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Special Issue

Flexibility Integration and Decarbonisation Pathways

Edited by

Dr. Marios Charilaos Sousounis and Dr. Panagiotis Fragkos



<https://doi.org/10.3390/en16166083>

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Electromobility Prospects in Greece by 2030: A Regional Perspective on Strategic Policy Analysis

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Abstract: Electromobility represents a strong option for reducing carbon emissions in the road transport sector. This study presents a methodology and a simulation tool that project the evolution of the market share of electric vehicles (EVs) in the new car market. The analysis adopts a stylized regional resolution, which accounts for attributes on the NUTS-2 level, such as the population density, GDP/capita, education levels, and current EV charger distribution, to simulate the uptake of BEVs in different regions. The methodology applies discrete choice modelling techniques, considering tangible and intangible factors, including purchasing and operation costs, an estimated cost for range anxiety and public charging, and a market maturity index. The analysis is based on four different scenarios, referring to the updated Greek National Energy Climate Plan. The results reveal that regions with a higher average income, GDP/capita, and population density show a higher uptake of EVs. Overall, the tool implements a method of simulating the market evolution of EVs up to 2030 in reference to regional parameters and, hence, highlights the regions that require the most attention in order to achieve national targets. The results can inform policymakers in developing tailored strategies and financial support to accelerate the adoption of BEVs, particularly in regions where their uptake prospects are lower.

Keywords: e-mobility adoption; consumer preferences; sustainable transportation; regional analysis; discrete choice model



Citation: Shaban, F.; Siskos, P.; Tjortjis, C. Electromobility Prospects in Greece by 2030: A Regional Perspective on Strategic Policy Analysis. *Energies* **2023**, *16*, 6083. <https://doi.org/10.3390/en16166083>

Academic Editors: Panagiotis Fragkos and Marios Charilaos
Sousounis

Received: 30 June 2023

Revised: 2 August 2023

Accepted: 9 August 2023

Published: 21 August 2023



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1. Introduction

The electrification of the transport sector is a key option for reducing carbon emissions, with the aim of mitigating climate change. In the European Union (EU), transportation accounts for approximately 22.5% of all greenhouse gas (GHG) emissions, making it a sector in which it is critical that we achieve progress [1]. As a result, electric vehicles (EVs) have gained traction as a cleaner and more sustainable alternative to traditional combustion engines. In Greece, the National Energy and Climate Plan (NECP) sets out to achieve the EU's Fit For 55 legislation, and aims to reduce carbon emissions by 55% of the 2005 levels by 2030, and achieve carbon neutrality by 2050. In this context, the electrification of transport is an essential step in contributing towards this goal [2].

According to the European Automobile Manufacturers' Association, the Greek market saw a 30% increase in battery electric vehicle (BEV) unit registrations in 2022, and a 15% increase in plug-in hybrid electric vehicle (PHEV) unit registrations. The market share of BEVs and PHEVs, however, falls very low, at 2.7% and 5.2% of total new vehicle registrations in 2022, respectively. While there is an upwards trend in electric vehicle registrations, EVs still only occupy a very small percentage of the vehicle market. Globally, the market share of EVs is highly geographically unbalanced, with Greece falling at the low-end, with its 7.9% EV market share [3]. However, the continuously increasing trend in EV sales is largely driven by two factors: the growth in the supply of EVs, and the growth in the demand. EVs are becoming more competitive every year, due to both the

improvements in EV technology, making them more desirable than internal combustion engines (ICE), and due to national and international policy and legislation promoting EVs, and setting transport decarbonization targets.

The uptake of electric vehicles, globally, can be defined within the technology adoption lifecycle parameters, which define the market uptake of new technologies introduced as a replacement for current technologies in developed markets [4]. The technology adoption lifecycle can also be defined by the consumers of the new technology, which can be classified into the following basic categories: innovators, early adopters, early majority, late majority, and laggards. These are specifically applicable to Greece, where regional characteristics could be highly influential in the further uptake of EVs.

In this context, the aim of this paper is to apply a simulation market analysis tool that estimates the EV uptake in Greece, by 2030, at a regional level. Our work contributes to the ongoing discussion of sustainable transportation, by incorporating key socio-economic factors that drive the growth of electromobility from a user-choice perspective. It provides a method of testing the market impact of policymaker actions in the electromobility market. The underlying analysis is framed within the context of the Greek NECP, which sets specific national targets for the EV uptake by 2030 [5]. By using a data-driven approach to understand the future of EVs in the EU, the results of this paper aim to inform policy decisions in the transition to sustainable transportation. Furthermore, the simulation results can guide the development of charging infrastructure in both the public and private sector. Methodologically, the simulation analysis is based on discrete choice modelling. We explain the reasons in choosing this established method in the Materials and Methods section. The originality of this work relates to its applicability in delivering a regional analysis of policy implications for the EV uptake in Greece by 2030, using a scenario analysis. The heterogeneity in consumer habits and preferences has a strong impact on EV uptake and, hence, it is a necessary factor to account for [6]. The regional granularity of the results enables the analysis and assessment of policy action at a regional level, rather than on a generalized national level and, hence, allows for the reassessment of policies to better account for the differences between regions. Several previous studies have simulated the market uptake of alternative fuel vehicles; however, demographic regional features are often not accounted for [7]. One study calculated the Beijing market penetration rate using a nested multinomial logit model for the choice between vehicle segments and technologies. The model attributes, however, only vary between the vehicle choices, and does not account for the utility function variation among the resident population of Beijing of 21 million people, which is nearly double the population of Greece [8]. Another study based in Iran acknowledges the variation in consumer choice based on different demographic features, yet only includes income segmentation in the utilized model [9]. Other studies focus on the demographic heterogeneity of EV adopters, such as a California-based study which used survey data from EV users to estimate the parameters of a Bass diffusion forecasting model based on socio-demographic data, further highlighting the importance of accounting for consumer sociodemographics when designing policy [10]. Several studies using stated preference surveys have revealed the significant impact of the demographic and socioeconomic attributes of the decision-maker, yet do not utilize these factors in the choice modelling [11]. This study builds on the studies analyzing and identifying the factors influencing the market uptake of EVs, by simulating the impact on each individual region [12–14]. Other studies have focused on characterizing the Greece EV market; however, those studies were applied on a national level [15–18]. While existing simulation tools have been used to analyze the national EV market uptake in the EU and worldwide, there is a lack of studies and tools generating results at a more granular regional level [7,19–21]. With the rapid developments in the EV market, this increased granularity is required by national and regional governments, for policy analysis and assessment. Additionally, the results obtained using the simulation tool can provide valuable support for the integration of electric vehicles (EVs) into urban mobility, by offering insights into the potential impacts and feasibility, and optimization strategies [22]. EV market growth

is highly dependent on the development of charging infrastructure, and several previous studies aimed to quantify the future EV market in order to ensure the sufficient availability of chargers [23–25].

The paper is organized as follows: Section 2 discusses the formulation of the simulation tool, and the parameters inputted, Section 3 presents the results of the analysed scenarios and identifies features of the regions adopting BEVs, and Section 4 discusses the scenario design, and the results and their significance, finally followed by the conclusions in Section 5.

2. Materials and Methods

2.1. Parameters and Scope

The simulation is based on a discrete choice model that accounts for the demographic features of different users, and is used to estimate the probability of a consumer making a specific choice when presented with other alternative options that can be discretely and independently defined [26]. The decision-making process of the consumer is based on a utility function which allows for a uniform comparison between the available options [27]. The utility function would ideally capture the consumer-specific attributes of the user, in combination with the attributes of the alternatives.

In the estimation of the market uptake of electric vehicles (EVs), the discrete choice model provides distinct advantages over alternatives, such as regression-based models or agent-based models, in that it does not assume a linear relationship between variables and, alternatively, captures the dynamic nature of consumer choice and decision-making between alternatives through simulating individual choices among the various alternatives. Discrete choice models integrate a wide range of influencing factors into the consumer's decision-making process, such as consumer attributes, vehicle attributes, and the market and environment readiness [28]. The inclusion of these attributes in a market uptake simulation allows for the analysis and understanding of the relative importance of these different attributes. Additionally, discrete choice modelling accounts for the heterogeneity of the consumers and, hence, is ideal for a regional simulation, and allows for more an accurate and tailored market simulation for each relevant consumer [29]. This allows for a clearer analysis of the consumer drivers, and provides deeper insights into the characterization of consumers based on their level of technological acceptance. On the other hand, the accuracy of discrete choice modelling is dependent on the accurate choice of the model parameters and the utility functions for each consumer and alternative and, hence, extensive research must accompany the model. The data source for the discrete choice model was chosen as statistical rather than stated preference, due to the inconsistency between the stated preference and observed data, as well as the challenges in generating a representative survey that accurately reflects real-world choices and preferences [30]. The use of discrete choice models to simulate the EV market uptake has been repeatedly demonstrated in previous studies [31–33].

In this paper, the developed tool incorporates two key features: a granular geographic scope at the NUTS2 level that accounts for socio-economic variation, and a temporal resolution of 1-year steps. The geographic granularity allows for a more comprehensive analysis of the e-mobility uptake variation among regions. In a discrete choice model, two important disaggregations must be defined: the decision-maker, and the alternatives. Regarding the alternatives, the model is applied at a vehicle segment level. This is based on the assumption that the consumer choice is between alternatives in the same segment and, hence, the market share must be calculated for each vehicle segment. Within each segment, the consumer is presented with four alternatives for vehicle choice: petrol, diesel, battery electric vehicles (BEVs), and plug-in hybrid electric vehicles (PHEVs). The decision-makers are the individuals making the choice between the different alternatives, based on their individual preference. For this application, the decision-maker attributes are defined by the average representative values from each region, as a measure of the typical average decision-maker in each region. In summary, the discrete choice model is applied independently for

each vehicle segment within each region, and the choice of the decision-makers is simulated among the fuel options, as can be seen in Table 1.

Table 1. Decision-makers and vehicle alternatives.

Decision Maker	Vehicle Segment	Vehicle Alternatives
Representative at NUTS-2 region	Small, medium, large-SUV	Petrol Diesel BEV PHEV

2.2. Tool Formulation

The form of the discrete choice model can be seen in Equation (1), and it is based on a Weibull functional form, as established in previous modelling approaches on new vehicle choice [7,34]. In discrete choice models, the choice between alternatives is based on the different utility of each option to the user [26]. As per the utility maximization framework, the user is assumed to make a rational choice through the maximization of utility [35]. We assume a Weibull distribution for the probability distribution of users' choice of an alternative, while noting that it can be transformed into a standard logit distribution through taking the logarithms of cost [36].

The results using this formulation have been repeatedly used in policy frameworks in the European Union, such as the EU Reference Scenario 2020, and the Greek National Energy and Climate Plan (NECP) [5,37]. The discrete choice model is applied at the vehicle segment level and, hence, the results are disaggregated by segment within each region. This functional form encompasses a cost index, the degree of substitution, and the market maturity index (MMI) in the utility function and, hence, accounts for hidden costs that cannot be expressed in monetary terms. The degree of substitution is a quantitative measure of how the choices in the discrete choice model are alternatives to each other. It signifies the ease of switching between one choice and another in response to a change in the cost. As cost is a negative determinant of consumer utility, the degree of substitution has a negative sign, to indicate that an increase in the cost of an alternative option leads to a reduction in its competitive advantage and, in turn, its market share, compared to other alternatives [34]. A recent study analyzing consumer behavior in choosing between vehicles demonstrated the relationship between the degree of substitution and income, with higher-income consumers observed as having a higher degree of substitution and, hence, the degree of substitution varied across regions, between -4 and -7 [38,39]. This indicates how higher-income individuals can more easily switch between the alternative choices, and the cost index has a smaller impact on their choices.

The MMI is a measure of the non-cost elements impacting consumer choice, such as their trust in technology, social influence, environmental awareness, etc. The regional variations are captured based on demographic statistics, using a quartile-based range-scaling approach. This process involves choosing the range of the parameters anticipated between the different regions and the demographic attribute that would drive the variation. The regions are then distributed into quartiles, based on the demographic attribute, and scaled, based on the identified range. This methodology allows for the consideration of the variation between regions based on the demographic attributes and parameter ranges analyzed in the existing literature. The cost inputs are set according to the most up-to-date studies and research, to provide an accurate simulation of future parameters. This enables the tool to be used in, and applied to, populations with no available survey capability or data.

$$MS_{u,v} = \frac{w_{u,v} \cdot C_{u,v}^{y_u}}{\sum_{u,v} w_{u,v} \cdot C_{u,v}^{y_u}} \quad (1)$$

u : user

v : vehicle

MS : market share (%)
 C : annual cost index (EUR/km)
 w : Market Maturity Index
 y : degree of substitution

2.3. Cost Index

The cost index is a unified and consistent measure of cost between different vehicle options for different users. In this tool, it is measured on a per-kilometer basis. This cost index does not only include the running costs for each vehicle choice, but also the initial costs, using an annuity rate based on the individual discount rate and economic lifetime. The equation used for the cost index can be seen in Equation (2), where it is represented in EUR/km terms. The rational consumer choice based on the cost index is combined with the MMI, due to the complexity of consumer behavior and the limited availability of data on consumer plans on purchasing electric vehicles.

$$C_{u,v} = \frac{IC_{u,v} + OC_{u,v}}{M_u} \quad (2)$$

IC : annual initial cost (EUR)
 OC : annual operation cost (EUR)
 M : annual mileage (km)

The initial costs are included in the calculation using an annuity rate, as can be seen in Equation (3), and include the vehicle-purchasing cost, and the respective home infrastructure accessory, such as a home charging unit, including taxes and subsidies.

$$IC_{u,v} = PC_v \cdot \partial_u \cdot \frac{(1 + \partial_u)^{n_u}}{(1 + \partial_u)^{n_u} - 1} \quad (3)$$

PC : purchasing cost (EUR)
 ∂ : discount rate
 n : economic lifetime (years)

The cost index is on a per km basis. To ensure that all the inputs are measured against the same base, the average yearly mileage is considered in the calculation. It is used specifically when calculating the fuel cost for a single year, with a higher mileage equating to higher fuel-operating costs. A study completed in Japan, analyzing passenger vehicle certifications across different regions, has found a strong inverse correlation between the average annual mileage and population density, varying around 10,000 km/year [40]. Several other studies have demonstrated the same relationship between vehicle miles traveled and population density in other global regions [41–43]. The mileage data from the European Commission New Mobility Patterns study present the national mileage data for passenger vehicles in Greece as varying by approximately $\pm 20\%$ over the years and across vehicle types [44]. A range of 9000 km–12,000 km is, hence, taken as the mileage across different population densities in the regions analyzed in the simulation, as per the base case national mileage of 10,000 km, and the variation in population densities [45]. Regarding the discount rate, it has been shown to vary widely for energy-efficient transport, and to be inversely correlated with household income, and varies between 8% and 20% across the regions [46,47].

The direct operation costs included in the calculation are the fuel costs, road tax, maintenance costs, insurance, and depreciation. In addition to the direct operation costs, two elements of indirect costs are included in the calculation: the cost of time using public recharging, and the cost of range anxiety. The public charging cost is based on the emergency public recharging stops in the middle of a trip, and the average hourly wage and, hence, it excludes curbside recharging near one's residence, workplace charging, or charging at a destination. The number of public charging stops is calculated based on a

methodology developed by the National Argonne Laboratory, as can be seen in Equation (4), and is assumed to reduce by 30% by 2030, with infrastructure developments, and developments in EV range [48]. For the baseline, the average BEV range is taken as 400 km, and the average of 10,000 km/year is taken for the yearly mileage, and it is assumed that 88% of EV trips can be completed with a single home charge, which would equate to 84% home charging and 16% public charging, or an average of nine public charging stops [49]. The number of stops varies between regions, based on the feasibility of home charging, which has been shown to correlate with homeownership rates [13]. A 30% variation from the baseline is assumed, based on the variation in homeownership rates, which results in the number of stops varying between 7 and 12 stops per year across the regions [50].

$$\text{Number of Public Charging Sessions} = \frac{\text{Mileage of Public Charging}}{\text{EV range}} \quad (4)$$

Number of Public Charging Sessions: the number of stops for public charging (stops/year)

Mileage of Public Charging: the yearly vehicle mileage using public charging (km/year)

EV range: the range of vehicles on a single charge (km)

The range anxiety cost is another hidden cost of BEVs. This cost can be calculated using a range-limitation cost approach that approximates the cost as the number of days requiring an alternative vehicle due to out-of-range trips, multiplied by the cost of the alternative vehicle [51]. The out-of-range trips are affected by two factors: vehicle ranges and infrastructure availability. For the purpose of this calculation, we simplify by assuming that the alternative option to the battery-depleted EV would be to rent a car. This calculation assumes the most expensive alternative, and does not account for the availability of another vehicle in the household, or the use of public transportation. As ranges and infrastructure develop, the number of out-of-range trips is reduced from 12 trips a year (one trip/month) in 2023 by 33%, to 8 trips per year by 2030 [52]. To account for the variation between regions in the charger infrastructure, the charger density of chargers/area was calculated for each region, and the number of steps was scaled from 12 trips at regions with a high charger density to 20 trips for the regions with the lowest charger density. Using data from the New Mobility Patterns study, in this particular calculation, proved challenging, as travelling habits in Greece focus on short-distance urban mobility, rather than long-distance inter-city trips and, hence, conservative approximations were used to simulate the consumer thought process when it came to range anxiety.

2.4. Market Maturity Index

The market maturity index is an essential component of the utility function that is included to account for the non-cost influencing factors on the consumer's decision-making process. In the application of this simulation tool, it represents two kinds of factors: factors specific to the vehicle alternatives, and factors specific to the consumer. The vehicle factors include the availability of convenient charging infrastructure, range anxiety, and the reliability of the vehicle [53]. The consumer-specific factors are a representation of the likeliness of an individual becoming an early adopter of EVs, and this is based on several factors, including knowledge of alternative vehicle options, consumer environmental responsibility, consumer knowledge of maintenance and technology, attitude, and willingness to take a risk [15].

Two main attributes have been chosen to control the market maturity index of different vehicles: range anxiety/available infrastructure, and consumer attitude independently of cost. The market maturity index values are tuned to the 2022 market statistics for all vehicle fuel types. While diesel and petrol vehicles' maturity is assumed to remain constant over the coming years, EVs exhibit very low market maturity as of 2022, which is expected to grow very rapidly over the coming years, as exhibited in other leading markets. The estimation of the future market maturity indices of BEVs and PHEVs has been conducted based on a logistic growth model, which starts from the current market maturity values

from the available data, consistent with technology adoption trends [54]. The formulation and parameters of a logistic growth function can be seen in Equation (5):

$$\omega_t = \frac{1}{1 + \frac{\omega_t - \omega_0}{\omega_0} \cdot e^{-tam_u \cdot g_u \cdot (t - t_0)}} \quad (5)$$

t : year

ω_t : market maturity index at year t

g_u : user-specific growth rate

tam_u : technology acceptance model score

A technology acceptance model (TAM)-based scoring methodology was used to scale the growth rate of the EV market maturity index [55]. The TAM is based on highlighting how the perceived usefulness (PU) and perceived ease of use (PEU) are at the core of technology acceptance by an individual [56]. The PEU is used as a parallel to the available infrastructure, and the PU is used as a parallel to the consumer attitude. Regarding the PEU, the charging infrastructure availability and ease of use of EVs varies depending on the region. We use the charger area density in charger/km as a measure of the PEU. On the other hand, it is more difficult to quantify and score the PU and consumer attitudes. Attributes of early adopters of EVs have been analyzed in several studies that have shown that regions with a higher GDP/capita and higher education levels have a more positive attitude towards EVs, due to their knowledge of the technology, and environmental awareness and responsibility [14,57]. We use the ratio of adults with a tertiary education and GDP/capita as a measure of the PU [58–61]. The TAM score is calculated based on the ranking of the following three factors between the regions: the charger density, based on Open Charge Map API [62], education levels, and GDP/capita, based on Eurostat data [63,64]. The scores for each region can be seen in Table 2.

Table 2. Key regional parameters.

Region	Discount Rate	Number of Public Charging Stops	Number of Out-of-Range Trips	Degree of Substitution	TAM Score
Attica	8%	12	12	−7.00	1.00
North Aegean	20%	7	21	−4.00	0.13
South Aegean	12%	12	15	−7.00	0.63
Crete	16%	11	15	−5.00	0.63
Eastern Macedonia and Thrace	20%	9	21	−4.00	0.00
Central Macedonia	12%	11	12	−5.00	0.75
Western Macedonia	8%	7	18	−6.00	0.50
Epirus	12%	11	18	−4.00	0.38
Thessaly	16%	11	18	−5.00	0.63
Ionian Islands	8%	7	12	−6.00	0.63
Western Greece	20%	12	18	−5.00	0.25
Central Greece	16%	9	21	−7.00	0.25
Peloponnese	16%	9	15	−6.00	0.38

It is also necessary to accurately approximate the base growth rate of the logistic growth model. Linear forecasting can be used to estimate the trend of the market maturity index. While logistic growth better accounts for slow early growth and rapid later growth, estimating the growth rate may prove challenging. We used linear forecasting to tune the growth parameter of the logistic growth model. Finally, the growth rate of the logistic growth model was tuned against the linear forecasting results, and the base logistic growth parameter was identified. This scoring methodology has been observed to show results consistent with the available data.

A summary of the key regional parameters can be seen in Table 2.

3. Results

3.1. Scenario Design

To further analyze the key factors influencing the EV uptake across regions, four different scenarios, summarized in Table 3, are designed. The scenarios are built around the Greek National E-mobility Plan (NEP) and the National Energy and Climate Plan (NECP) goals. The existing BEV measures and incentives in Greece, as of 2023, are a 30% subsidy on BEVs up to EUR 8000, a reduced VAT rate of 13% instead of 24%, and a yearly road tax exemption [65]. The Greek National Energy and Climate Plan sets the goal of a 20% BEV market share from new registrations, and a 30% EV market share including PHEVs. The NEP reference scenario anticipates the removal of subsidies by the end of 2023, and maintains tax reductions until 2030 for the reference scenario, which, consistently with the baseline scenario, achieves a 24% market share.

Table 3. Scenario parameters.

Scenario	Baseline	Gradual Subsidy Removal	Optimistic Scenario	ICE Disincentives
Subsidies	2022 subsidies removal at end of 2023	Yearly 5% subsidy reduction until 2030	Yearly 5% subsidy reduction until 2030	2022 subsidies removal at end of 2023
Additional ICE Purchase Tax	0%	0%	0%	10%
Market maturity	Baseline	Baseline	Market maturity acceleration by 25%	Baseline

The gradual subsidy removal scenario presents an alternative to the abrupt removal of the subsidies in the baseline scenario; in the former, the subsidies are reduced by 5% yearly, to be completely removed by 2030. This scenario continuously matches the price reduction of BEVs relative to ICE vehicles and, hence, reduces the purchase price barrier of EVs.

Two alternative scenarios are designed to achieve the national target: the optimistic scenario and the ICE disincentives scenario. Firstly, in the optimistic scenario, the gradual subsidy removal is accompanied by a 25% MMI growth acceleration, which demonstrates the impact of an accelerated MMI, when combined with fiscal incentives. The main factors affecting the MMI, based on the TAM, including the charging infrastructure and consumer attitude, are relevant to government policy design and action. Finally, the ICE disincentives scenario demonstrates how an additional purchase tax on ICE vehicles would increase the relative competitiveness of EVs. This scenario involves the addition of a purchase tax on ICE vehicles, to disincentivize the purchasing of ICE vehicles, and increase the relative competitiveness of EVs.

3.2. Scenario Analysis

The national results of each scenario can provide significant guidance on recommended measures that can help with achieving the national targets. The gradual subsidy removal scenario achieves a 26% market share of EVs, which is still below the 30% national target. The results of this scenario show the necessity of simultaneously increasing the MMI, to achieve the NECP goals. The optimistic scenario develops on the gradual subsidy removal scenario, and successfully achieves a 30% market share for EVs, through accelerating the MMI growth rate by 25%. The ICE disincentives scenario similarly achieves the national target of a 30% EV market share, through a 10% purchase tax on ICEs, which shows how disincentivizing ICEs would have a significant impact on the EV market share.

Overall, the scenarios demonstrate different types of measures that can be undertaken by policymakers in an effort to increase the market uptake of BEVs. The results of the aggregated national market share of EVs, including both BEVs and PHEVs, can be seen in Figure 1.

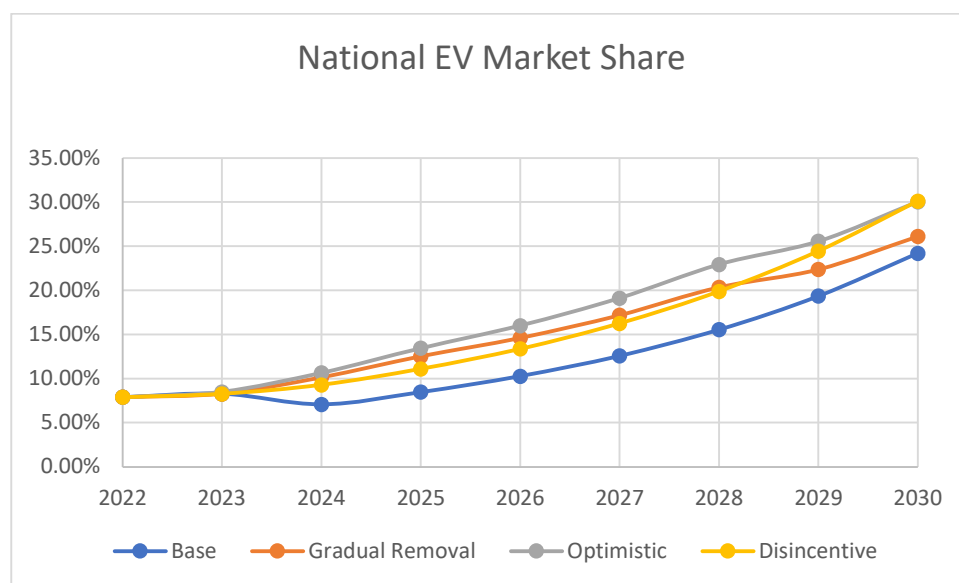


Figure 1. BEV market share of new registrations for different scenarios.

3.3. Results

The optimistic scenario is used as the main scenario for the regional analysis. First of all, the cost index varies across regions based on the variations discussed in Section 2.3, and the results can be seen in Table 4. The largest variation in the cost index can be attributed to the discount rate and the mileage variations.

Table 4. Cost index of vehicles in EUR/km in 2030.

Region	Small	Medium	Large—SUV
Attica	0.56	0.87	1.33
North Aegean	0.67	1.05	1.61
South Aegean	0.56	0.87	1.33
Crete	0.61	0.95	1.46
Eastern Macedonia and Thrace	0.62	0.96	1.47
Central Macedonia	0.60	0.95	1.46
Western Macedonia	0.44	0.67	1.03
Epirus	0.48	0.74	1.13
Thessaly	0.56	0.88	1.34
Ionian Islands	0.55	0.86	1.32
Western Greece	0.61	0.96	1.47
Central Greece	0.53	0.82	1.24
Peloponnese	0.55	0.87	1.33

The BEV market share in each region varies, based on their respective utility functions for the vehicle alternatives to range between 4% and 13% in 2027, and between 8% and 27% in 2030 for the baseline scenario; and to range between 7% and 20% in 2027, and between 10% and 30% in 2030 for the optimistic scenario, as can be seen in Figure 2. These results indicate how not all regions are individually achieving national targets, despite the aggregate results for the optimistic scenario. On the other hand, the results indicate that the baseline scenario fails to achieve the optimistic NECP goals across all regions. However, some regions are leading the market uptake, and are very close to achieving the NECP goals without any additional policy action, such as Attica and Central Macedonia, and some regions are severely lagging, such as Eastern Macedonia and Thrace and the North Aegean, and require targeted and customized policy action. Some demographic data for each region can be seen in Appendix A.

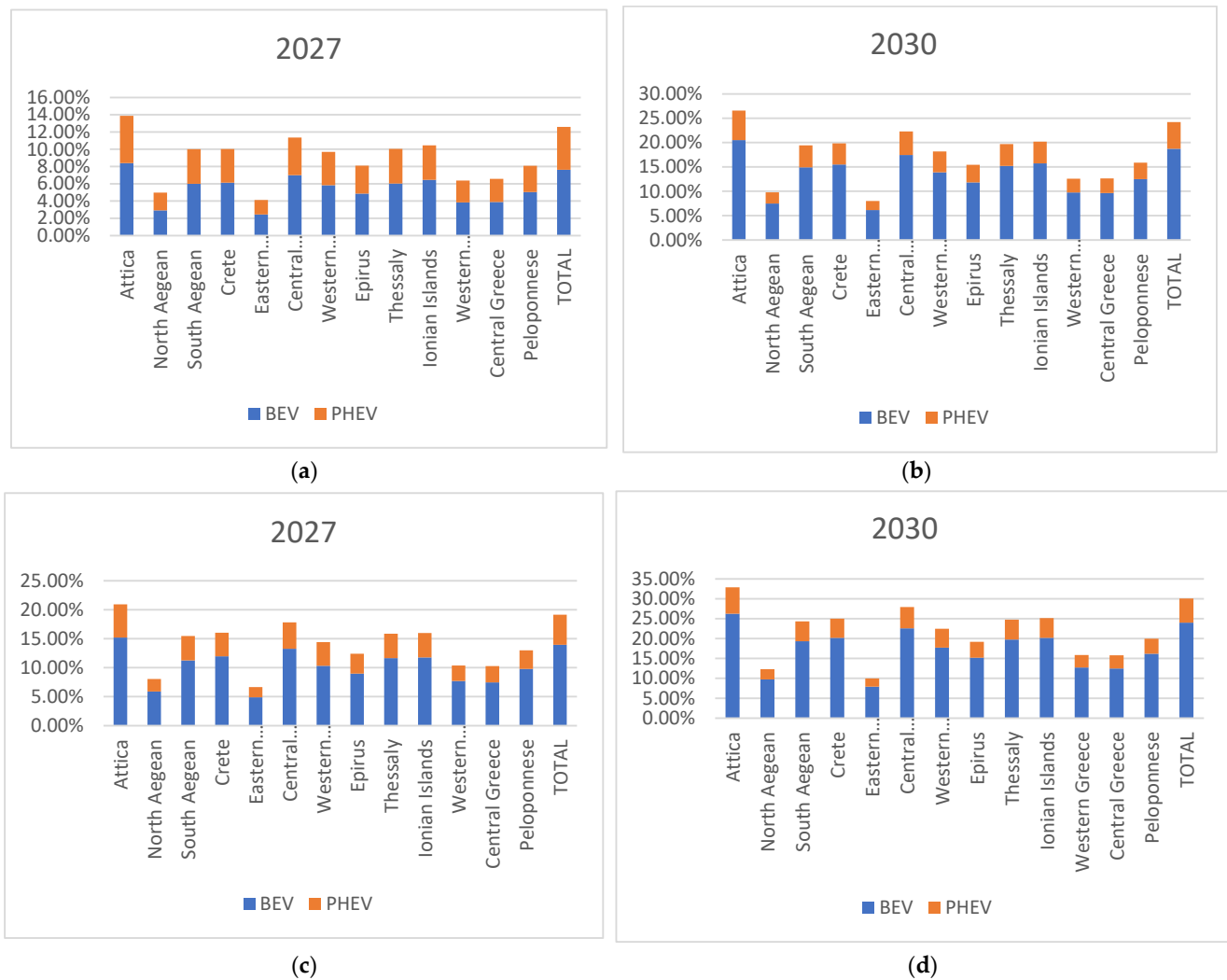


Figure 2. New BEV registration market share: (a) baseline scenario 2027 results; (b) baseline scenario 2030 results; (c) optimistic scenario 2027 results; and (d) optimistic scenario 2030 results.

The number of EVs in circulation in the fleet, as well as the ratio of EVs in the total fleet, are calculated for each region based on an average scrappage age of 15 years, and can be seen in Table 5 for the optimistic scenario. The results show how there is a large variation in the stock ratio of EVs in each region. This is due to how the purchasing of new vehicles is heavily concentrated in the most population-dense regions, and there is a lower rate of replacement of old ICE vehicles with new EVs. Additionally, Greece has one of the highest average vehicle ages in Europe, and this is clearly reflected in the low stock ratio, and the overall rate of vehicle replacement [66].

The three main factors of the utility function are the cost index, market maturity index, and degree of substitution. Their relative impact on the market share result was studied using a correlation analysis based on the Pearson correlation coefficients. The results, as can be seen in Table 6, show the strongest correlation (>0.7) with the market maturity, which is followed by a moderate negative correlation (>0.4) with the cost index, and a weak negative correlation with the degree of substitution, indicating that the market share of EVs is most strongly impacted by the market maturity, followed by the cost index, and is weakly impacted by the degree of substitution. This result has a strong implication on policy strategy, as it demonstrates how the market maturity has a strong influence on BEV uptake, as there is a stronger correlation between high-maturity regions and a high market share. Fiscal tools incentives, independently, are not sufficient in increasing the

electromobility uptake, and it is necessary to simultaneously improve the market maturity of BEVs, and not only the cost index and the degree of substitution.

Table 5. Stock of EVs and stock ratio in the total fleet in 2030 in the optimistic scenario.

Region	EVs in Circulation (Units)	EV Stock Ratio of the Total Fleet (%)
Attica	196,504	6.6%
North Aegean	803	1.4%
South Aegean	2459	2.1%
Crete	10,376	3.7%
Eastern Macedonia and Thrace	2014	0.9%
Central Macedonia	15,625	2.0%
Western Macedonia	3868	3.9%
Epirus	3466	2.9%
Thessaly	4818	1.9%
Ionian Islands	1299	1.5%
Western Greece	2805	1.5%
Central Greece	1793	1.4%
Peloponnese	2210	2.1%

Table 6. Correlation analysis results for the market share of BEVs and the inputs to the utility function.

Independent Variable	Correlation Coefficient
Cost index	−0.56
Market maturity	0.88
Degree of substitution	−0.22

A correlation analysis was completed with the normalized market share results from 2022–2030 and the different demographic data of each region, in order to identify the factors contributing to the variation, and their relative impacts; the results can be seen in Table 7. The results indicate a strong positive correlation (>0.7) for average income, and a moderate positive correlation (>0.4) for tertiary education, GDP/capita, population density, and current charger density. While there is a positive correlation between household ownership and BEV adoption due to the feasibility of home charging, a weak negative correlation (<0.4) is observed for household ownership.

Table 7. Correlation analysis results with normalized BEV market share across regions.

Independent Variable	Correlation Coefficient
Tertiary education of ages 25–64	0.52
GDP/capita	0.62
Population density	0.56
Charger density	0.66
Household ownership	−0.38
Average income	0.77

This unexpected behavior can be attributed to the negative cross-correlation of household ownership with the other more impactful variables in EV adoption, such as education, GDP/capita, and average income, as can be seen in the correlation matrix in Table 8. A large concentration of individuals in urban areas of Greece exhibit low household ownership. In our results, other factors, such as average income, GDP/capita, charger availability, or education seem to have a stronger impact on the results, and act as counter drivers to the market uptake of EVs. Additionally, a low regional level of household ownership is a characteristic of larger urban cities, which exhibit a higher level of technology acceptance and adoption.

Table 8. Correlation matrix for socio-economic data.

	Education	GDP/Capita	Population Density	Charger Density	Household Ownership	Average Income
Education	1.00					
GDP/capita	0.47	1.00				
Population density	0.79	0.80	1.00			
Charger density	0.76	0.83	0.99	1.00		
Household ownership	−0.61	−0.50	−0.58	−0.61	1.00	
Average income	0.33	0.67	0.65	0.71	−0.21	1.00

Additionally, the correlation matrix reveals a strong correlation with the other factors, which can be attributed to the high likeliness of a more developed charging infrastructure to be located in regions with high BEV adoption rates. The correlation analysis reveals that the regions with the highest BEV uptake relative to the other regions can most distinctly be identified by a high average income, followed by a high GDP/capita, population density, and education. In parallel, those regions also exhibit a higher charger density. Those factors strongly define cities and urban centers, in contrast to rural areas and lower-density towns.

3.4. Fuel Price Sensitivity Analysis

The fuel price of vehicles, whether electricity, petrol, or diesel, has a strong impact on consumer choice. The fuel own-price elasticity is calculated for both petrol/diesel and electricity for each region, in reference to the BEV market share. The results, in Table 9, show the expected negative results for electricity, and positive results for ICE fuels, which indicates that the lower electricity prices and higher ICE fuel prices increase the BEV market share. The variations between the regions provide guidance as to which regions would be most strongly impacted by a change in fuel prices. Additionally, the results show how changing the price of ICE fuels has a stronger impact on the market share than electricity prices, due to how the electricity prices make a significantly lower contribution to the cost index in EVs. Additionally, this further highlights the importance of increasing the relative competitiveness of EVs to ICE vehicles, through disincentivizing ICE vehicles, and increasing their cost index.

Table 9. Own-price elasticity of fuel of vehicles on the BEV market share in each region.

Region	Electricity	Petrol/Diesel
Attica	−4.00%	9.99%
North Aegean	−2.19%	5.72%
South Aegean	−3.19%	8.02%
Crete	−3.07%	7.63%
Eastern Macedonia and Thrace	−1.35%	3.44%
Central Macedonia	−3.34%	8.30%
Western Macedonia	−3.73%	9.38%
Epirus	−3.03%	7.63%
Thessaly	−3.23%	8.08%
Ionian Islands	−3.37%	8.39%
Western Greece	−2.08%	5.24%
Central Greece	−2.35%	5.96%
Peloponnese	−2.82%	6.96%

4. Discussion

The market analysis simulation tool presented in this paper contributes to electromobility uptake in Greece, by providing granular regional results, rather than generalized national results, consistent with the National Energy and Climate Plan [7]. The results of this tool have several policy implications. The scenario analysis demonstrates the effectiveness of disincentivizing ICE vehicles in increasing the BEV market uptake, as an alternative to budget-heavy subsidization. On the other hand, the scenarios show how subsidies on their own are insufficient for achieving NECP e-mobility goals in Greece, and the significance of the MMI on the EV market uptake. The fuel price elasticity analysis demonstrates the low impact of electricity price changes relative to ICE fuel price changes, due to how BEVs are currently very cost-competitive in regard to fuel costs.

The impact of the Market Maturity Index is additionally demonstrated in the scenario analysis, and further shown in the utility function correlation analysis, to show the significance of the non-financial factors in the consumer decision-making process regarding BEVs. Policymakers must, hence, prioritize increasing the market maturity index. This can be done through two routes: firstly, improving the consumer attitude towards BEVs through educational campaigns and, secondly, increasing the ease of use of BEVs through the acceleration of the development of charging infrastructure. Furthermore, the variation in the relative impact of the cost index and MMI between different regions further highlights the importance of region-specific policy and strategy in order to address the barriers and limitations most efficiently. Surveys completed on a regional level can capture the demographic variations, and help to better identify the appropriate approach to increasing the market acceptance of BEVs. It is essential to effectively inform and educate decision-makers on the current technologies of BEVs, and to highlight their benefits, in order to build their trust in the technology and its future prospects and, hence, increase the perceived benefit. Moreover, the continuous developments in charging infrastructure will increase the exposure of consumers to BEVs, and will further highlight the perceived ease of use, which is essential to technology acceptance, as per the technology acceptance model.

The regional variation in the market share is shown to favor higher-income regions with a higher population density and education levels. There is no one-size-fits-all strategy that will be suitable for all regions and, hence, strategy must be designed with regional differences in mind. Moreover, despite the predominant influence of the market maturity, the cost index retains a significant relevance in shaping the market. Therefore, fiscal instruments can be employed at a regional level, to compensate for the lower market maturity in lagging regions. Additionally, this is a valuable tool for testing the impact of different strategies on the electromobility market, and it provides regional results that can be used to guide policy design and infrastructure planning.

While the results provide valuable insights, it is necessary to acknowledge the limitations of the design methodology, and the opportunity for future work. The current scope of the simulation tool is the general passenger vehicle market; however, a further disaggregation into public and private vehicles would account for the varying costs and motivations affecting the decision-maker, due to the different driving habits between private vehicles, business cars, taxis, and rental cars. Furthermore, an additional analysis and segmentation of users within each region, based on their driving habits and socio-economic characteristics, can further increase the accuracy of the results. Additionally, given the identified importance of the MI, it is necessary to further decompose the MMI into its constituent parts, which would, most notably, include consumer acceptance and infrastructure development. The tool currently does not account for the effect of rising technologies, such as vehicle-to-grid (V2G) technology, which could have impact on consumer decision-making as the technology develops and spreads. Based on data availability, the simulation could be enhanced to operate on a more granular level, and provide more localized results that could further guide strategy and infrastructure design. Additionally, the tool design methodology can be easily adapted to other regions, through a careful tuning of the relevant parameters. Despite its limitations, the tool serves as a valuable resource by offering data-driven insights into the electromobility market, and thereby enabling the development of strategic designs at a regional level.

5. Conclusions

The EV market simulation tool, and the generated results, can potentially enable policy makers to assess the impact of existing policy and potential future initiatives on a national scale. As demonstrated through the 2030 results, despite the national market share achieving the required targets, many regions in Greece are still lagging behind and are severely below target; hence, regional targets must be designed and introduced. Furthermore, the results can enable more targeted and region-specific policy planning to account for the variations between different regions, and allow for more efficient policy planning. Distributed network operators can additionally benefit from the results, by

identifying the future EV volumes in different regions and, hence, effectively allocating resources for demand planning and grid fortification.

The replacement of the current ICE fleet with EVs is a long process that not only requires incentivizing EVs, but also disincentivizing ICEs, and promoting the replacement of old ICE vehicles with new EVs. Currently, there is an imbalance between the regions of Greece, as the distribution of locations where new vehicles are registered is inconsistent with the stock distribution of vehicles; effectively meaning that specific regions, such as Attica and Central Macedonia, replace their fleet at a faster rate. It is, hence, important to balance the new vehicle registration distribution with the stock distribution, to ensure that all regions are on track to achieve an EV fleet in accordance with national targets.

Future development of this work can be steered to address the identified limitations in this work, as mentioned in the Discussion section, and provide further granularity to the results. It is additionally important to acknowledge how the e-mobility industry is still volatile when it comes to market changes and, hence, it is necessary to reassess the parameters used in future utilizations of the results, and to adjust the relevant parameters accordingly.

Author Contributions: Conceptualization, F.S., P.S. and C.T.; methodology, F.S. and P.S.; software, F.S.; validation, F.S., P.S. and C.T.; formal analysis, F.S., P.S. and C.T.; investigation, F.S., P.S. and C.T.; resources, P.S. and C.T.; data curation, F.S.; writing—original draft preparation, F.S.; writing—review and editing, P.S. and C.T.; visualization, F.S.; supervision, P.S. and C.T.; project administration, P.S. and C.T.; funding acquisition, C.T. All authors have read and agreed to the published version of the manuscript.

Funding: The APC was funded by ERASMUS+: Key Action 1—Erasmus Mundus Joint Master Degrees (EMJMDs), “MSc in Smart Cities and Communities”.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments: The authors would like to thank Agamemnon Papastergiou, Partner, Strategy Consulting Leader and Sotiris Batzias, Partner, Strategy Consulting, for their continuous support in this cooperation between Deloitte and IHU.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Appendix A

Some demographic data extracted from EUROSTAT and ELSTAT for each region in Greece are presented in Table A1.

Table A1. Demographic data of the Greek NUTS-2 regions.

Region	Population (Residents)	Population Density (Residents/km ²)	GDP/Capita (EUR)	Average Annual Income (EUR)	Percentage of Population Aged 24–64 with Tertiary Education (%)
Data Source	[67]	[68]	[69]	[70]	[71]
Attica	3,792,469	987.5	23,000	11,646	45
North Aegean	324,542	59.3	11,100	8703	27.9
South Aegean	194,136	66.1	17,200	10,028	24.1
Crete	617,360	76.5	14,000	9175	27.6
Eastern Macedonia and Thrace	562,069	42.8	12,000	8775	24.9
Central Macedonia	1,792,069	101.2	13,400	9681	33.3
Western Macedonia	255,056	28.8	14,100	10,448	27.7
Epirus	319,543	36.8	12,200	9639	30
Thessaly	687,527	51.4	13,200	9217	32.8
Ionian Islands	200,726	89.4	15,100	11,246	18.8
Western Greece	643,349	59.2	12,700	8851	26
Central Greece	505,269	36.1	17,400	8862	24.7
Peloponnese	538,366	37.1	14,800	9375	24.7

References

1. European Environment Agency. Approximated Estimates for Greenhouse Gas Emissions. Available online: <https://www.eea.europa.eu/data-and-maps/data/approximated-estimates-for-greenhouse-gas-emissions-5> (accessed on 13 May 2023).
2. “Fit for 55”: Council Adopts Key Pieces of Legislation Delivering on 2030 Climate Targets. Available online: <https://www.consilium.europa.eu/en/press/press-releases/2023/04/25/fit-for-55-council-adopts-key-pieces-of-legislation-delivering-on-2030-climate-targets/> (accessed on 13 May 2023).
3. ACEA. *Fuel Types of New Cars: Battery Electric 12.1%, Hybrid 22.6% and Petrol 36.4% Market Share Full-Year 2022*; European Automobile Manufacturers’ Association (ACEA): Brussels, Belgium, 2023.
4. Meade, P.T.; Rabelo, L. The Technology Adoption Life Cycle Attractor: Understanding the Dynamics of High-Tech Markets. *Technol. Forecast. Soc. Chang.* **2004**, *71*, 667–684. [CrossRef]
5. National Energy and Climate Plans (NECPs). Available online: https://energy.ec.europa.eu/topics/energy-strategy/national-energy-and-climate-plans_en#final-necps (accessed on 26 May 2023).
6. Desai, R.R.; Hittinger, E.; Williams, E. Interaction of Consumer Heterogeneity and Technological Progress in the US Electric Vehicle Market. *Energies* **2022**, *15*, 4722. [CrossRef]
7. Siskos, P.; Capros, P.; Zazias, G.; Fiorello, D.; Noekel, K. Energy and Fleet Modelling within the TRIMODE Integrated Transport Model Framework for Europe. *Transp. Res. Procedia* **2019**, *37*, 369–376. [CrossRef]
8. Zhang, Q.; Ou, X.; Yan, X.; Zhang, X. Electric Vehicle Market Penetration and Impacts on Energy Consumption and CO₂ Emission in the Future: Beijing Case. *Energies* **2017**, *10*, 228. [CrossRef]
9. Allahmoradi, E.; Mirzamohammadi, S.; Bonyadi Naeini, A.; Maleki, A.; Mobayen, S.; Skruch, P. Policy Instruments for the Improvement of Customers’ Willingness to Purchase Electric Vehicles: A Case Study in Iran. *Energies* **2022**, *15*, 4269. [CrossRef]
10. Lee, J.H.; Hardman, S.J.; Tal, G. Who Is Buying Electric Vehicles in California? Characterising Early Adopter Heterogeneity and Forecasting Market Diffusion. *Energy Res. Soc. Sci.* **2019**, *55*, 218–226. [CrossRef]
11. Li, L.; Wang, Z.; Xie, X. From Government to Market? A Discrete Choice Analysis of Policy Instruments for Electric Vehicle Adoption. *Transp. Res. Part A Policy Pract.* **2022**, *160*, 143–159. [CrossRef]
12. Statharas, S.; Moysoglou, Y.; Siskos, P.; Zazias, G.; Capros, P. Factors Influencing Electric Vehicle Penetration in the EU by 2030: A Model-Based Policy Assessment. *Energies* **2019**, *12*, 2739. [CrossRef]
13. Shom, S.; James, K.; Alahmad, M. Understanding the Correlation of Demographic Features with BEV Uptake at the Local Level in the United States. *Sustainability* **2022**, *14*, 5016. [CrossRef]
14. Chandra, M. Investigating the Impact of Policies, Socio-Demography and National Commitments on Electric-Vehicle Demand: Cross-Country Study. *J. Transp. Geogr.* **2022**, *103*, 103410. [CrossRef]
15. Mpoi, G.; Milioti, C.; Mitropoulos, L. Factors and Incentives That Affect Electric Vehicle Adoption in Greece. *Int. J. Transp. Sci. Technol.* **2023**, in press. [CrossRef]
16. Chatzikomis, C.; Spentzas, K.; Mamalis, A. Environmental and Economic Effects of Widespread Introduction of Electric Vehicles in Greece. *Eur. Transp. Res. Rev.* **2014**, *6*, 365–376. [CrossRef]
17. Geronikolos, I.; Potoglou, D. An Exploration of Electric-Car Mobility in Greece: A Stakeholders’ Perspective. *Case Stud. Transp. Policy* **2021**, *9*, 906–912. [CrossRef]
18. Christidis, K.; Profillidis, V.; Botzoris, G.; Iliadis, L. Forecasting the Passenger Car Demand Split from Public Perceptions of Electric, Hybrid, and Hydrogen-Fueled Cars in Greece. In *Proceedings of the Smart Energy for Smart Transport*; Nathanail, E.G., Gavanas, N., Adamos, G., Eds.; Springer Nature: Cham, Switzerland, 2023; pp. 77–90.
19. Predicting the Potential Market for Electric Vehicles. *Transportation Science*. Available online: <https://pubsonline.informs.org/doi/abs/10.1287/trsc.2015.0659> (accessed on 29 June 2023).
20. Gnann, T.; Plötz, P.; Kühn, A.; Wietschel, M. Modelling Market Diffusion of Electric Vehicles with Real World Driving Data—German Market and Policy Options. *Transp. Res. Part A Policy Pract.* **2015**, *77*, 95–112. [CrossRef]
21. Rietmann, N.; Hügler, B.; Lieven, T. Forecasting the Trajectory of Electric Vehicle Sales and the Consequences for Worldwide CO₂ Emissions. *J. Clean. Prod.* **2020**, *261*, 121038. [CrossRef]
22. Al-Thani, H.; Koç, M.; Isaifan, R.J.; Bicer, Y. A Review of the Integrated Renewable Energy Systems for Sustainable Urban Mobility. *Sustainability* **2022**, *14*, 10517. [CrossRef]
23. Tsiropoulos, I.; Siskos, P.; Capros, P. The Cost of Recharging Infrastructure for Electric Vehicles in the EU in a Climate Neutrality Context: Factors Influencing Investments in 2030 and 2050. *Appl. Energy* **2022**, *322*, 119446. [CrossRef]
24. Ou, S.; Lin, Z.; He, X.; Przesmitzki, S.; Bouchard, J. Modeling Charging Infrastructure Impact on the Electric Vehicle Market in China. *Transp. Res. Part D Transp. Environ.* **2020**, *81*, 102248. [CrossRef]
25. Mastoi, M.S.; Zhuang, S.; Munir, H.M.; Haris, M.; Hassan, M.; Usman, M.; Bukhari, S.S.H.; Ro, J.-S. An In-Depth Analysis of Electric Vehicle Charging Station Infrastructure, Policy Implications, and Future Trends. *Energy Rep.* **2022**, *8*, 11504–11529. [CrossRef]
26. Manski, C.F. Daniel McFadden and the Econometric Analysis of Discrete Choice. *Scand. J. Econ.* **2001**, *103*, 217–229. [CrossRef]
27. Train, K.; Weeks, M. Discrete Choice Models in Preference Space and Willingness-to-Pay Space. In *Applications of Simulation Methods in Environmental and Resource Economics*; Scarpa, R., Alberini, A., Eds.; The Economics of Non-Market Goods and Resources; Springer: Dordrecht, The Netherlands, 2005; pp. 1–16, ISBN 978-1-4020-3684-2.

28. Daina, N.; Sivakumar, A.; Polak, J.W. Modelling Electric Vehicles Use: A Survey on the Methods. *Renew. Sustain. Energy Rev.* **2017**, *68*, 447–460. [CrossRef]
29. Crooks, A.T.; Heppenstall, A.J. Introduction to Agent-Based Modelling. In *Agent-Based Models of Geographical Systems*; Heppenstall, A.J., Crooks, A.T., See, L.M., Batty, M., Eds.; Springer: Dordrecht, The Netherlands, 2012; pp. 85–105, ISBN 978-90-481-8927-4.
30. Jia, W.; Chen, T.D. Are Individuals' Stated Preferences for Electric Vehicles (EVs) Consistent with Real-World EV Ownership Patterns? *Transp. Res. Part D Transp. Environ.* **2021**, *93*, 102728. [CrossRef]
31. El Zarwi, F.; Vij, A.; Walker, J.L. A Discrete Choice Framework for Modeling and Forecasting the Adoption and Diffusion of New Transportation Services. *Transp. Res. Part C Emerg. Technol.* **2017**, *79*, 207–223. [CrossRef]
32. Wang, N.; Tang, L.; Pan, H. Effectiveness of Policy Incentives on Electric Vehicle Acceptance in China: A Discrete Choice Analysis. *Transp. Res. Part A Policy Pract.* **2017**, *105*, 210–218. [CrossRef]
33. Byun, H.; Shin, J.; Lee, C.-Y. Using a Discrete Choice Experiment to Predict the Penetration Possibility of Environmentally Friendly Vehicles. *Energy* **2018**, *144*, 312–321. [CrossRef]
34. Siskos, P.; Capros, P.; De Vita, A. CO₂ and Energy Efficiency Car Standards in the EU in the Context of a Decarbonisation Strategy: A Model-Based Policy Assessment. *Energy Policy* **2015**, *84*, 22–34. [CrossRef]
35. McFadden, D. The Choice Theory Approach to Market Research. *Mark. Sci.* **1986**, *5*, 275–297. [CrossRef]
36. Castillo, E.; Menéndez, J.M.; Jiménez, P.; Rivas, A. Closed Form Expressions for Choice Probabilities in the Weibull Case. *Transp. Res. Part B Methodol.* **2008**, *42*, 373–380. [CrossRef]
37. Directorate-General for Climate Action (European Commission); Directorate-General for Energy (European Commission); Directorate-General for Mobility and Transport (European Commission); De Vita, A.; Capros, P.; Paroussos, L.; Fragkiadakis, K.; Karkatsoulis, P.; Höglund-Isaksson, L.; Winiwarter, W.; et al. *EU Reference Scenario 2020: Energy, Transport and GHG Emissions: Trends to 2050*; Publications Office of the European Union: Luxembourg, 2021; ISBN 978-92-76-39356-6.
38. Train, K.E.; Winston, C. Vehicle Choice Behavior and the Declining Market Share of U.S. Automakers. *Int. Econ. Rev.* **2007**, *48*, 1469–1496. [CrossRef]
39. Estimating Consumer Substitution between New and Used Passenger Vehicles. Available online: <https://www.journals.uchicago.edu/doi/epdf/10.1086/715814> (accessed on 15 May 2023).
40. Matsushashi, K.; Ariga, T.; Ishikawa, M. Estimation of Passenger Car CO₂ Emissions by Population Density Class Based on Japanese Vehicle Inspection Certificate Data. *IATSS Res.* **2023**, *47*, 179–184. [CrossRef]
41. Hymel, K.M. *Factors Influencing Vehicle Miles Traveled in California: Measurement and Analysis*; California State University: Northridge, CA, USA, 2014.
42. Zhang, L.; Hong, J.; Nasri, A.; Shen, Q. How Built Environment Affects Travel Behavior: A Comparative Analysis of the Connections between Land Use and Vehicle Miles Traveled in US Cities. *J. Transp. Land Use* **2012**, *5*, 40–52. [CrossRef]
43. Akar, G.; Guldmann, J.-M. Another Look at Vehicle Miles Traveled. *Transp. Res. Rec.* **2012**, *2322*, 110–118. [CrossRef]
44. Directorate-General for Mobility and Transport (European Commission); EMISIA; Panteia; STRATEC; TRT; Papadimitriou, G.; Mellios, G.; Borgato, S.; Maffii, S.; Rodrigues, M.; et al. *Study on New Mobility Patterns in European Cities: Final Report. Task C, Development of a Consistent Dataset for Quantitative Analysis*; Publications Office of the European Union: Luxembourg, 2022; ISBN 978-92-76-56397-6.
45. ODYSSEE-MURE. Change in Distance Travelled by Car. Available online: <https://www.odyssee-mure.eu/publications/efficiency-by-sector/transport/distance-travelled-by-car.html> (accessed on 14 May 2023).
46. Beggs, S.D.; Cardell, N.S. Choice of Smallest Car by Multi-Vehicle Households and the Demand for Electric Vehicles. *Transp. Res. Part A Gen.* **1980**, *14*, 389–404. [CrossRef]
47. Haq, G.; Weiss, M. Time Preference and Consumer Discount Rates—Insights for Accelerating the Adoption of Efficient Energy and Transport Technologies. *Technol. Forecast. Soc. Chang.* **2018**, *137*, 76–88. [CrossRef]
48. Duoba, M. Developing a Utility Factor for Battery Electric Vehicles. *SAE Int. J. Alt. Power.* **2013**, *2*, 362–368. [CrossRef]
49. Harto, C. *Electric Vehicle Ownership Costs: Today's Electric Vehicles Offer Big Savings for Consumers*; Consumer Reports: New York, NY, USA, 2020.
50. Lee, J.H.; Chakraborty, D.; Hardman, S.J.; Tal, G. Exploring Electric Vehicle Charging Patterns: Mixed Usage of Charging Infrastructure. *Transp. Res. Part D Transp. Environ.* **2020**, *79*, 102249. [CrossRef]
51. Lin, Z. Optimizing and Diversifying Electric Vehicle Driving Range for U.S. Drivers. *Transp. Sci.* **2014**, *48*, 635–650. [CrossRef]
52. Hao, X.; Lin, Z.; Wang, H.; Ou, S.; Ouyang, M. Range Cost-Effectiveness of Plug-in Electric Vehicle for Heterogeneous Consumers: An Expanded Total Ownership Cost Approach. *Appl. Energy* **2020**, *275*, 115394. [CrossRef]
53. Egbue, O.; Long, S. Barriers to Widespread Adoption of Electric Vehicles: An Analysis of Consumer Attitudes and Perceptions. *Energy Policy* **2012**, *48*, 717–729. [CrossRef]
54. Rodríguez Salvador, M.; Lezama Nicolás, R.; Río Bolver, R.M.; Rodríguez Andara, A. Lessons Learned in Assessment of Technology Maturity. In *Proceedings of the Engineering Digital Transformation*; Ortiz, Á., Andrés Romano, C., Poler, R., García-Sabater, J.-P., Eds.; Springer International Publishing: Cham, Switzerland, 2019; pp. 103–110.
55. Park, E.; Lim, J.; Cho, Y. Understanding the Emergence and Social Acceptance of Electric Vehicles as Next-Generation Models for the Automobile Industry. *Sustainability* **2018**, *10*, 662. [CrossRef]
56. Müller, J.M. Comparing Technology Acceptance for Autonomous Vehicles, Battery Electric Vehicles, and Car Sharing—A Study across Europe, China, and North America. *Sustainability* **2019**, *11*, 4333. [CrossRef]

57. Ruoso, A.C.; Ribeiro, J.L.D. The Influence of Countries' Socioeconomic Characteristics on the Adoption of Electric Vehicle. *Energy Sustain. Dev.* **2022**, *71*, 251–262. [CrossRef]
58. Dixit, S.K.; Singh, A.K. Predicting Electric Vehicle (EV) Buyers in India: A Machine Learning Approach. *Rev Socionetw. Strat* **2022**, *16*, 221–238. [CrossRef] [PubMed]
59. Sovacool, B.K.; Kester, J.; Noel, L.; de Rubens, G.Z. The Demographics of Decarbonizing Transport: The Influence of Gender, Education, Occupation, Age, and Household Size on Electric Mobility Preferences in the Nordic Region. *Glob. Environ. Chang.* **2018**, *52*, 86–100. [CrossRef]
60. Coffman, M.; Bernstein, P.; Wee, S. Electric Vehicles Revisited: A Review of Factors That Affect Adoption. *Transp. Rev.* **2017**, *37*, 79–93. [CrossRef]
61. Mandys, F. Electric Vehicles and Consumer Choices. *Renew. Sustain. Energy Rev.* **2021**, *142*, 110874. [CrossRef]
62. Open Charge Map. API Documentation. Available online: <https://openchargemap.org/site/develop/api#/> (accessed on 16 July 2023).
63. Eurostat. Statistics. Available online: <https://ec.europa.eu/eurostat/databrowser/view/TGS00005/default/table> (accessed on 16 July 2023).
64. Eurostat. Statistics. Available online: https://ec.europa.eu/eurostat/databrowser/view/EDAT_LFSE_04/default/table?lang=en (accessed on 16 July 2023).
65. I Move Electrically II. Available online: <https://www.gov.gr/en/ipiresies/polites-kai-kathemerinoteta/periballon-kai-poioteta-zoes/kinoumai-elektrika-ii> (accessed on 26 May 2023).
66. Held, M.; Rosat, N.; Georges, G.; Pengg, H.; Boulouchos, K. Lifespans of Passenger Cars in Europe: Empirical Modelling of Fleet Turnover Dynamics. *Eur. Transp. Res. Rev.* **2021**, *13*, 9. [CrossRef]
67. European Commission. *Eurostat Population by Current Activity Status, Educational Attainment Level and NUTS 2 Region*; European Commission: Brussels, Belgium, 2023.
68. European Commission. *Population Density by NUTS 2 Region*; European Commission: Brussels, Belgium, 2023.
69. European Commission. *Eurostat Gross Domestic Product (GDP) at Current Market Prices by NUTS 2 Regions*; European Commission: Brussels, Belgium, 2023.
70. European Commission. *Eurostat Income of Households by NUTS 2 Regions*; European Commission: Brussels, Belgium, 2023.
71. European Commission. *Eurostat Tertiary Educational Attainment, Age Group 25-64 by Sex and NUTS 2 Regions*; European Commission: Brussels, Belgium, 2023.

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