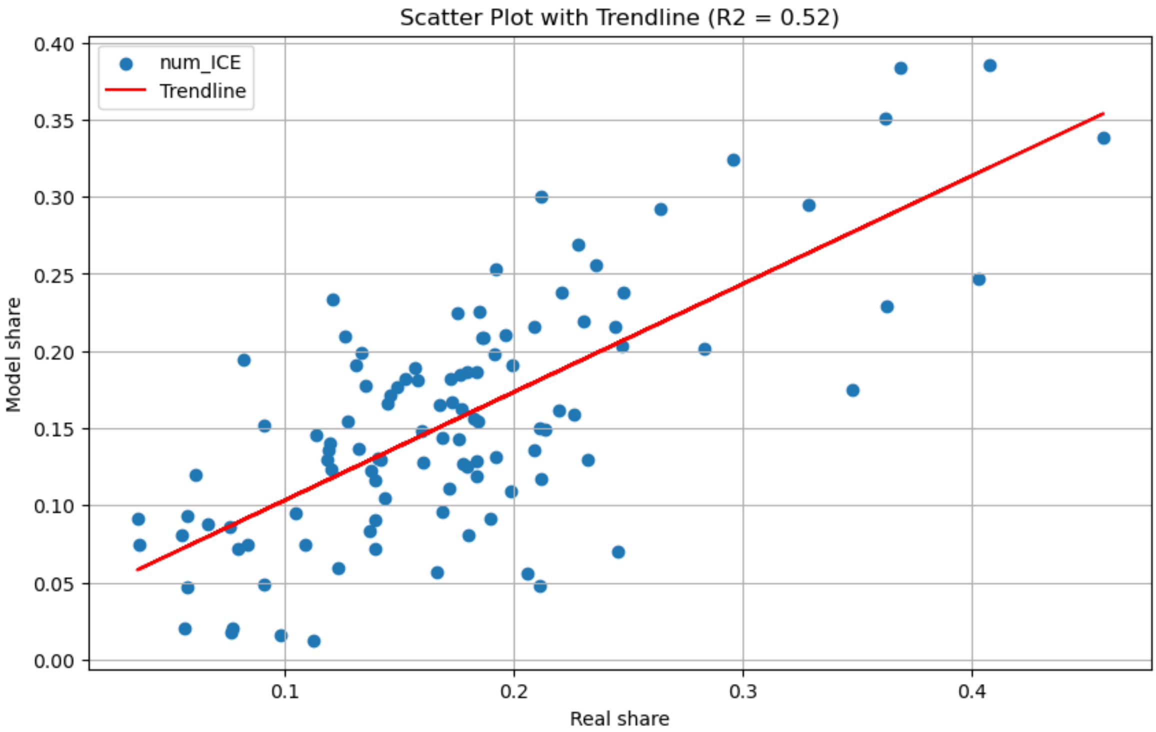

Figure 9: Model accuracy

In an ideal scenario, a perfect model would result in points lying exactly on the bisector, indicating a perfect prediction match. However, the model achieved an R^2 value of 52%, which signifies that while the model captures a significant portion of the variability in the data, there is still room for improvement in accurately predicting the EV market share. The R^2 value indicates that 52% of the variance in the real EV market share is explained by the model, demonstrating moderate predictive accuracy.

CHAPTER 5. RESULTS

5.1 SCENARIOS

With the development of the predictive model customer decisions can be determined regarding the purchase of new vehicles, specifically evaluating their likelihood of opting for BEVs, PHEVs, or ICE vehicles. The model leverages current data and trends within Spain's automotive market, providing insights into how various scenarios might impact vehicle sales.

To thoroughly analyze these potential outcomes, three distinct scenarios have been created:

1. **Net Zero Emissions (NZE) Scenario**:

The Net Zero Emissions (NZE) Scenario is the most ambitious, focusing on achieving zero net emissions for the entire vehicle fleet. Key measures include:

- **Zero Premium Price for BEVs**: This scenario eliminates the premium price of BEVs over ICE vehicles, making BEVs equally priced as their ICE counterparts. This reduction is achieved through extensive government subsidies, tax incentives, and technological advancements that lower production costs.
- **Availability of Raw Materials**: To support the large-scale production of BEVs, there is a secure and stable supply of essential raw materials such as lithium, cobalt, and nickel. Sustainable mining practices and international cooperation ensure that the supply chain remains robust.
- **Strict Emissions Regulations:** Strict emissions standards and regulations are imposed on ICE vehicles, further incentivizing consumers to switch to BEVs.

In this scenario, the market environment is heavily optimized for BEVs, leading to a significant increase in their adoption rate. Consumers are motivated by the cost parity with ICE vehicles and regulatory pressures.

2. **Steady progress scenario**

The Economic Transition Scenario represents a more gradual and economically balanced approach to vehicle adoption. Key measures include:

- **Reduced Premium Price for BEVs:** The extra cost of BEVs compared to ICE vehicles is reduced to a level that is economically feasible and sustainable. This reduction is driven by moderate government incentives and anticipated advancements in battery technology and manufacturing processes.
- **Stable Supply of Raw Materials:** The availability of raw materials is managed to ensure a stable supply for battery production, although the scale is less aggressive than in the NZE scenario. Efforts include investment in alternative materials and recycling technologies.
- **Balanced Regulatory Measures:** Emissions regulations are introduced gradually, allowing the automotive industry and consumers to adapt over time. These regulations aim to encourage a steady transition towards BEVs and PHEVs without causing significant market disruptions.

This scenario envisions a balanced market where consumers have more economically viable choices among BEVs, PHEVs, and ICE vehicles. The steady reduction in BEV prices encourage a gradual increase in BEV adoption rates.

3. **Lagging behind scenario**

In contrast to the other two, the negative scenario increases the extra price of BEVs compared to their 2023 levels.

- **Increased BEV Costs**: A combination of factors, such as reduced government incentives, rising production costs, and supply chain disruptions, leads to an increase in the premium price of BEVs. This makes BEVs less financially attractive to consumers.

- **Limited Availability of Raw Materials**: Scarcity or high costs of essential raw materials for battery production lead to increased manufacturing costs for BEVs. This scenario might be driven by geopolitical tensions, environmental regulations on mining, or increased global demand.
- **Lax Emissions Regulations**: Weak or inconsistent emissions regulations fail to provide sufficient motivation for consumers to switch from ICE vehicles to BEVs or PHEVs.

In this scenario, the market for BEVs struggles to gain traction, and consumers are more likely to continue purchasing ICE vehicles due to their perceived economic advantages and convenience.

A summary of the scenarios compared to the base case is shown below:

Table 13: Scenario summary.

Scenarios	**Net zero emissions**	**Steady progress**	**Lagging behind**
Premium price of the BEV vehicles	0 * Premium_Price_BEV	50% * Premium_Price_BEV	150% * Premium_Price_BEV

5.2 SCENARIO RESULTS

The market share for each scenario is shown below.

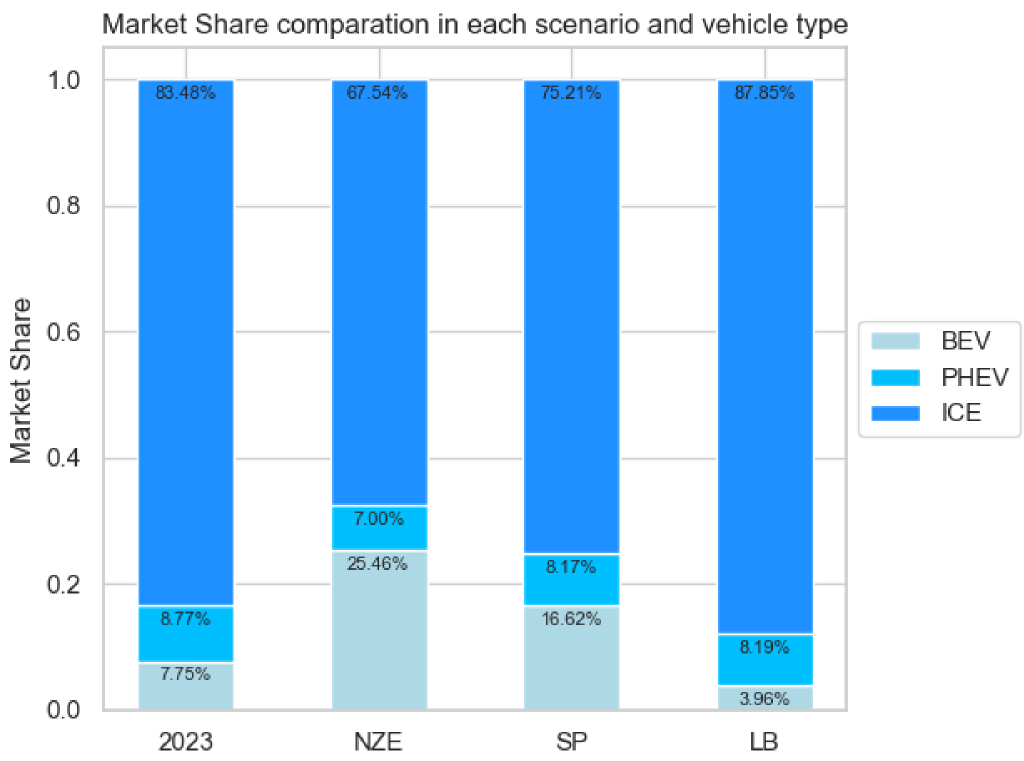

Figure 10: Vehicle market share per scenario.

In the baseline scenario, ICE vehicles dominate the market with a significant majority share of 83.48%. PHEVs and BEVs have relatively small shares at 8.77% and 7.75%, respectively. This reflects the current market dynamics where traditional ICE vehicles are still the preferred choice for most consumers in Spain.

In the NZE scenario, which aims for net zero emissions and eliminates the price premium for BEVs, there is a noticeable reduction in the market share of ICE vehicles to 67.54%. The share of BEVs increases significantly to 25.46%, indicating a shift towards electric solutions as a transitional step. However, PHEVs still hold a relatively small share at 7.00%, suggesting that while policies and price reductions are impactful, additional factors still play a critical role.

In the Economic Transition Scenario, the share of ICE vehicles decreases moderately to 75.21%, reflecting a gradual market shift. BEVs see an increased share at 16.62%, while PHEVs experience a slight increase to 8.17%. This scenario indicates a balanced approach where both hybrids and electric vehicles become more prevalent, but ICE vehicles remain dominant.

In the Lagging behind scenario, the share of ICE vehicles increases moderately to a total of 87.85%. On the other hand, BEVs and PHEVS are significantly affected, as their market share is reduced to 3.96% and 8.19% respectively. This last scenario represents the possible consequences of an scenario where politics and future strategies for road mobility enhances the registrations of conventional vehicles.

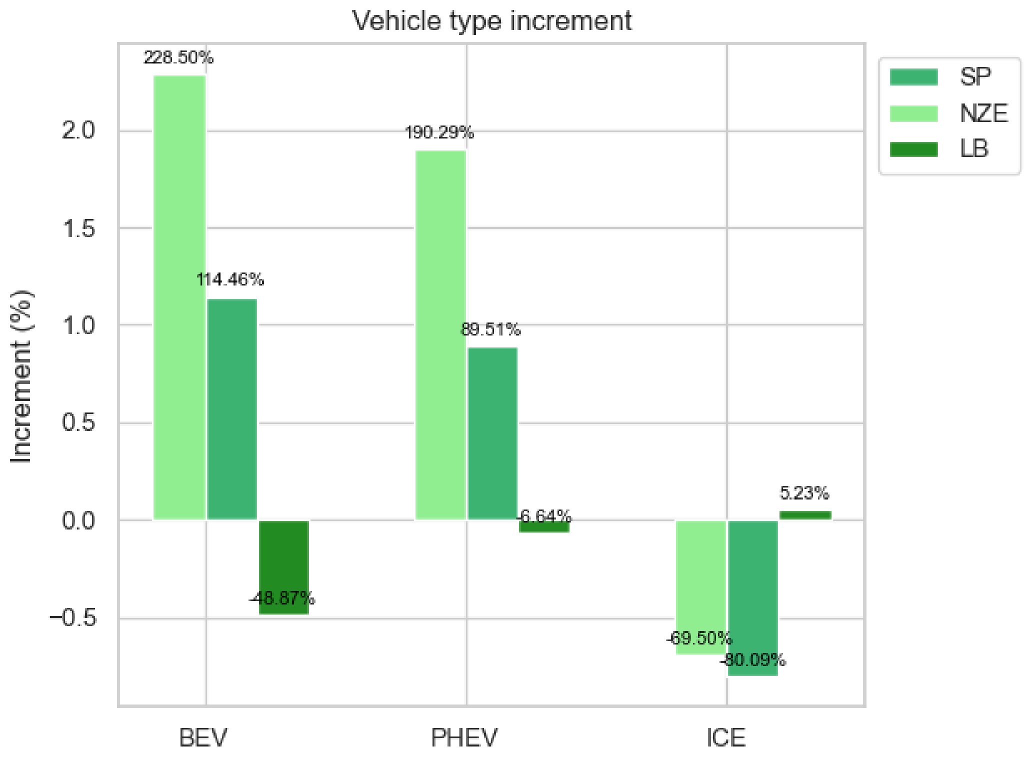

Figure 11: Vehicle increment per scenario.

It is also interesting to assess by how much each vehicle type increases or decreases in each scenario.

Under the steady progress scenario (SP), BEV adoption increases by 114.46%, PHEV by 89.51%, and ICE decreases by 69.50%. The NZE scenario shows the most substantial growth, with BEV adoption soaring by 228.50%, PHEV by 190.29%, and a significant decline in ICE adoption by 80.09%. Conversely, the Negative scenario results in a 48.87% decrease in BEV adoption, a modest 6.64% increase in PHEV adoption, and a slight 5.23% increase in ICE adoption. The analysis highlights that supportive policies (NZE) can significantly boost the adoption of electric vehicles, while adverse conditions (Negative scenario) can slow progress and potentially increase reliance on traditional ICE vehicles.

5.3 COMPARISON WITH BLOOMBERG EV OUTLOOK

Segment	Current share of road transport CO2 emissions	Current estimated global fleet size	Zero-emission vehicle (ZEV) fleet share in 2050 – Economic Transition Scenario	Level of policy intervention needed to hit Net Zero Scenario (100% ZEV share) by 2050
Three-wheeled vehicles	<1%	120 million	95%	On track
Two-wheeled vehicles	5%	1.1 billion	80%	Almost on track: minor additional measures needed
Municipal buses	1%	3.4 million	86%	Almost on track: minor additional measures needed
Light commercial vehicles	11%	170 million	77%	Positive trajectory: moderate additional measures needed
Passenger vehicles	53%	1.3 billion	69%	Positive trajectory: moderate additional measures needed
Medium + heavy commercial vehicles	30%	83 million	28%	Not on track: strong additional measures needed urgently

Source: BloombergNEF, various government sources. Note: Fleet size represents vehicles of all drivetrain types and are estimates based on various sources and BNEF data. Some values rounded. Current emissions and fleet size data are for 2023.

Figure 12: BloombergNEF EV outlook.

Compared to the results and estimates made by BloombergNEF [18], we observe that our estimations for the most favorable scenarios for BEV (Battery Electric Vehicle) adoption are not as optimistic. This discrepancy may be due to BloombergNEF incorporating other variables and considerations that we have not accounted for in our analysis.

It's important to note that our study specifically focuses on passenger vehicle estimates. Therefore, when comparing our results with those of BloombergNEF, we should concentrate on their estimates for passenger vehicles. In our most favorable scenario, we obtain a 32% market share of zero-emission vehicles. According to regulations, the target for a similar scenario is to achieve a 100% market share of zero-emission vehicles by 2050.

Additionally, in the steady progress scenario, our model projects a 24% market share, whereas BloombergNEF estimates a significantly higher 70% market share. BloombergNEF's more optimistic outlook likely includes factors such as broader market trends, policy impacts, technological advancements, and consumer behavior patterns, which may not be fully captured in our current model.

Finally, it should be noted that the conclusion for our model is similar to the one that Bloomberg mentions. We currently are on a positive trajectory towards achieving the level of policy established but further measures are needed.

5.4 *SENSITIVITY ANALYSIS*

The sensitivity analysis graph is shown below:

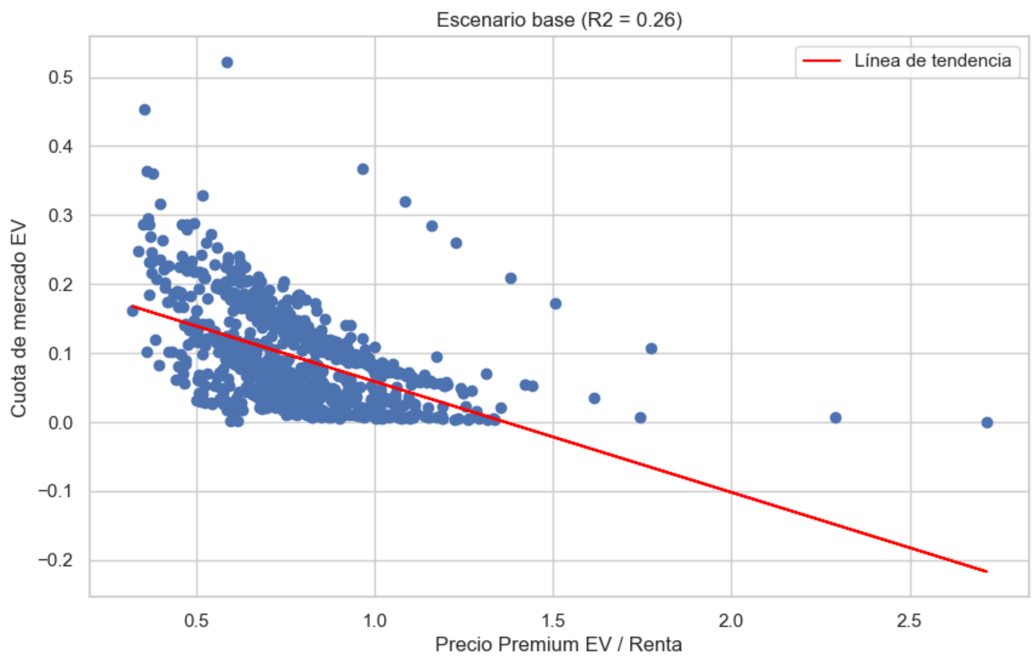

Figure 13: EV market share vs premium EV price (Base)

The sensitivity analysis conducted on the premium price of BEVs relative to premium price of these vehicles and its impact on the market share reveals insightful trends.

The analysis shows a clear negative correlation for all scenarios: as the premium price of BEVs increases relative to income, the market share of these vehicles decreases. This inverse relationship is logical, as higher prices typically reduce affordability and thus lower consumer adoption rates.

The trendline in the scatter plot, further highlights this negative trend. These findings suggest that pricing strategies are crucial in influencing the adoption of BEVs. To increase market share, it may be necessary to consider reducing the premium price of BEVs or providing subsidies to make these vehicles more affordable relative to consumer's income.

5.5 NATIONAL STUDY

In the next phase of our analysis, we will use the available data on vehicle market shares for each scenario to perform a detailed mapping of market shares across Spain at the postal code level. This analysis will enable us to compare the adoption rates of BEVs in various regions, allowing for a deeper understanding of how BEV adoption varies between wealthier and less affluent areas.

By mapping the market share data, we can identify trends and patterns in BEV adoption, which will be crucial for formulating targeted strategies to enhance BEV penetration.

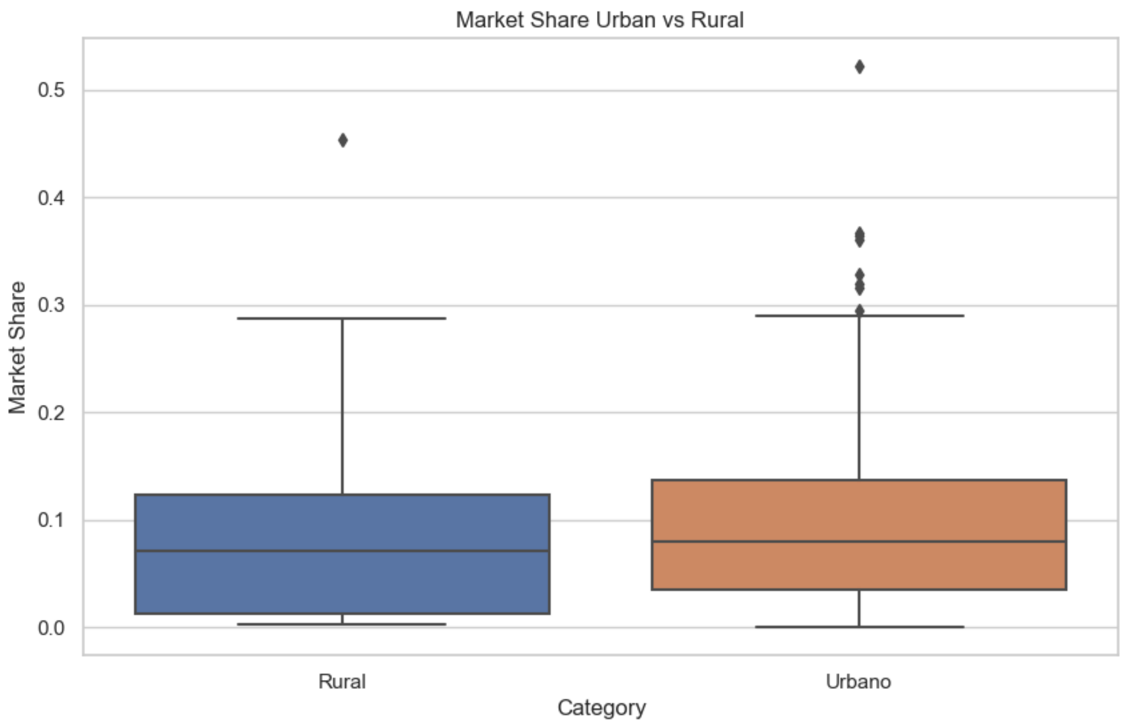

Figure 14: Box plot Urban vs Rural BEV market share.

The box plot compares the market share of products between rural and urban categories. The median market share for urban areas is slightly higher than that for rural areas, indicating that, on average, urban markets might have a larger share. This suggests that electric vehicles in urban areas may perform better in terms of market penetration compared to rural areas.

The interquartile range (IQR) for both categories is relatively similar, indicating that the spread of the middle 50% of data points is almost the same for both rural and urban markets.

This implies that the variability in market share within the central range is consistent across both categories.

Outliers are more prominent in the urban category, indicating the presence of some urban areas with significantly higher market shares compared to the rest of the data. The rural data has fewer outliers, suggesting less extreme variations in market share within rural markets.

Overall, the distributions for both rural and urban categories are fairly similar, but the urban category shows a slightly higher concentration of higher market share values compared to rural areas. This higher concentration and the presence of outliers in urban markets indicate greater potential for market share growth and success in urban areas compared to rural areas.

CHAPTER 6. CONCLUSION AND FUTURE STEPS

6.1 CONCLUSION

The predictive model developed for analyzing customer decisions in the purchase of new vehicles offers valuable insights into the future of BEV, PHEV, and ICE vehicle adoption in Spain. By evaluating three distinct scenarios—Net Zero Emissions (NZE), Steady Progress, and Lagging Behind—the model helps us understand how different factors influence market dynamics and vehicle preferences. Below are the key conclusions drawn from the analysis:

1. **Impact of Policy and Pricing on BEV Adoption:**

- In the NZE scenario, eliminating the premium price for BEVs and implementing strict emissions regulations significantly increase BEV adoption, reducing ICE vehicle market share. This scenario highlights the effectiveness of strong government interventions and incentives in accelerating the transition to electric vehicles.
- The Steady Progress scenario, with moderate reductions in BEV prices and balanced regulatory measures, results in a gradual but steady increase in BEV and PHEV adoption. This indicates that even incremental policy changes and technological advancements can positively impact the market.
- Conversely, the Lagging Behind scenario, characterized by increased BEV costs and lax emissions regulations, shows a decline in BEV adoption and a slight increase in ICE vehicle market share. This underscores the importance of supportive policies and stable supply chains for the growth of the electric vehicle market.

2. **Vehicle Market Share Trends:**

- The baseline scenario shows a dominant market share for ICE vehicles (83.48%), with BEVs and PHEVs holding smaller shares (7.75% and 8.77%, respectively). This reflects current consumer preferences and market conditions in Spain.

- In the NZE scenario, BEV market share increases substantially to 25.46%, with a corresponding decrease in ICE vehicle share to 67.54%. This demonstrates the potential for significant market shifts with aggressive policy and pricing strategies.
- The Steady Progress scenario results in a moderate decline in ICE vehicle share (75.21%) and increased shares for BEVs (16.62%) and PHEVs (8.17%). This balanced approach suggests a gradual transition towards electric vehicles, maintaining a diverse vehicle market.

3. Vehicle Adoption Increment Analysis:

- The NZE scenario shows the highest increase in BEV adoption (228.50%) and a significant decline in ICE vehicle adoption (80.09%). This scenario emphasizes the impact of strong incentives and regulations on accelerating BEV adoption.
- The Steady Progress scenario also shows substantial increases in BEV (114.46%) and PHEV (89.51%) adoption, with a decrease in ICE vehicle adoption (69.50%). This further highlights the benefits of a balanced policy approach.
- In the Lagging Behind scenario, BEV adoption decreases by 48.87%, while ICE vehicle adoption sees a slight increase (5.23%). This scenario underscores the risks of inadequate policy support and supply chain disruptions.

4. Comparison with BloombergNEF EV Outlook:

- Our most favorable scenario (NZE) estimates a 32% market share for zero-emission vehicles, compared to BloombergNEF's more optimistic 70% estimate for passenger vehicles. This discrepancy suggests that our model may not fully capture broader market trends and policy impacts considered by BloombergNEF.
- Despite the differences, both our model and BloombergNEF highlight the positive trajectory towards achieving policy targets for zero-emission vehicles, though further measures are needed to reach the ambitious 100% market share by 2050.

5. Sensitivity Analysis:

- The sensitivity analysis reveals a clear negative correlation between the premium price of BEVs and their market share across all scenarios. Higher BEV prices reduce their affordability and adoption rates, emphasizing the importance of pricing strategies and subsidies.
- The varying R^2 values across scenarios indicate different levels of market sensitivity to BEV pricing, with the Lagging Behind scenario showing the strongest negative impact of high BEV prices on market share.

6. Regional Analysis of BEV Adoption:

- The box plot analysis comparing urban and rural market shares for BEVs shows that urban areas have a slightly higher median market share and more outliers with significantly higher shares. This suggests greater potential for BEV market penetration in urban areas compared to rural areas.
- The similar interquartile ranges for both categories indicate consistent variability in market share, while the wider range of values in rural areas reflects more diverse adoption patterns.

The analysis underscores the critical role of government policies, pricing strategies, and stable supply chains in shaping the future of vehicle adoption in Spain. Aggressive measures to eliminate BEV price premiums and enforce strict emissions regulations can drive substantial growth in the BEV market. Conversely, inadequate support and higher costs can hinder progress and maintain the dominance of ICE vehicles. The sensitivity and regional analyses highlight the importance of targeted strategies to address different market conditions and consumer behaviors, ultimately contributing to a more sustainable and balanced transition to electric vehicles.

6.2 FUTURE STEPS

Enhancing data collection and refining the model are crucial next steps. Expanding data sources to include detailed consumer surveys, real-time market data, and insights from international markets with advanced electric vehicle adoption will improve the robustness and accuracy of the predictive model. Additionally, integrating more sophisticated statistical techniques and machine learning algorithms can help capture the complexities of consumer behavior and market dynamics more effectively.

Incorporating additional variables into the model is essential for a more comprehensive analysis. Variables related to technological advancements in battery technology, charging infrastructure, and vehicle performance should be included. Moreover, integrating broader economic factors such as GDP growth, employment rates, and consumer income levels will provide a better understanding of how macroeconomic conditions affect vehicle purchase decisions.[19][20]

Analyzing the impact of different policy measures is another key area. Conducting more detailed scenario analyses will help evaluate the effects of varying levels of subsidies, tax incentives, and emissions regulations. Extending the model's time horizon to forecast long-term trends and the potential impact of future policies aimed at achieving net zero emissions by 2050 is also necessary.[21]

A more detailed regional and demographic analysis can provide valuable insights. Performing granular regional analysis to identify specific areas with high or low BEV adoption rates can help tailor policies and incentives to local conditions. Additionally, analyzing how different demographic groups (e.g., age, income, education) respond to various incentives and policies can inform targeted marketing and policy initiatives[22].[23]

Understanding consumer behavior through qualitative research is vital. Conducting focus groups and in-depth interviews will provide deeper insights into consumer attitudes, perceptions, and barriers to BEV and PHEV adoption. Applying principles of behavioral economics can further elucidate the psychological factors influencing consumer decisions and help develop strategies to encourage more sustainable choices.

Collaboration and stakeholder engagement will enhance the research's relevance and impact. Partnering with automotive manufacturers, suppliers, and industry associations can provide access to proprietary data and insights, aligning the research with industry trends and innovations. Engaging with government agencies and non-governmental organizations will align the research with public policy goals and leverage their support for data collection and policy implementation.

Technological and infrastructure considerations are crucial for promoting BEV adoption. Assessing the current state and future needs of charging infrastructure,[24] including fast-charging networks [25]and home charging solutions, will help understand their impact on BEV adoption. Exploring the integration of renewable energy sources with electric vehicle charging infrastructure can promote sustainable energy usage and reduce the overall carbon footprint.

Finally, making international comparisons can identify best practices and successful strategies. Benchmarking Spain's market and policies against those of leading countries in electric vehicle adoption, such as Norway, the Netherlands, and China, can provide valuable insights. Analyzing global market trends and emerging technologies will help anticipate future developments and their potential impact on the Spanish automotive market. It would be highly beneficial to collaborate with a fellow partner from my university in future studies, allowing us to build upon our collective work and further advance our research, such as "*Análisis de las decisiones de particulares en la compra de vehículos eléctricos*" by Jorge Fernández. [26]

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ANEXO I

All the code and Excel sheets utilized in my thesis are available for reference on the following GitHub link. This repository includes detailed analyses, models, and data used to investigate customer decisions in vehicle purchases, focusing on the adoption of BEVs, PHEVs, and ICE vehicles in Spain under various scenarios. Accessing this repository provides transparency and facilitates further exploration of the methodologies and findings presented in the thesis.

https://github.com/mperezbravo/EVRegistrations.git