July 2024

Fondazione Eni Enrico Mattei

Working Paper

19.2024

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Summary

The transition to a zero-emission car fleet is a pivotal element of Europe's decarbonisation strategy. Italy's participation in this trajectory is significant, given the size of its car fleet. Currently, only battery electric (BEVs) and hydrogen-powered are considered zero-emission vehicles. The final update of the National Energy and Climate Plan (NECP) includes an ambitious target for the diffusion of electric cars in the Italian fleet. The aim is to have a total of 4.3 million electric cars on the roads by 2030. However, by the end of 2023, the Italian e-fleet totalled 220,000 cars, which equals a mere 0.5% of the overall car population and 5% of the target. The objective of this study is threefold: firstly, to estimate the likely diffusion of electric cars in the Italian market; secondly, to assess the prospects for their penetration in the fleet in the coming years; and thirdly, to evaluate the consistency of the current diffusion path with the NECP target. Diffusion paths are derived using Bass and logistic diffusion models. We consider a business-as-usual scenario based solely on historical trends, and an accelerated diffusion alternative scenario, in which we assume that by 2023 new BEV models will enter the Italian car market, raising the market potential for this powertrain to the same level as the most successful non-plug-in hybrid models. Both scenarios show that, in the absence of further significant shifts, the deployment paths will be totally insufficient to meet NECP 2030 target. Fewer than half a million consumers appear to be interested in buying one of the battery electric models currently on sale in the business-as-usual scenario. The low share of enthusiastic potential adopters of BEVs, the increasing useful life of passenger cars, the lack of highly successful BEV models, the limited impact of the incentive schemes until 2023 and the strong competition from other alternative technologies (besides non-plug-in hybrids and LPG) continue to impede the penetration of electric powertrains in the Italian fleet. Incentive schemes and decarbonisation strategies must undergo major revision to achieve a path consistent with net-zero emission goals.

Keywords: sustainable mobility, road transport decarbonization, electric vehicle adoption, automotive market, Italian National Energy and Climate Plan (NECP)

JEL classification: N74, Q55, Q58, R40

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Abstract

The transition to a zero-emission car fleet is a pivotal element of Europe's decarbonisation strategy. Italy's participation in this trajectory is significant, given the size of its car fleet. Currently, only battery electric (BEVs) and hydrogen-powered are considered zero-emission vehicles. The final update of the National Energy and Climate Plan (NECP) includes an ambitious target for the diffusion of electric cars in the Italian fleet. The aim is to have a total of 4.3 million electric cars on the roads by 2030. However, by the end of 2023, the Italian e-fleet totalled 220,000 cars, which equals a mere 0.5% of the overall car population and 5% of the target. The objective of this study is threefold: firstly, to estimate the likely diffusion of electric cars in the Italian market; secondly, to assess the prospects for their penetration in the fleet in the coming years; and thirdly, to evaluate the consistency of the current diffusion path with the NECP target. Diffusion paths are derived using Bass and logistic diffusion models. We consider a business-as-usual scenario based solely on historical trends, and an accelerated diffusion alternative scenario, in which we assume that by 2023 new BEV models will enter the Italian car market, raising the market potential for this powertrain to the same level as the most successful non-plug-in hybrid models. Both scenarios show that, in the absence of further significant shifts, the deployment paths will be totally insufficient to meet NECP 2030 target. Fewer than half a million consumers appear to be interested in buying one of the battery electric models currently on sale in the business-as-usual scenario. The low share of enthusiastic potential adopters of BEVs, the increasing useful life of passenger cars, the lack of highly successful BEV models, the limited impact of the incentive schemes until 2023 and the strong competition from other alternative technologies (besides non-plug-in hybrids and LPG) continue to impede the penetration of electric powertrains in the Italian fleet. Incentive schemes and decarbonisation strategies must undergo major revision to achieve a path consistent with net-zero emission goals.

1. Introduction

European policy makers have identified battery electric cars as an indispensable ally for the decarbonisation of road transport. Italy's participation in these electrification trajectories is decisive for the success of the EU strategy. With almost 41 million passenger cars in 2023, Italy has one of the largest fleets in the Europe Union - second only to Germany (48.8 million in 2023). Yet, in Italy more than elsewhere, electric mobility is struggling to take the lead.

The final update of the NECP, submitted to the European Commission in June 2024, sets the normative backbone of Italy's environmental policy up to 2030. The finalised document confirms ambitious goals for the diffusion of BEVs. Specifically, the plan targets the presence of 4.3 million electric cars and 2.3 million plug-in hybrids in the Italian fleet – which is currently dominated by fossil-fuelled internal combustion engines (ICE) – by 2030. This threshold does not appear to align with the current diffusion trajectories of these powertrains. In fact, by the end of 2023, the Italian e-fleet will have reached a total of around 220,000 cars, representing just 0.5% of the total car population and 5% of the NECP target. Furthermore, the effectiveness of existing incentive programmes in influencing consumer choice towards BEVs has proven to be limited (Bonacina and Sileo, 2024). This indicates that market forces face a significant challenge to electrify the Italian fleet.

The plausibility of the Italian e-mobility target raises concerns among experts. It seems clear that achieving European and national policy goals implies following dramatically new fleet trajectories. Assessing the feasibility of such trajectories is a task that requires reliable forecasts based on comprehensive data. However, none of the studies carried out so far have relied on standard models for the diffusion of durable products.

To date, the most prominent fleet projections are based on policy targets and the idea that the fleet will shrink as the green transition unfolds. According to ACEA (2024), the EU passenger car fleet grew by 1.1% in 2022 compared to 2021. The increase is observed in all EU countries except Sweden (-0.03%) and Finland (-0.5%). Although this is partly explained by the economic recovery after COVID-19, there is no evidence that the fleet is about to shrink. In Italy, the number of cars in the fleet has increased by an average of about 550,000 units per year over the last five decades. Part of the story is that the scrapping of old cars is not progressing at the pace required for realistic replacement. As a result, the age composition of the fleet has changed over the years. Compared to the early 2000s, the age distribution is now heavier at the tail, with a growing number of cars over 30 years old in the fleet (2.7 million in 2000, but 8.7 million in 2022). This distribution has obvious implications for emissions and energy efficiency.

This study aims to study the diffusion dynamics of electric passenger cars in the Italian fleet. In our framework, the forecast does not rely on policy targets, as we recognise that the policies implemented so far have failed to stimulate the scrapping of old cars and the uptake of (new) electric cars. We argue that a data-driven approach to forecasting provides the kind of cautious reference scenario needed to consider realistic and far-reaching policy measures. To the best of our knowledge, no such study has been carried out in Italy.

The rest of the paper is structured as follows. Section 2 reviews the literature on the likely adoption of innovative propulsion technologies. Section 3 presents the data. The diffusion dynamics of battery electric models sold since 2011 are derived and discussed in Section 4. The outlook for the diffusion of battery electric cars in Italy until 2030 is in Section 5. Finally, section 6 concludes with policy recommendations, highlighting potential limitations of the present work and suggesting avenues for further development.

2. Literature review

Researchers have developed mathematical models to estimate the penetration rate of new powertrains. These models can be distinguished by the modelling technique employed to represent the interactions within the marketplace. The three principal modelling techniques used in the literature on market forecasting are agent-based, consumer choice and diffusion-based models (Ayyadi and Maaroufi, 2018).

2.1 Agent-based and consumer choice models

Agent-based models (AM) are computer simulations that create a virtual environment where the actions and interactions of agents can be observed and analysed. The intrinsic characteristics of agents influence their actions and, as a consequence, the overall outcome. Four main actors have been identified in the field of vehicle technology adoption: consumers, automakers, policy-makers and fuel suppliers. A comprehensive overview of the applications of AMs in transport simulation is in Huang et al. (2022).

The main advantage of agent-based models is the capacity to incorporate agents' distinctive characteristics, needs, and constraints when simulating their behaviour and interactions. The main drawback is the inherent complexity of the approach. The verification and validation of agent-based models' results is a challenging process, particularly when it comes to agent-level data and elasticities. These elements can have a significant impact on the overall modelling results (Ayyadi and Maaroufi, 2018).

In the academic literature, discrete choice and logit models have been extensively employed to describe individual and collective decision-making processes. Logit models are a commonly utilised tool for modelling probabilistic consumer preferences, whereas discrete choice models calculate the probability of selecting a specific product from the available alternatives, taking into account the influence of these preferences (Liao et al. 2016). The conventional approach to describing consumer preferences for cars is through the use of either multinomial logit models[1] or nested logits[2] (Al-Alawi and Bradley, 2013).

Consumer choice models are more accessible, transparent and less complex than agent-based models. However, they require detailed, historical data on consumers' preferences and sales. Additionally, the focus of consumer choice and agent-based models is the relationship between vehicle ownership and a set of individual and social preferences (see Lieven et al., 2010). Although these models are well suited for depicting consumption behaviours at a specific point in time, they are less fit for the purpose of forecasting. Consequently, although these models are useful for identifying purchasing drivers and barriers, they are not well suited to the scope of this work.

2.2 Diffusion-based models (DM)

The term 'diffusion' is defined as the process by which a new invention or product is accepted by the market. The rate of diffusion is the speed with which a novel product gains acceptance in the market. It is influenced by a range of internal and external factors (such as metrics of innovation, communication, time, and the surrounding social system), which may be subject to control or not. DMs seek to capture the life cycle of new products over time (Rogers, 1976; Robinson, 2009). A common approach to modelling the diffusion of innovation is to represent it as a normal distribution over time with five categories of adopters: first-innovators, early adopters, early majority, late majority, and laggards (Campbell, 2015; Robinson, 2009; Robert, 1979; Rogers, 1983; Sahin, 2006). First-innovators are defined as individuals who are the first to adopt new products, despite the potential risks involved (Rogers, 2003). Early adopters rank second in the timing of the adoption of an innovation. Their social connections to first-innovators (and other adopters) exert a significant influence on their behaviour. Early adopters are naturally inclined to set trends and play a central role in the success of an innovation. While first-innovators are idealistic, energetic, and fixated on innovation, early

[1] Multinomial logit models represent the probability of selecting an alternative over all the options available.

[2] Nested logit models represent the probability of selecting an alternative over a cluster (or nest) of options available.

adopters are socially respected, well-informed, and economically successful (Robinson, 2009). The remaining categories have a slower adoption rate due to their lower level of social influence and lower financial status.

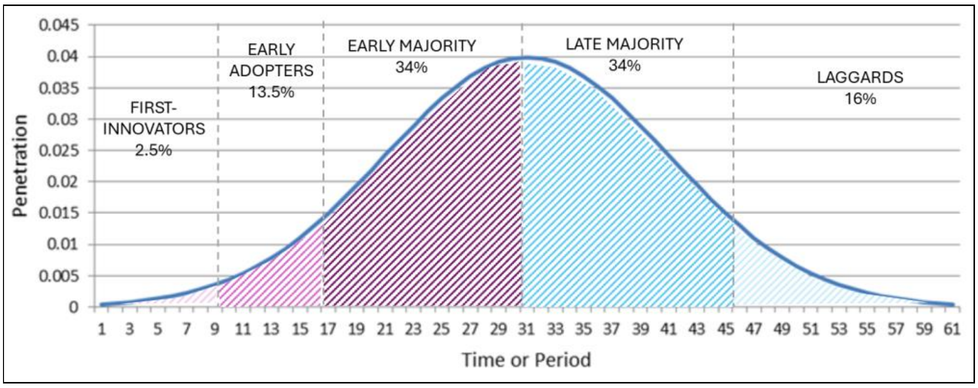

Figure 1. The normally distributed rate of diffusion for a new product and the five categories of adopters.

The most well-known diffusion-based models in the automotive industry are the Bass, logistic, generalised Bass, and Gompertz models. For example, Zue et al. (2015) employed the Bass model to predict the rate of adoption of natural gas vehicles in Japan, while Qian and Soopramanien (2014) used Bass, logistic, and Gompertz models to forecast automobile sales in China. Ayyadi and Maaroufi (2018) utilized the aforementioned models to forecast car sales in Morocco. Dhakal et al. (2021) conducted a comparative evaluation of Bass and logistic diffusion models to forecast the diffusion of electric vehicles in major countries. Rietman et al. (2020) employed both Bass and logistic models to forecast global electric vehicle sales. Lamberson (2009) employed both Bass and Gompertz models to estimate hybrid and plug-in hybrid new car sales in the United States. Bitencourt et al. (2021) employed a Bass model to examine the factors influencing the adoption of electric vehicles in North America. Ensslen et al. (2019) employed diffusion models to predict the diffusion of electric vehicles in France and Germany.

DMs are deterministic time functions with S-shaped (or sigmoid) curves (Michalakelis et al., 2008). The rate of diffusion (adoption or penetration) at time t, y_t, is represented in Fig. 1 and can be expressed as:

$$y_t = \varphi_t \times (1 - Y_{t-1})$$

where φ_t is the probability of purchase at time t, Y_{t-1} is the portion of potential adopters who have adopted the novel product by time $t-1$. Therefore, the term in round brackets is the fraction of potential adopters who have yet to embrace the innovation.

Peak penetration is observed when the last innovator adopts the new product. Subsequent adoptions are made by the imitators, that is to say the late majority and laggards. The cumulative penetration, obtained by summing marginal adoption at each period, has the S-shaped (sigmoid) form illustrated in Fig. 2.

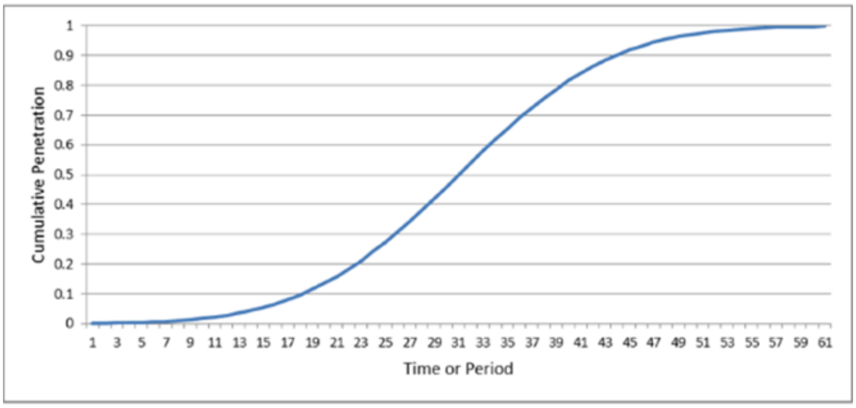

Figure 2. S-shaped (sigmoid) form of cumulative penetration.

Diffusion-based models are routinely used by analysts to study the market potential of innovative propulsion technologies, especially when diffusion plays a decisive (or critical) role. They take in the inherent regularity of diffusion processes and use math formula to elaborate on its core characteristics over time. The success of these models relates to different factors. Firstly, DMs' diffusion paths align with real-market outcomes and have face value which is consistent with the common perception of a slow uptake and saturation. Secondly, diffusion-based models are data parsimonious: they typically require only a time series of the seminal diffusion (i.e. first purchases) of a given technology (Al-Alawi and Bradley, 2013). Thirdly, DMs fit sales almost as well as much more complex models that seek to correct their limitations (Bass et al.,1994; Chandrasekaran and Tellis, 2007). This approach aligns with the aims of the present study. The next subsections provide an overview of the Bass and Logistics diffusion models.

2.2.1. Bass (diffusion-based) model (BM)

The BM posits that the probability of purchase at any given time (φ_t) is *linearly related to the number of previous buyers* (Bass, 1969). This implies that the rate of innovation adoption at a given point in time is influenced (exclusively) by previous adoptions communicated through channels such as marketing, word-of-mouth, and social networking (Kumar et al. 2022). Formally,

$\varphi_t = p + qY_{t-1}$ and, by substitution, $y_t = (p + qY_{t-1}) \times (1 - Y_{t-1})$ with $p, q > 0$

where p and q represent the probability that an innovator and an imitator, respectively, will adopt the new product. The cumulative penetration is then

$$Y_t = \int_0^t y_t dt = \frac{1 - e^{-(p+q)t}}{[1 + (^q/_p) e^{-(p+q)t}]}.$$

Higher values of p indicate an increased adoption rate in the earlier years, which can be represented by a leftward shift of the S-shaped curve. Conversely, higher values of q indicate an increased adoption rate in later years, which can be represented by a rightward shift of the sigmoid curve. Following this narrative, the number of first time purchases, n_t, at time t can be expressed as follows:

$$(1)\; n_t = My_t = (M - N_{t-1})\left(p + q\frac{N_{t-1}}{M}\right) = pM + (q - p)N_{t-1} - \frac{q}{M}N_{t-1}^2$$

where M is the market potential[3] and N_{t-1} is cumulative purchases until beginning of time t.

2.2. Logistic (diffusion-based) model (LM)

Demographic considerations drove the initial development of LMs, but the underlying principles of such models were soon validated for innovations (Berger, 1981). In both cases, the initial and final growth rates are observed to be relatively slow (Trappey and Wu, 2008). The LM posits that the probability of purchase at any given time (φ_t) is positive and constant (Berger, 1981). Formally,

$$\varphi_t = a \text{ and, by substitution, } y_t = a \times (1 - Y_{t-1}) \text{ with } a > 0$$

The cumulative penetration is then

$$Y_t = \int_0^t y_t dt = \frac{1}{1+e^{-a(t-b)}}$$

where b is the offset in the timescale. Using the logistic equation curve, the number of adopters at time t can be expressed as follows:

$$(2)\; n_t = My_t = aM \times (1 - Y_{t-1}) = a(M - N_{t-1})$$

where $N_{t-1} = M/[1 + e^{-a(t-b)}]$ (see Kumar et al., 2022; Trappey and Wu, 2008; Lee et al. 2011).

3. Data collection and summary statistics

This section presents a summary of the data employed for the regression analyses. The likely data sources are Unione Nazionale Rappresentanti Autoveicoli Esteri (UNRAE) and Automobile Club d'Italia (ACI), which are both duly authorised to disseminate data from the Italian Ministry of Transport. UNRAE's publications contain data on new passenger car registrations by fuel type on a monthly and annual basis. The monthly data set encompasses the period from December 2011 to May 2024 (150 observations), while the annual data set covers the period from 2000 to 2023 (24 observations). ACI website provides access to a variety of data, including those on the Italian car fleet by fuel type from 2000 to 2023 (24 observations). Both sources permit to isolate battery electric cars from other powertrains, including non plug-in hybrids and plug-in hybrids. The data used in the estimation constitute the most recent available at the time the study is conducted. The battery electric car models that were available for sale prior to 2011 exhibited notable differences from those currently on the market. Consequently, data before 2011 must be excluded. Furthermore, as more data becomes available, the accuracy of diffusion models' predictions increases. For these reasons, we have elected to utilise monthly data on new registrations of battery electric cars. Table 1 illustrates the statistics for the data used in the regressions as well as those on the monthly trend of new car registrations for all powertrains and fuels, and on the annual data on the car fleet. The plot of new registrations of passenger cars (battery electric cars vs. all powertrains) is in Figure 3. In the period under consideration, new registrations of battery electric cars accounted for less than 1.5 per cent (on average) of the total. Monthly peaks of over 8,000 newly registered BEVs were observed in September 2021 (post-Covid-19 rebound), March and November 2023.

[3] The market potential, M, is assumed to be fixed at the time of the prediction.

Table 1. Summary statistics of data used for regressions. Source: our elaborations on UNRAE & ACI data, last access, June 2024.

	New registrations of passenger car Monthly data Dec. 2011-May 2024			**Passenger car fleet Annual data 2000-2023**		
	All powertrains	BEV	Non plug-in hybrid	All powertrains	BEV	Non plug-in hybrid
Max	227,118	8,496	63,905	40,909,630	219,540	575,212
Min	4,325	8	246	36,960,500	3,430	5
Mean	133,033	1,758	15,530	38,802,429	55,408	84,746
Median	134,390	256	6,134	39,018,170	12,156	7,160
Std. dev.	35,022	2,371	18,267	1,341,884	75,492	160,620

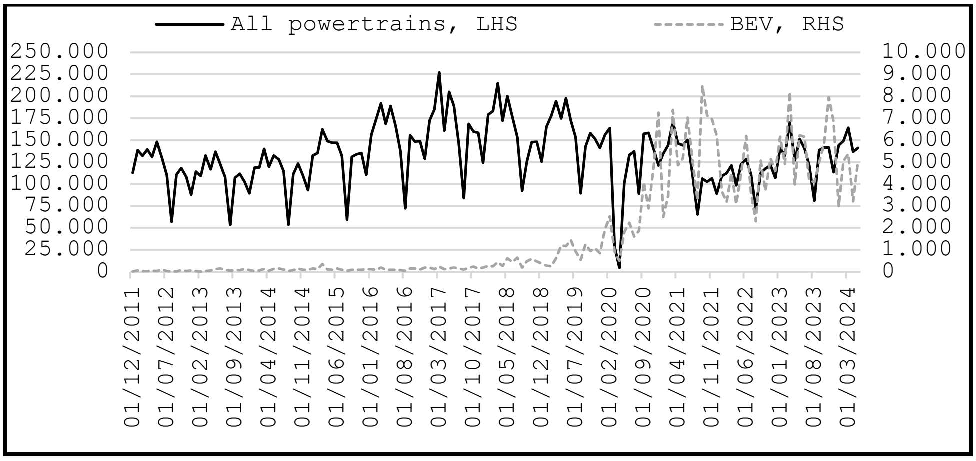

Figure 3. The number of new registrations of passenger cars in Italy. On the left-hand side (LHS) of the graph, we have data on all powertrains, while on the right-hand side (RHS), we have data for battery-electric cars. Source: UNRAE, last access, June 2024.

4. In-sample estimations based on Italian market data

This section presents the estimated BM and LM parameters based on monthly new BEV registrations from 1.12.2011 to 31.5.2024. The estimated equations are (1) and (2). In both cases the dependent variable is the number of new registrations of battery electric cars (n_t) while the explanatory variable is the cumulative purchases up to t-1 (N_{t-1}). The parameters are estimated by non-linear least squares (NLS). Note that the market potential M is also estimated endogenously in this specification. Srinivasan and Mason, (1986) and Mahajan and Sharma (1986) demonstrated that NLS outperforms maximum likelihood estimation for this kind of models.

Table 2. The NLS fit of Bass and logistic models' parameters, mean absolute deviation (MAD) and mean absolute percentage error (MAPE).

	R^2	***M***	***p***	***q***	***a***	***b***	***MAD***	***MAPE***
Logistic	*0.9976*	*312,013*			*13.5092*	*129 (08/2022)*	*590.3287*	*276.4428*
Bass	*0.9982*	*311,970*	*0.0000053*	*0.0740*			*590.4547*	*283.0367*

The in-sample trends are accurately estimated by the two models. The Mean Absolute Deviation (MAD) and the Mean Absolute Percentage Error (MAPE) indices,[4] calculated by applying the formulae

$$MAD = \frac{\sum_{t=0}^{N}|n_t-\widehat{n_t}|}{N} \quad \text{and} \quad MAPE = \frac{100}{N}\sum_{t=0}^{N}\frac{|n_t-\widehat{n_t}|}{\widehat{n_t}},$$

indicate a slight superiority of the logistic over the Bass in-sample fit (Table 2). Indeed, the in-sample diffusion paths of the two models are strikingly similar. Looking at battery electric cars sold since 2011, both models identify a penetration peak at the end of 2022 (see Figure 4). This would suggest that all innovators have already purchased one of the battery electric car models available for sale before 2022, and that the adoption rate is about to decline. However, in 2023, new electric car models and new car manufacturers have entered the EU (and therefore Italian) car market, which could give a new impetus to the diffusion path. If these models are perceived as something new compared to what was available before, we could observe the activation of a new diffusion dynamic in the coming years. This would explain, among other things, the peaks in 2023 alluded to in section 3. We will return to this point later (see section 5).

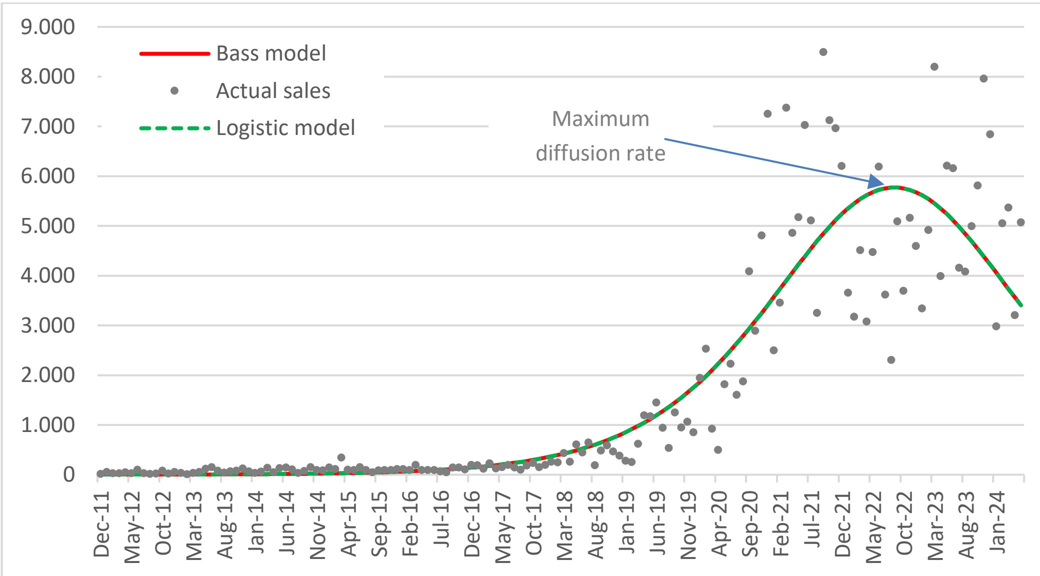

Figure 4. Actual and fitted first purchases of battery electric cars.

Furthermore, both models indicate a market potential of 320,000 units (M) over the forecast horizon. This figure should be interpreted as follows: in Italy, according to the diffusion models used in this study, there are 320,000 potential first-time buyers of battery electric cars sold between 2011 and 2023 (375,000 using the underestimation coefficient of Dhakal et al., 2021). The fitted imitation and innovation coefficients are consistently lower than those commonly reported in the literature, regardless of the country, time frame and powertrain considered (Figure 5). This may be attributed to the fact that battery electric vehicles in Italy face competition not only from plug-in and non-plug-in hybrid powertrains, but also from internal combustion engines fuelled with CNG or LPG. It is noteworthy that even in 2023, the demand for LPG-powered cars outweighed that of BEV and plug-in hybrids combined. Also in 2023, the best-selling BEV model accounted for 6% of the demand met by the best-selling

[4] N is the number of observations (150) and $\widehat{n_t}$ is the forecast of n_t.

non-plug-in hybrid model and 30% of the demand met by the best-selling LPG model. Section 4.1 provides further insight by calibrating the Bass coefficients (p and q) to an exogenous market potential.

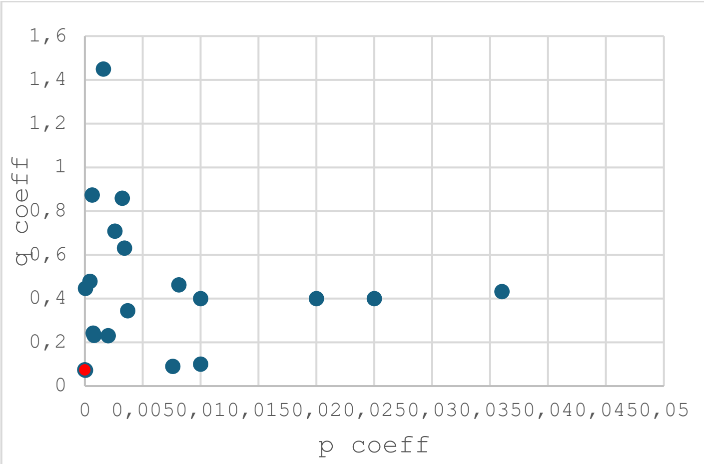

Figure 5. Scatter plot of Bass' innovation (p) and imitation (q) coefficients in the literature. Source: Massiani and Gohs, 2015. Our predictions for Italy are shown in red.

4.1 Bass model coefficients with exogenous market potential

This subsection presents a calibration of the Bass parameters (p and q) under the assumption that the market potential (M) is exogenously fixed. If both N_{t-1} and M are known, eq. (1) can be rewritten as

$$n_t = (M - N_{t-1})p + q\left(1 - \frac{N_{t-1}}{M}\right)N_{t-1} = X_{t-1}p + Y_{t-1}q$$

where $X_{t-1} = M - N_{t-1}$and $Y_{t-1} = (1 - N_{t-1}/M)N_{t-1}$. The calibrated p and q values of the Bass model for market potentials of 500,000, 1,000,000, 2,000,000, 4,000,000 and 6,000,000 are estimated through ordinary least squares and illustrated in Table 3. According to our estimation, an exogenous M exceeding 6,000,000, is associated to statistically insignificant p and q, indicating an implausible diffusion pattern under the Bass distribution.

*Table 3. Calibration of Bass parameters. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.*

M	500,000	1,000,000	2,000,000	4,000,000	6,000,000
p	0.09859***	0.19719**	0.39438**	0,78875*	1.18312
q	0.03120***	0.12979***	0.32698**	0,72136*	1.11573

The results of the calibrations are consistent with the findings in Section 4. The limited uptake of battery electric cars can be attributed to the relatively small number of adopters in the early stages of the innovation process: low numbers of innovators (first-innovators and early adopters) generate slow diffusion paths and small cumulative penetrations.

The Bass model indicates that it is possible, but highly unlikely, to extend the pool of adopters up to 4 million, which equals 1/10th of the Italian population between the ages of 18 and 70 (Istat, 2023). Further extensions are – *ceteris paribus* - unfeasible.

This result provides an intriguing insight into the matter under discussion. Beyond policy goals, BEV adoption, like all sort of innovations, is determined by peer effects. An interesting venue for further research and enlightened policy-making is considering the power of user experiences and word-of-mouth in boosting new acquisitions. Failure to provide support in a timely manner or to target the appropriate demographic may result in unclaimed funds and/or a lack of efficacy. In the years 2022 and 2023, more than 50% of the funds allocated by the Italian government to incentivise the purchase of battery electric passenger cars remained unclaimed.

5. Forecasting the diffusion of BEV in Italy

Many research institutions have sought to ascertain the number of electric vehicles that will be in use in the Italian fleet by 2030. Subsection 5.1 presents a review of existing findings, which have several shortcomings. Firstly, several studies fail to distinguish between the figures for battery electric powertrains and those for plug-in hybrids. Secondly, some studies focus on the fleet, while others concentrate on new registrations. Thirdly, the underlying assumptions that inform the estimates are not always clearly delineated. Finally, there is a general tendency for downward revisions of initial forecasts.

As previously stated, diffusion models do not quantify the number of battery electric cars in use. Conversely, they provide estimates of the likely diffusion of these vehicles, that is, they quantify the number of first-time buyers of BEVs. However, with ad hoc integration, diffusion paths could be used to forecast the likely number of BEVs in use and hence the size of the e-fleet. Subsection 5.2 and 5.3 present two diffusion scenarios for BEVs: one based on the historical trend of BEVs in Italy (business-as-usual scenario, BAU) and the other based on the historical trend of non-rechargeable hybrids (accelerated diffusion scenario, AD). The rationale of the BAU scenario is straightforward: if no changes are made, what can be expected in 2030? The idea of applying the historical diffusion paths of non-plug-in hybrids to BEV models on sale by 2023 may seem unusual, but let's explain the underlying rationale. In 2023, new carmakers have entered the EU automotive market, launching novel battery electric models. These models can be referred to as post-2023 BEVs. Should Italian consumers express greater satisfaction with post-2023 BEV models than they did with pre-2023 ones, the diffusion path of battery electric cars will accelerate in the years to come. The data currently available is insufficient to permit the quantification of the diffusion path of post-2023 BEVs. Nevertheless, it is possible to calculate the diffusion path of the most recent and most successful models in Italy and extend this trajectory to post-2023 battery electric cars. Over the past decade, Italian consumers have exhibited a clear preference for non-plug-in hybrid vehicles. Consequently, in the AD scenario, the historical diffusion dynamics of non-plug-in hybrids are applied to post-2023 BEVs. It is not certain that post-2023 BEVs will enjoy the same degree of success as past non-plug-in hybrids. However, should post-2023 BEVs be more successful than pre-2023 ones, their diffusion paths could, at most, mirror that of non-plug-in hybrid powertrains. From this perspective, the adoptions in the AD scenario can be understood as the maximum possible BEV diffusion path under contingent conditions. The BAU and AD scenarios are based on the same policy measures, as stipulated by Law 178/2020, which states that the measures supporting the automotive sector will stay in force until 2030. At the end of each scenario, a quantitative assessment of the Italian e-fleet by 2030 is provided.

5.1 Battery electric cars in Italy by 2030: a literature review

According to Motus-E et al. (2023), annual sales of electric vehicles in Europe will increase from 1.5 million to 12 million in the decade 2020-2030; from 0.07 to 1.13 in Italy. This trend corresponds to a CAGR (compound annual growth rate) of 23% for Europe and 32% for Italy. In Motus-E (2021), Italy's e-fleet (BEVs and plug-in hybrids) is expected to grow from 0.099 million to 5.3 million between 2020 and 2030. In 2023, the Smart Mobility Report of the Politecnico di Milano laid out three scenarios for the deployment of electric mobility by 2025 and 2030: BAU (business-as-usual), PD (policy-driven) and FD (fully decarbonised). Depending on the scenario, the number of battery electric and plug-in hybrid cars in the Italian fleet is expected to reach 1.1 million (BAU), 1.5 million (PD) or 1.7 million (FD) in 2025; 3.8 million (BAU), 6.6 million (PD), 7.8 million (FD) in 2030. Franceschini et al. (2021) propose two growth scenarios for BEVs up to 2030. In the “baseline growth” scenario, the Italian fleet will consist of 2.7 million BEVs by 2030; 3.5 million in the “accelerated growth” case. According to Motus-E et al. (2022), battery electric cars will account for 27% of new registrations by 2030. In this case, the authors focus on the factors that influence the propensity of consumers to buy an electric car, and therefore price plays a crucial role: the (stated) propensity to buy an electric model increases by 10% for prices above €49,000, up to 87% for prices below €21,000. Finally, Rie and Unem (2022) propose two scenarios - RSE FF55 and SA FF55 - which are both compatible with the objectives of Fit-for55. The first scenario foresees 6.2 million battery electric cars in 2030. The second, which the authors themselves consider more plausible given the dynamics of recent years, assumes 1.7 million BEVs in 2030. Despite the heterogeneity of the figures, there is a tendency for the most recent works to moderate earlier projections (Table 4).

Table 4. Summary of projections for the Italian e-fleet up to 2030.

Author	Type of aggregate	Value
Motus-E (2021)	BEV in the fleet	4.4 million BEV
Franceschini et al. (2021)	BEV in the fleet	Basic growth: 2.7 million BEV (±200,000) Accelerated growth: 3.5 million BEV
Motus-E and Quintenergia (2022)	New registrations of BEV	27% of new registrations
RiE and Unem (2022)	BEV in the fleet	RSEFF55: 6.2 million BEV SAFF55 1.7 million BEV
Motus-E et al. (2023)	Sales of BEV	1.127 million BEV
Politecnico di Milano (2023)	BEV & plug-in hybrids in the fleet	Business as usual: 3.8 million Policy-driven: 6.6 million Fully decarbonised: 7.8 million

5.2 Potential adopters and projections of the Italian e-fleet in the BAU scenario

The historical diffusion dynamics calculated in Section 4 are extended from June 2024 to December 2030 to obtain the cumulative penetration in Figure 6 (N_t). In the absence of changes and assuming that post-2023 battery electric cars are as satisfactory as pre-2023 ones, by 2030 the Italian BEV market will reach the saturation level: all 320,000 individuals (private and companies) who are willing to purchase a battery electric car will have made (at least) one purchase.

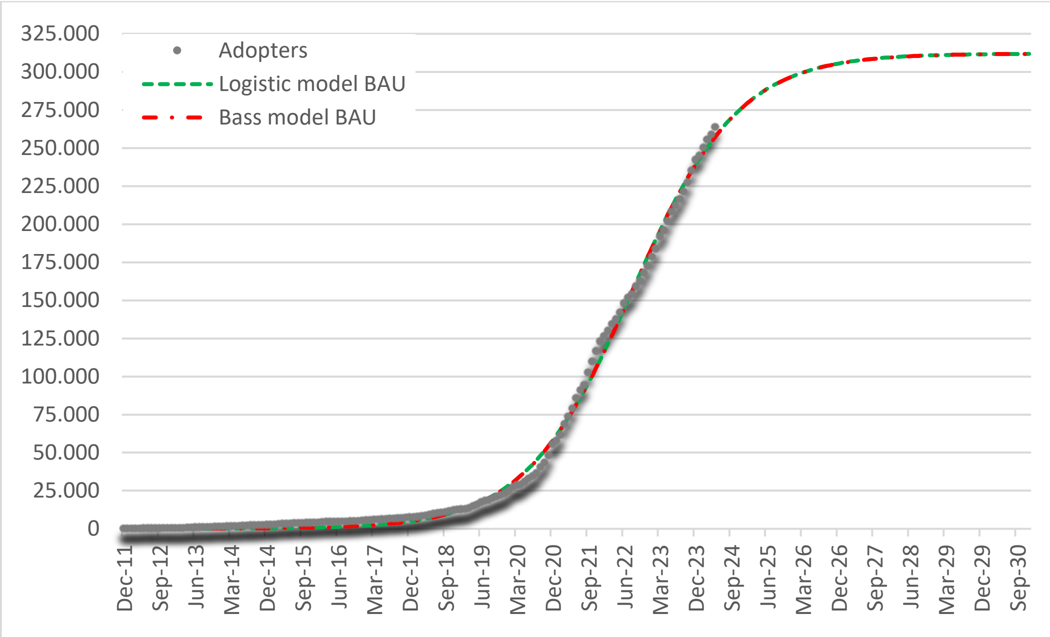

Figure 6. Cumulative out-of-sample diffusion forecast of battery electric cars in BAU scenario.

In order to quantify the Italian electric fleet by 2030 in the BAU scenario, it is necessary to refine the above information with data on the usage habits of electric car buyers. This data should include information on the frequency with which they are willing to replace their car and the point in time at which electric cars are going to be definitively scrapped. Once again, we cannot rely on historical data: BEV series are too short. In addition, there would seem to be significant differences in usage patterns between electric car and ICE owners; therefore, it is not possible to extend the dynamics observed for conventional powertrains to BEVs. The available data indicate that the main purchasers of battery electric cars are legal entities. It is well established that societies have a faster car turnover rate than privates. This indicates that the initial purchasers of battery electric vehicles may repeat their purchase every 36-48 months. It is unlikely (and inadvisable) that a 36-48 month old BEV will be removed from the fleet; it is more probable that it will be sold on the second-hand market. The question then arises as to how long they will remain operational. According to ACEA, the average age of cars in the Italian fleet is 12 years and a few months. There is no guarantee that battery electric cars will have a similar lifespan. Since car manufacturers offer 8-year warranties on the batteries of new electric cars, it might be plausible to assume that electric cars have an average lifetime of 10 years. If usage patterns of electric car users are as above, the BAU diffusion path would result in almost 0.6-0.75 million battery electric cars in the Italian fleet by 2030. Lower (higher) scrappage rates or shorter (longer) turnover will lead to higher (lower) figures. The saturation level and the time horizon over which it will be reached provide an indication for carmakers and policymakers, among others, of the number of potential (and residual) first-time buyers of BEV models. In the BAU scenario, battery electric cars do not appear to be a compelling alternative to ICEs.

5.3 Potential adopters and projections of the Italian e-fleet in the AD scenario

The AD scenario assumes that the diffusion trajectory of non-plug-in hybrid cars will be extended to post-2023 BEV models. Consequently, the initial step is to determine the diffusion trajectory of non-plug-in hybrid models. Table 4 shows the BM and LM coefficients estimated via the NLS method on new monthly registrations of non-plug-in hybrid cars over the period 1/1/2011 to 31/5/2024. As with battery electric cars, the data were obtained from monthly reports published by UNRAE. The application of the coefficients presented in Table 4 to post-2023 data yields the cumulative projection represented in Figure 7. The value at 2030 is just under 700,000, which is more than twice the cumulative adopters in BAU. Furthermore, in the AD scenario, only 7% of potential buyers have made their first purchase by December 2030. This implies that there would be still 93% residual first-purchases. In the absence of further shocks, according to the AD scenario, the adoption peak should be reached between 2033 and 2035, while market saturation could occur between 2040 and 2045.

Table 4. The NLS fit of Bass and Logistic models' parameters for non-plug-in hybrids, mean absolute deviation (MAD) and mean absolute percentage error (MAPE).

	R^2	*M*	*p*	*q*	*a*	*b*	*MAD*	*MAPE*
Logistic	*0.9988*	*5,384,584*			*2.34*	*157 (12/2024)*	*16,601.3471*	*44.6417*
Bass	*0.9991*	*5,620,381*	*0.0000055*	*0.0042*			*17,936.8284*	*15.7895*

Assuming, as before, a turnover rate of BEV owner of 36-48 months and an average life time of 10 years for BEV models, the AD diffusion path would be consistent with 1,2-1,4 million battery electric cars in the Italian fleet by 2030.

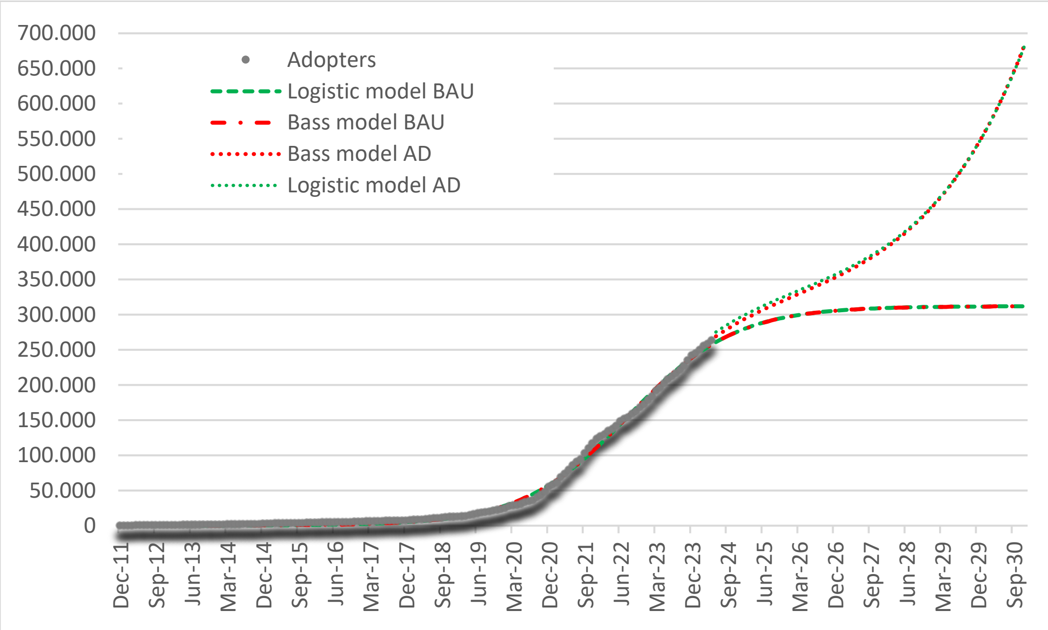

Figure 7. Cumulative out-of-sample diffusion forecast of battery electric cars in AD scenario.

Although the market potential is considerably higher than in the BAU scenario, the effects on the vehicle fleet in 2030 remain limited. The low innovation coefficients characterising the Italian market and the late entry of new BEV models (late with respect to NECP timeline) are in stark contrast with ambitious and urging policy objectives.

6. Final remarks and policy recommendations

While deep-diving into the current state and market potential of electric vehicle adoption in Italy, our study reveals several challenges in achieving the targets set by the National Energy and Climate Plan (NECP) for 2030.

Based on new registration data, our forecasts for first-time purchases indicate that battery-electric passenger cars are struggling to become an attractive option for consumers. This lack of enthusiasm for BEVs suggests a structural diffidence towards electric vehicles among Italian consumers. As things stand, the policy goals seem to be poorly anchored in the current reality of the automotive market and risk being missed if not accompanied by far-reaching policy action and, even more, by new electric models with features that meet consumer preferences.

Policymakers must assess the reasons behind this reluctance, outlining a clear and realistic roadmap to build consumer confidence and encourage the adoption of electric vehicles. Among the supporting measures, we believe that work should be done on incentives for the purchase of second-hand BEVs, which are not offered today.

An aspect that cannot be overlooked is that the Italian market shows greater sensitivity to hybrid EVs and alternative fuels. In June 2024, when this work was finished, the number of new BEV registrations reached an all-time high of 13,415, due to new incentive schemes brought forward by the Italian government. As these were implemented later than the initially announced date, we argue that this outstanding figure is the result of a build-up of orders, more than of a structural change in the BEV market. In fact, it should be noted that - albeit with much lower incentives than BEVs - registrations of LPG and hybrid cars also rose sharply in the same period. As an example, the Fiat Panda, the best-selling car in Italy since 2012 and since 2020 also a best-selling hybrid, has nearly doubled its registrations in June 2024 compared to June 2023. In line with our assumptions, we reiterate that the mass deployment of BEVs could only take place if more popular car models emerge. However, we note that the marketing of the hybrid Panda has been extended first to 2027 and then to 2030. At the same time - after the unsuccessful launch of the electric 500, a 500 hybrid is planned to start production between late 2025 and early 2026.

Policymakers should recognize this preference and reframe environmental strategies to include other options alongside electrification efforts. This approach could involve initiatives to reduce the total number of vehicles and consider alternative fuel sources.

References

ACEA (2024). Vehicles on European roads. February 2024.

Ayyadi, S. and Maaroufi, M. (2018). Diffusion models for predicting electric vehicles market in Morocco. In: 2018 international conference and exposition on electrical and power engineering (EPE). IEEE; 2018, 46-51.

Al-Alawi, B. M., and Bradley, T. H. (2013). Review of hybrid, plug-in hybrid, and electric vehicle market modeling Studies. *Renewable and Sustainable Energy Reviews*, *21*, 190–203.

Bass, F. M. (1969). A new product growth for model consumer durables. Management Science, 15(5), 215-227.

Bento, A., Roth, K., and Zuo, Y. (2018). Vehicle Lifetime and Scrappage Behavior: Trends in the U.S. Used Car Market. The Energy Journal, 39(1), 159-184.

Berger, R. D. (1981). Comparison of the Gompertz and Logistic Equations to describe plant disease progress. The Florida Agricultural Experiment Station, 71(7), 716-719.

Bitencourt, L., Abud, T., Santos, R. and Borba, B. (2021) Bass diffusion model adaptation considering public policies to improve electric vehicle sales – A Brazilian casa study. Energies 14 (17) 5435.

Bonacina, M., Sileo, A. (2024). 'The automotive industry: when regulated supply fails to meet demand. The Case of Italy. Nota di Lavoro 01.2024, Milano, Italia: Fondazione Eni Enrico Mattei.

Bui, K. H. N., Cho, J., and Yi, H. (2022). Spatial-temporal graph neural network for traffic forecasting: An overview and open research issues. *Applied Intelligence*, *52*(3), 2763–2774.

Campbell, B. G. (2015). Diffusion of innovations of videoconference technology: An instrumental case study concerning undergraduate degree-seeking nontraditional learners. Nova Southeastern University. Fischler College of Education: Theses and Dissertations.

Dhakal, T., Min, K.S. and Lim, D.E. (2021) Macro analysis and forecast of global expansion of electric vehicles. Foresight STI Gov 2021;15(1), 67-73.

Ensslen, A., Will, C. and Jochem, P. (2019) Simulating electric vehicle diffusion and charging activities in France and Germany, World Electric Vehicle Journal, 10, 73.

Franceschini D., Cirimele V., Longo M., 2021, Analysis of Possible Scenarios on the Future Development of Electric Mobility: Focus on the Italian Context, AEIT International Annual Conference, 10/2021.

Greenspan, A., and Cohen, D. (1999). Motor Vehicle Stocks, Scrappage, and Sales. The Review of Economics and Statistics, 81(3), 369–383.

Held, M., Rosat, N., and Georges, G., 2021, Lifespans of passenger cars in Europe: empirical modelling of fleet turnover dynamics. Eur. Transp. Res. Rev. 13, 9.

Huang, J., Cui, Y., Zhang, L., Tong, W., Shi, Y. and Liu, Z., 2022, An Overview of Agent-Based Models for Transport Simulation and Analysis, Journal of Advanced Transportation, 2022, 1252534, 17 pages.

Jovanović, R., Sretenović, A. A., & Živković, B. D. (2015). Ensemble of various neural networks for prediction of heating energy consumption. *Energy and Buildings*, *94*, 189–199.

Konstantinos, S. and Vasilios, S. (2011). A new empirical Model for short-term forecasting of the broadband penetration- A short research in Greece. Hindawi Publishing Corporation, 1-10.

Kumar, R.R., Guha P. and A. Chakraborty, 2022, Comparative assessment and selection of electric vehicle diffusion models: A global outlook, Energy, Volume 238, Part C, 2022, 121932, ISSN 0360-5442.

Lamberson, P.J. (2009) The diffusion of hybrid electric vehicles, Center for the Study of Complex Systems. University of Michigan, Ann Arbor, MI, 2009.

Lee, S., Marcu, M. and Lee, S. (2011). An empirical analysis of fixed and mobile broadband diffusion. Information Economics and Policy, 23(3-4), 227-233.

Liao, F., Molin, E., and van Wee, B., (2016), Consumer preferences for electric vehicles: a literature review. Transport Reviews, 37(3), 252–275.

Lieven, T., Mühlmeier, S., Henkel, S., & Waller, J. F. (2011). Who will buy electric cars? An empirical study in Germany. *Transportation Research Part D: Transport and Environment*, *16*(3), 236–243.

Mahajan, V., and Sharma, S., 1986, Simple algebraic estimation procedure for innovation diffusion models of new product acceptance. Technological Forecasting and Social Change, 30, pp. 331-346.

Michalakelis, C., Varoutas, D. and Sphicopoulos, T. (2008). Diffusion models of mobile telephony in Greece. Telecommunication Policy, 234-245.

Montavon, G., Samek, W., & Müller, K. R. (2018). Methods for interpreting and understanding deep neural networks. *Digital Signal Processing*, *73*, 1–15.

Motus-E, Strategy& and Politecnico di Milano, 2023, Report, Il riciclo delle batterie dei veicoli elettrici @2050: scenari evolutivi e tecnologie abilitanti, 3/2023.

Motus-E & Quintegia Spa, 2022, La mobilità elettrica: inevitabile o no? Analisi dal punto di vista dei consumatori, 2/2022.

Motus-E, 2021, PNRR e infrastruttura di ricarica per la mobilità elettrica in Italia @2030: opportunità e indirizzi strategici, 10/2021.

Oguchi, M., & Fuse, M. (2015). Regional and longitudinal estimation of product lifespan distribution: A case study for automobiles and a simplified estimation method. Environmental Science and Technology, 49(3), 1738–1743.

Politecnico di Milano, 2023, Smart Mobility Report 2023. La "via italiana" per la decarbonizzazione dei trasporti nel nuovo scenario geo-politico internazionale, 2023.

Qian, L. and Soopramanien, D. (2014) Using diffusion models to forecast market size in emerging markets with applications to the Chinese car market. Journal of Business Resources, 67(6), 1226-1232.

Robinson, L. (2009). A summary of diffusion of innovations. Enabling Change. Retrieved from

Rie – Ricerche Industriali ed Energetiche e Unem – Unione Energie per la Mobilità, 2022, Decarbonizzare i trasporti. Più soluzioni per un obiettivo comune, Studio 7/2022

Rietmann, N., Hügler, B., & Lieven, T. (2020). Forecasting the trajectory of electric vehicle sales and the consequences for worldwide CO_2 emissions. *Journal of Cleaner Production*, *261*, 121038.

Rogers, E. M. (1976). New product adoption and diffusion. Journal of Consumer Research, 2, 336-347.

Rogers, E. M. (1983). Diffusion of innovations (3rd ed.). New York: The Free Press, A Division of Macmillan Publishing Co.

Rogers, E. M. (2003). Diffusion of innovations (5th ed.). New York: Free Press.

Rozemberczki, B., Scherer, P., He, Y., Panagopoulos, G., Riedel, A., Astefanoaei, M., Kiss, O., Beres, F., López Tryolabs Uruguay, G., Collignon, N., Sarkar, R., and López, G. (n.d.). PyTorch Geometric Temporal: Spatiotemporal Signal Processing with Neural Machine Learning Models CCS CONCEPTS. *Virtual Event*.

Srinivasan, V., and Mason, C. H., 1986, Nonlinear least squares estimation of new product diffusion models. Marketing Science, 15(4), pp. 169-178.

Trappey, C. V. and Wu, H.-Y. (2008). An evaluation of the time-varying extended logistic, simle logistic, and Gompertz models for forecasting short product lifecycles. Advanced Engineering Informatics, 421-430.

Turk, T. and Trkman, P. (2012). Bass model estimates for broadband diffusion in European countries. Technological Forecasting & Social Change, 79(1), 85-96.

Zhu, Y., Tokimatsu, K. and Matsumoto, M. (2015), A diffusion model for natural gas vehicle: a case study in Japan, Energy Procedia, 75, 2987-2992.

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