Simulating electric vehicle uptake in Italy in the small-to-medium car segment: A system dynamics/agent-based model parametrized with discrete choice data.

Mariangela Scorrano[a,b,*], Romeo Danielis[a,b]

[a] Dipartimento di Scienze Economiche, Aziendali, Matematiche e Statistiche "Bruno de Finetti", Università degli Studi di Trieste, Via Valerio n. 4/1 - 34127 Trieste, Italy
[b] Centro Interdipartimentale per l'Energia, l'Ambiente e i Trasporti Giacomo Ciamician, Trieste, Italy

ARTICLE INFO

Keywords:
Electric car
Simulation
Supply-demand model
Agent-based model
System dynamics model

ABSTRACT

The main goal of the paper is to provide a simulation of the potential uptake of electric vehicles in Italy up to the year 2030, as a base for transport and energy planning by public and private decision makers. We develop a hybrid model, integrating an agent-based approach for the demand module and a system dynamics approach for the supply module. The demand module is parametrized with data derived from a discrete choice survey to car users ($N = 1521$), representative of the Italian population. The supply module interacts with the demand module and incorporates the available data on the evolution of battery production costs. Because of the characteristics of the choice data, the model is parametrized with data relative to the small-to-medium sized car segment only, and does not include PHEVs. Word-of-mouth and advertisement induce a growing number of potential buyers to include BEVs in their choice set. Car buyers choose between the two propulsion systems based on the relative utility. We estimate that in the period 2019–2030 BEVs will gradually overtake conventional vehicles (CVs) in Italy. In terms of annual sales, the share of BEVs will be equal to that of CVs in July 2030. By the end of 2030, BEVs will represent 52.4% of new sales. A total fleet of almost 5 million BEVs will be on the Italian roads by 2030, i.e. about a sixth of the Italian car fleet. Scenario analyses lead us to conclude that BEV subsidies are important but that they are likely sub-optimal.

1. Introduction

The main goal of this paper is to provide a simulation of the potential uptake of electric vehicles in Italy up to the year 2030, as a base for transport and energy planning by public and private decision makers.

The transport sector is responsible for a large share of greenhouse gas (GHG) emissions. At European level, the transport sector generated 27% of total EU-28 GHG emissions in 2017, 71.7% of which caused by road transport. Passenger cars contributed 44.3% of the total road transport, heavy-duty trucks and buses 19.2%, light duty trucks 8.7% and motorcycles 0.9% (EEA, 2019b). In the period 1990–2017, Italy increased its GHG emissions by 3.9%.

To reduce GHG emissions in general and in transport specifically, the EU has enacted several pieces of legislation. The Renewable Energy Directive (2009/28/EC) established an overall policy for the production and promotion of energy from renewable sources in the EU. The recast Renewable Energy Directive (2018/2001/EU) reinforced the goals and obligations, in accordance with the Paris agreement. Among other requirements, the Directive set a 14% target for the share of renewable fuels to be consumed by transport by 2030. Each Member State is required to submit a National Energy and Climate Plan for the 2021–2030 period, outlining the policies they will enact to reach the preset goals. Italy submitted a plan based on two main strategies: the introduction of higher blending levels of biofuels (biodiesel, bioethanol, biomethane) and the electrification of the car fleet.

Although the amount of electricity produced using renewable sources to be used in transport sector in the years 2025 and 2030 is quantified, the path of diffusion of electric vehicles in Italy has not been explicitly modelled and quantified.

A second important obligation of the Italian transport authorities is to reduce local air pollution in urban areas. Italy is characterized by worrying concentration levels of NOx, O3, PM10 and PM2.5, frequently

---

* Corresponding author at: Dipartimento di Scienze Economiche, Aziendali, Matematiche e Statistiche “Bruno de Finetti”, Università degli Studi di Trieste, Via A. Valerio, 4/1, 34127 Trieste, Italy

E-mail addresses: mscorrano@units.it (M. Scorrano), romeo.danielis@deams.units.it (R. Danielis).

exceeding the recommended limits set by Directive 2008/50/EC for the protection of human health. EEA (2019) estimates that in Italy there were a total of 1183 years of life lost per 105 inhabitants (908 due to PM2.5, 227 due to NOx, and 48 due to O3 exposure) against a EU28 average of 930. Since electric vehicles have the potential to reduce drastically air pollution, at least in the urban areas, national and local authorities face the challenge to develop policies that facilitate electric vehicle uptake. Because of the interdependence between electromobility and electricity production and distribution, the challenge is complex and multi-faceted.

At national level, the governments have to set up the proper regulatory and fiscal policies to promote the diffusion of electric vehicles and the construction of a dense public charging network with the appropriate mix of fast and low charging stalls, while at local level regional and city authorities have the task to integrate them in their city transport plans. In parallel, the energy sector should strive for a “clean” electricity mix in order to reduce CO_2 emissions and the energy providers should strengthen and modernize the energy distribution infrastructure in order to cope with the growing electricity demand. The automotive sector and its entire supply chain is also challenged by the need to significantly alter their manufacturing process, produce or source vehicles’ batteries, develop the proper disposal or reuse processes and extract the needed raw materials (lithium and other rare materials).

The simulation results presented in this paper might provide a guide to the above discussed public and private decision makers. Our aim is to develop a model drawing from the previous literature and attempting to integrate demand and supply features.

The demand module adopts the agent-based modelling (ABM) approach and is parametrized with data derived from an empirical survey. A sample of individuals ($N = 1521$), representative of the Italian population, have been asked to report and state their choices among a petrol and a battery electric car with a full characterization of their size, brand, purchase price, fuel economy, driving range. The choice scenarios included the density of the charging network and the hours of free parking. The choice data are analyzed using the discrete choice modelling techniques, accounting for the socio-economic characteristics of the respondents.

The supply module adopts the system dynamics approach; it interacts with the demand module and incorporates the available data on the evolution of battery electric vehicle (BEV) production costs. From a methodological point of view, hence, our model can be described as a SD/ABM model, integrating the agent-based and system dynamics approach. Because of the characteristics of the choice data, our model is parametrized with data referring to the small-to-medium sized car segment only, disregarding PHEVs, which often belong to higher car market segments.

After the usual validation, the model is used to estimate the reference scenario and to perform a scenario analysis on the impact on the BEV diffusion path of different subsidy regimes and of the introduction of a carbon tax on fuel.

Besides being, to the best of our knowledge, the first paper to simulate BEV uptake in Italy, this paper contributes to the literature by grounding the demand module on the car drivers’ preference structure, estimated using discrete choice modelling techniques on revealed/stated-choice data collected from a representative sample of Italian car drivers. In our view, this represents an improvement over models based on synthetic indicators or part-worth utilities derived from conjoint data (e.g., Klein, Lüpke, & Günther, 2020; Zhang, Gensler, & Garcia, 2011). A second contribution is the attempt to model both the demand and the supply sides of the market, capturing as much as possible their interaction, along the lines suggested by Gómez Vilchez and Jochem (2019).

The paper includes a related literature Section, a description of the discrete choice experiment (Section 3), a presentation of the simulation model (Section 4), an illustration of the reference scenario (Section 5), a policy scenario analysis (Section 6) and a discussion and conclusion Section.

2. Related literature

2.1. Agent-based modelling

Agent-based models (ABMs) aim at capturing the complex interaction among agents (e.g., consumers, sellers, distributors) whose motivations and actions combine resulting in surprising micro- and macro-patterns. Agents are characterized by researchers as having own properties and behaviors, including sending signals to/receiving signals from other agents. Hence, they learn, adapt and modify their choices based on the information and messages they are exposed to.

As Rand and Rust (2011) pointed out, ABMs are particularly appropriate when there is a large number of heterogeneous agents so that agents themselves cannot be modelled using a representative agent. Moreover, ABMs allow for the development of a virtual environment characterized by local information and complex interactions, which cannot be handled with the tools of game theory. In addition, ABMs can be developed for specific geographical settings, ranging from simple as two-dimensional abstract spaces to more realistic spaces derived from geographic information systems (Brown, Riolo, Robinson, North, & Rand, 2005; Heppenstall, Crooks, See, & Batty, 2012) or networked-based spaces based on social network analysis (Carley, 1996).

Furthermore, ABMs are well suited for examining how systems change over time allowing the researcher to examine the dynamics that give rise to different equilibrium states (e.g., how consumers react to an information and process their choice decisions). Consequently, they differ fundamentally from other simulation approaches, such as differential equation models and system dynamics models, which describe the diffusion of new technology/products mainly at the aggregate level without considering the heterogeneity of actors and the underlying social structure.

Given their properties, ABMs have been used in many sciences, including economics (Caiani et al., 2016; Tesfatsion, 2002), transport studies (Wang, Mostafizi, Cramer, Cox, & Park, 2016), medicine (Folcik & Orosz, 2006), population dynamics (Pablo-Martí, Santos, & Kaszowska, 2015), geographical systems (Heppenstall et al., 2012), land-use changes (Rindfuss et al., 2008), risk analysis (Haer, Botzen, de Moel, & Aerts, 2017), innovation diffusion (Palmer, Sorda, & Madlener, 2015), energy systems (Ernst & Briegel, 2017) and also in archeology (Wurzer, Kowarik, & Reschreiter, 2015).

With reference to the automotive sector and specifically to the adoption of alternative fuel cars, ABMs proved a valuable modelling tool. A categorization of a selected number of studies is illustrated in Table 1.

ABMs were initially used to model car choice among conventional vehicles (CVs) to capture the complexity of choice determinants and the heterogeneity of the decision makers (Mueller & de Haan, 2009). Subsequently, various papers (Cui et al., 2010; Eppstein, Grover, Marshall, & Rizzo, 2011; Sullivan, Salmeen, & Simon, 2009) examined the prospects of PHEVs and HEVs uptake, introducing charging issues and their impact on the electric infrastructure, and the role of social networks in stylized geographical context.

The NetLogo software provided a sufficiently user-friendly environment to master the complexities of the programming tasks. Choice and demand data were mainly derived from aggregate sources developing synthetic agents from population characteristics. Zhang et al. (2011) presented a pioneering attempt to model demand on the basis of choice-based conjoint data derived from a specific survey ($N = 7595$), including a word-of-mouth adjustment factor. Together with Sullivan et al. (2009), Zhang et al. (2011)’s ABM explicitly models car manufacturers’ decisions. Using an external module, car manufacturers alter the design parameters (vehicle design, fuel type, engine power, and aluminum content) of vehicle offerings. Subsequent contributions (Shafiei et al., 2012; Brown, 2013; McCoy & Lyons, 2014; Querini & Benetto, 2014; Cho & Blommestein, 2015) paid growing attention to model demand by specifying detailed rule choices. Although they referred to the economic

Table 1
Review of the papers dealing with agent based models to investigate the uptake of BEVs.

Author/s	Agents	Propulsion systems other than CVs	Demand data	Region	Social network	Geographical network	Charging infrastructure	Car Supply	Software
Mueller and de Haan (2009)	Households		Discrete choice model from the literature	EU	No	No	No	No	n.a.
Sullivan et al. (2009)	Consumers, government, fuel producers and vehicle producers/dealers	PHEV, HEV	Constant budget assumption	US	No	No	No	Yes	NetLogo
Cui et al. (2010)	Households	PHEV, HEV	Synthetic agents from population characteristics	Knox County, TN	Yes	Yes	Yes	No	NetLogo
Eppstein et al. (2011)	Consumers	HEV, PHEV	Synthetic agents from population characteristics	Virtual US space	Yes	Yes	No	No	n.a.
Zhang et al. (2011)	Consumer, manufacturer, government, vehicle	HEV, AFV	Choice-based conjoint data ($N = 7595$)	US	Yes	Yes	No	Yes	n.a.
Shafiei et al. (2012)	Consumers	BEV	Danish data on preference weights	Iceland	No	No	No	No	n.a.
Brown (2013)	Consumers	BEV, PHEV	2009 National Household Travel Survey	Boston MA MSA	Yes	No	No	No	n.a.
McCoy and Lyons (2014)	Households	BEV	Income utility and environmental utility	Ireland	Yes	Yes	No	No	Matlab
Querini and Benetto (2014)	Households	BEV, PHEV	Personal attitude, ecological perception and economical motivation	Luxembourg and Lorraine	Yes	Yes	Yes	No	NetLogo
Cho and Blommestein (2015)	Households	BEV	Monthly costs	n.a.	Yes	No	No	No	NetLogo
Wolf et al. (2015)	Individuals	Bicycle, car, public transport, BEV, car sharing	Network of constraints, emotional coherence	Berlin, Germany	Yes	No	No	No	InnoMind
Yang et al. (2015)	Consumers, manufactures, government, charger operator, grid operator, gas suppliers	BEV	System dynamics and ABM	China	No	No	No	No	Vensim
Choi (2016)	Consumers, manufacturers, fuel suppliers and government	HEV	Costs	Seoul	No	Yes	No	No	n.a.
Noori and Tatari (2016)	Consumers, regions, governments, and vehicles	BEV, HEV, EREV, PHEV	From previous studies	USA	Yes	Yes	Yes	No	AnyLogic
Silvia and Krause (2016)	Initial BEV drivers and non-BEV drivers	BEV	Synthetic agents from population characteristics	USA	No	No	No	No	NetLogo
Adepetu and Keshav (2017)	Potential buyers	BEV	National Renewable Energy Laboratory's secure transportation data project	Los Angeles, CA	Yes	Yes	Yes	No	n.a.
Wojnarová (2017)	Vehicles	BEV	Cost-benefit approach	Czech Republic	No	Yes	Yes	No	NetLogo
Kangur et al. (2017)	Consumers	BEV	Large-scale national internet-based questionnaire	Netherlands	Yes	Yes	Yes	No	Repast Simphony 2.1
Ahkamiraad and Wang (2018)	Zip code	BEV	Synthetic utility function, word of mouth, Rogers' adoption categories	New York City	Yes	Yes	Yes	No	n.a.
Ramsey, Kowalska-Pyzalska, and Bienias (2018)	Consumers	BEV	Survey on purchasers of new cars	Wrocław and Katowice, Poland	Yes	Yes	No	No	n.a.
Yang et al. (2018)	Synthetic heterogeneous consumer	PEV	Parameters from regional statistical yearbook	Urban area	Yes	Yes	Yes	No	n.a.
	A worker group and a student group	BEV	Questionnaire surveys	Shanghai, China	Yes	Yes	No	No	Matlab

(*continued on next page*)

Table 1 (*continued*)

Author/s	Agents	Propulsion systems other than CVs	Demand data	Region	Social network	Geographical network	Charging infrastructure	Car Supply	Software
Ning, Guo, Liu, and Pan (2019)									
Sun et al. (2019)	Consumers, vehicles, firms	BEV	Data from government departments, existing literature, and reality-based assumptions	USA	No	No	No	Yes	Matlab
Zhuge, Wei, Dong, Shao, and Shan (2019)	Consumer, government and manufacturer	BEV, PHEV	Activity-based travel demand model	Beijing, China	Yes	Yes	No	No	SelfSim
Klein et al. (2020)	Vehicles, consumers, producers, government	BEV	Choice-based conjoint data ($N = 552$)	Germany	Yes	No	Yes	No	AnyLogic
Vouzavalis (2020)	Car manufacturers, customers, dealers	BEV	Hypothetical scenarios on consumers' weights	Europe	Yes	No	No	Yes	AnyLogic
Buchmann, Wolf, and Fidaschek (2021)	Households, vehicle	BEV, PHEV	Computational lab cost–utility analysis	Germany	Yes	Yes	Yes	No	NetLogo
Scorrano and Danielis (this study)	Car buyers, car industry	BEV, CV	Revealed and stated preference data (N = 1521)	Italy	Yes	No	No	Yes	AnyLogic

concept of utility theory, these contributions used a combination of heuristics, cost analysis and weights derived from the literature. Wolf, Schröder, Neumann, and de Haan (2015) examined a set of network constraints and extended the analysis of psychological and attitudinal aspects developing the notion of emotional coherence.

In parallel with BEV market diffusion, BEVs became an essential part of the considered vehicles' choice set, and issues such as driving range limitations, charging time and charging infrastructure became more prominent within ABMs. Noori and Tatari (2016) modelled CO_2 potential reductions and the role of policy makers setting up fiscal policies to alleviate transport's environmental issues.

The number of available software progressively increased, including InnoMind, Vensim, Matlab, SelfSim and Anylogic.

Among the recent contributions, Kangur, Jager, Verbrugge, and Bockarjova (2017) derived car demand characteristics from aggregate or synthetic data, while Zhang et al. (2011) and Klein et al. (2020) collected *ad hoc* choice-based conjoint data ($N = 552$, mostly young Germans) to estimate the weights of a set of attributes (engine type, purchase price, consumption cost, station density, station charging time, driving range, home charging possibility) of the utility function.

With regards to the supply side of the market, few papers attempted to incorporate car manufacturers in the ABM and to model their behavior. Sullivan et al. (2009) considered both new and used cars. However, car manufacturers were not supposed to adjust new car sale prices based on demand and inventory, while in the case of used cars, they did it in every cycle. In Zhang et al. (2011), manufacturers decide upon engine type, fuel economy, vehicle type, and price in order to maximize the profit function analytically provided by Michalek, Papalambros, and Skerlos (2004).

Sun, Liu, Wang, and Yuan (2019) assumed the existence of only two kinds of firms competing in the automobile market: CV firms incumbents and BEV potential entrants. The technology frontiers are uniform within each propulsion type, while heterogeneous products result from firms' differentiated R&D efforts. Firms' decisions on entry and exit, R&D investment and production investment are modelled in detail and parametrized using U.S. data. They were able to simulate dynamics of the BEV industry in the U.S. over 40 years, from 2010 to 2050.

Finally, Vouzavalis (2020) considered three typical car manufacturers ("Volkswagen", "Toyota" and "Tesla") with differing strategies with regards to BEVs. Focusing on some important technical and financial characteristics of the vehicles, they illustrated the expected base price developments of the vehicles over the years and the corresponding production cost. Their model incorporates the European fleet regulations and the possible fines when the given fleet CO_2 quotas are not reached. As a result, they derived the R&D expenses, the investment budgets and profits for each of the three selected car manufacturers. Consumers via a scoring mechanism evaluate the vehicles supplied.

2.2. System dynamics modelling

System dynamics (SD) models aim at describing the behavior of complex systems over time. The SD modelling approach captures delays, feedbacks and disequilibrium dynamics (Sterman, 2000). Forrester (1961) is the seminal work of SD. In transport research, Abbas and Bell (1994) were the first who discussed the strengths and weaknesses of the method (Abbas & Bell, 1994). Shepherd (2014) and Jochem, Gómez Vilchez, Ensslen, Schäuble, and Fichtner (2018) illustrated the potential of the SD method to study the market uptake of alternative fuel vehicles. Nieuwenhuijsen, de Correia, Milakis, van Arem, and van Daalen (2018) developed a model to simulate the innovation diffusion of automated vehicles in the Netherlands.

Gómez Vilchez and Jochem (2019) proposed a distinction between 'public policy-oriented' and 'automotive industry-oriented' SD-based studies. In the former, the focus in on policy questions while the latter centers on strategic business decisions in the automotive industry, though recognizing that some models display overlapping features. A well-known example of a 'public policy-oriented' model is the ASsessment of TRAnsport Strategies (ASTRA) model, developed since 1997 (Fiorello, Fermi, & Bielanska, 2010). The model covers European countries and a module devoted to the vehicle stock contains eight car technologies. Another important example is the Powertrain Technology Transition Market Agent Model (PTTMAM) that encompasses 16 different powertrains disaggregated by three vehicle sizes (Harrison, Thiel, & Jones, 2016). Four market agents with different decision rules are modelled: users, authorities, manufacturers and infrastructure providers. Another example of 'automotive industry-oriented' SD-based studies is Thies, Kieckhäfer, and Spengler (2016) who modelled market introduction strategies, powertrain improvements, timing of powertrain market commercialization and pricing decisions.

Ford (1995) is the first model that embedded a discrete choice structure in a SD model, while Struben and Sterman (2008) introduced the notion of willingness-to-consider in the SD framework.

However, Gómez Vilchez and Jochem (2019) pointed out that "the distinction between 'public policy-oriented' and 'automotive industry-oriented' SD-based studies is somewhat artificial, for an advanced understanding of the car market requires explicit consideration of a variety of demand-side and supply-side factors". They argue in favor of integrating SD modelling with discrete choice models incorporating the socio-economic characteristics of the consumers and ABM, for instance, modelling a small set of car manufacturers.

In this paper, we move along the lines suggested by Gómez Vilchez and Jochem (2019), developing a model that attempts to integrate a SD and an ABM but, contrary to their suggestion, we adopt the SD framework to model the supply side of the market (i.e. the car industry) and the ABM framework to model consumers' choice.

2.3. *Discrete choice modelling*

Discrete choice models play an important role in transportation modelling (Ben-Akiva & Lerman, 1985; McFadden, 1973; Train, 2009). They are used to analyze consumers' preferences and how these translate into rational consumers' choices. Consumers are assumed to choose the alternative with the maximal benefit or utility. With reference to electric vehicles, they have been used extensively in the last three decades.

Coffman, Bernstein, and Wee (2017) reviewed 50 studies, published up to the year 2015, all based on stated choices in hypothetical situations. They identified three main factors influencing BEV adoption: a) internal factors (vehicle ownership costs, driving range and charging time); b) external factors (fuel prices, consumer characteristics, charging networks, public visibility and social norms); and c) policy mechanisms (financial and non-financial incentives, supporting charging infrastructure, raising awareness).

More recently, Kumar and Alok (2020) reviewed 239 articles identifying five categories having an impact on BEV adoption: antecedents, mediators, moderators, consequences, and socio-demographics. They argued that, while topics such as charging infrastructure development, total cost of ownership, and purchase-based incentive policies have been the subject of numerous studies, other topics such as dealership experience, charging infrastructure resilience, and marketing strategies have been relatively neglected.

With reference to the Italian market, Valeri and Danielis (2015) conducted face-to-face interviews to a small sample ($N = 121$) of drivers asking them to state their choice among 7 alternative powertrain technologies, comparing 5 attributes: purchase price, annual operating cost, acceleration, driving range, and refueling distance. Using the same data, Valeri and Cherchi (2016) analyzed how the self-evaluated level of car expertise influences the choice between alternative powertrain technologies. Giansoldati, Danielis, Rotaris, and Scorrano (2018) conducted a survey in June 2017 interviewing a slightly larger sample ($N = 318$) of respondents, restricting the hypothetical choices to an electric and a petrol car. More recently, Danielis, Rotaris, Giansoldati, and Scorrano (2020) analyzed a stated preference survey collected in October–December 2018. They found a positive alternative specific constant for the BEV alternative, signaling a change in the perception of the Italian drivers towards BEVs. They estimated a lower willingness to pay for an additional driving range kilometer, indicating that Italian drivers are becoming more confident with the BEV driving range. Their scenario analyses reveal that in Italy financial incentives would have a larger impact on the probability of buying a BEV than technological improvements.

Most of the above-described stated-preference studies focus on eliciting and analyzing the consumers' preference structure, identify which observed and/or unobserved (latent) factors play a role or make cross-country or cross-temporal comparisons. Only few studies carry out scenario analyses (e.g., Cherchi, 2017; Giansoldati et al., 2018). None has been used so far to make medium-to-long run predictions.

2.4. *Goal of the study*

Our paper builds on the previous literature attempting to improve the following issues. Similarly to Zhang et al. (2011) and Klein et al. (2020), the buyers' preference structure is derived by an empirical survey, overlapping in part with that analyzed by Danielis et al. (2020). Instead of conjoint-based data deriving part worth utilities for the vehicles' attributes, our survey employs the discrete choice experiment approach using a large sample of individuals ($N = 1521$) representative of the Italian population, whom have been asked to report and state their choices among CVs and BEVs with a full characterization of their size, brand, purchase price, fuel economy, driving range. Furthermore, the alternatives included the density of the charging network and the hours of free parking. The data have been analyzed using the discrete choice modelling technique, accounting for the socio-economic characteristics of the respondents.

A second important feature of this paper is the attempt to develop a supply module, interacting with the demand module, and incorporating the available data on the evolution of the BEV production costs. Given the characteristics of the discrete choice data, our model will be parametrized with data referring to the small-to-medium sized car segment only, disregarding PHEVs that often belong to higher car market segments.

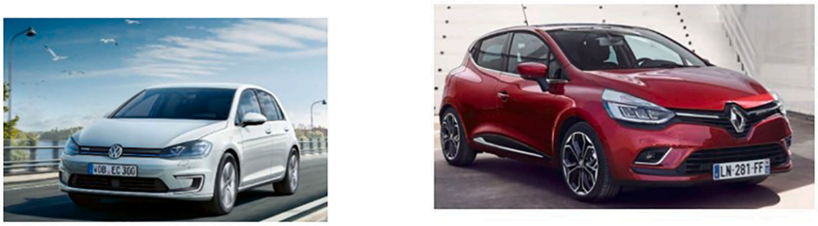
3. Discrete choice survey and econometric results

We collected choice data using a CAWI (Computer Assisted Web Interviewing) questionnaire, administered in the period October–December 2018 to a sample of the Italian population by SWG s.r.l., a Trieste-based company performing since 1981 market research, opinion and institutional polls, and sectoral studies. Overall, we interviewed 1763 individuals. Persons aged between 18 and 65 with a driving license were eligible to fill in the questionnaire. Individuals with lexicographic preferences have been excluded from the dataset. The survey resulted in 1521 valid interviews.

The questionnaire consisted of two parts. In the first part, respondents were asked to provide socio-economic data including personal information, car and garage availability, car mobility habits. The descriptive statistics of the sample are illustrated in SM 1.0. The sample includes respondents from 18 of the 20 Italian regions (the Aosta Valley and Molise are missing). All the regions have a representativeness accurate at ±10%. The distribution by city resembles the actual proportion for the medium sized cities, while small towns (under 10 thousand inhabitants) are under-represented (20% vs. 33%) to the advantage of the large towns (over 100 thousand inhabitants, 42% vs. 23%). The sample is balanced between women and men and is representative of the Italian population in terms of age distribution. Most of the respondents (51%) are white-collar workers with a high-school degree (42%) and earn a family income (less than €70,000 per year for 94% of the respondents) perceived as able to allow a comfortable lifestyle. Almost two thirds of the families own more than one car. Garage availability is high (more than 70%). Only a small percentage of respondents (0.3%) have a BEV. In terms of mobility habits, the large majority (83%) of our sample drives daily mileage well below the current BEV driving range (only 3% travel more than 100 km per day), but annual distances lower than 10 thousand km, thus hardly able to make BEVs cost-competitive with respect to CVs (Scorrano, Danielis, & Giansoldati, 2020; Wu, Inderbitzin, & Bening, 2015). Only a small number of respondents perform frequently (more than 10 times per year) round trips longer than 400 km. Hence, a dense network of fast charging stations is likely not perceived as a barrier for most of our sample, as well as the need of BEVs with longer driving ranges.

The second part of the questionnaire consisted of 12 hypothetical choice scenarios comparing each time a BEV and a petrol CV. An example of the choice task is shown in Fig. 1.

Respondents were asked to indicate in each scenario their preference



VW eGolf kWh 35.8 - Electric

Purchase price: € 33,000
Fuel economy (€/100 km): € 5
Driving range: 400 km
Fast charging time: 40’
Max distance between fast charging stations: 80 km
Free parking in urban areas: 3 hours

Renault Clio – Internal combustion

Purchase price: € 14,000
Fuel economy (€/100 km): € 5
Driving range: 400 km

Fig. 1. Example of the choice tasks proposed to the respondents.

taking into account specific characteristics of the cars. We selected 5 pairs among the best-selling BEVs in Italy in 2018 and compared them with their petrol counterparts. The BEVs are the BMW i3 125 kW 94 Ah, the Volkswagen e-Golf 2018, the Renault Zoe Life Q90, the Nissan Leaf 40 kWh Visia Plus and the Daimler Smart forfour Electric Drive Youngster. Their petrol equivalents are the BMW Series 1-116i 5 doors, the Volkswagen 1.0 Golf TSI 85 cv Trendline BlueMotion, the Renault Clio 1.2 Zen, the Nissan Qashqai 1.2 DIG-T Visia, and the Daimler Smart forfour 70 Twinamic Perfect.[1] We have included a figure of each car to make the respondent more familiar with the vehicle type, thus to increase the realism of the choice scenarios and to capture additional features such as comfort, style, prestige, safety, size, and vehicle type. The choice of the attributes to include in the stated choice experiments was based on a detailed literature review (Coffman et al., 2017; Greene, Hossain, Hofmann, Helfand, & Beach, 2018; Liao, Molin, & van Wee, 2017), by selecting among the very large number of potential attributes and metrics, in order to prevent respondents’ fatigue and cognitive burden (Hensher, 2006; Hess, Fowler, Adler, & Bahreinian, 2012). We selected the following attributes: purchase price (€), fuel economy specified as cost per 100 km, driving range (km), the time required for a fast charge, the maximum distance between fast charging stations and the hours of free parking. We defined the attributes’ levels as follows. We assumed that economies of scale and future developments in battery technology would decrease BEVs purchase prices and raise the average driving range compared to the 2018’s levels. On the contrary, for petrol cars we assumed a lower and a higher level compared to the 2018 mean value for both the attributes. As for the BEV-specific attributes, we assumed three levels for fast charging time: 25′, 40′ and 55′; free parking could be 1 h, 3 h, or unlimited, while concerning the maximum distance between fast charging stations, we assumed an optimistic level of 20 km, a realistic level of 80 km and an intermediate distance of 50 km. Using the Ngene Software, we developed a D-efficient design of the choice tasks (Bliemer & Rose, 2011).

We analyzed the collected stated choice data using a discrete choice model specification (Ben-Akiva & Lerman, 1985; McFadden, 1973; Train, 2009). Thus, we assume that an individual q selects alternative j in the choice situation t from a finite set of J alternatives when that alternative yields the highest possible level of utility. The utility U_{qjt} associated with alternative j in the choice task t can be written as follows:

$$U_{qjt} = ASC_j + \beta_j^{'} X_{qjt} + \gamma_j^{'} Z_q + \varepsilon_{qjt}$$

where ASC is the alternative specific constant that describes the preference of the sample for a specific propulsion system *ceteris paribus,* i.e. holding constant all attributes and socio-economic interactions used in the specification, X is a vector that includes all the attributes presented in the experiment (in our case, purchase price, fuel economy, driving range, the time required for a fast charge, the maximum distance between fast charging stations, hours of free parking and car model/brands), Z is a vector of socioeconomic characteristics (in our case, the socio-economic variables collected in the first part of the questionnaire), and β and γ are the respective vectors of coefficients. ε is an error term varying by individual q, alternative j and choice situation t. If ε is distributed IID extreme value type 1, the model is a standard logit model. Defining V_{qj} the systematic part of the utility function (i.e., not including the error term), the probability of an individual q choosing alternative j can be computed as:

$$P_{qj} = \frac{e^{V_{qj}}}{\sum_j e^{V_{qj}}}$$

The simplicity of the model solution (closed form) comes at the price of three limitations: random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time or individuals (Train, 2009). The mixed logit obviates these limitations allowing more flexible substitution patterns. The model is thus reformulated as follows:

$$U_{qjt} = ASC_{qj} + \beta_{qj}^{'} X_{qjt} + \gamma_j^{'} Z_q + \varepsilon_{qjt}$$

where β_q is a vector of coefficients for individual q representing that person’s tastes. The coefficients vary over decision makers in the population with density $f(\beta|\Delta)$, where Δ refers collectively to the parameters of this distribution (such as the mean and covariance of given β). This specification is the same as for standard logit except that β varies over decision makers rather than being fixed. The choice probability becomes:

$$P_{qj} = \int L_{qj}(\beta) f(\beta|\Delta) d\beta$$

where $L_{qj}(\beta)$ is the logit probability evaluated at parameters β:

$$L_{qj}(\beta) = \frac{e^{V_{qj}(\beta)}}{\sum_j e^{V_{qj}(\beta)}}$$

Since the probability is not a closed form, the probabilities are approximated through simulation for any given value of Δ. It is up to the researcher to test which distribution $f(\beta|\Delta)$ best fits the data (e.g., normal, lognormal, uniform, triangular, etc.). The term “mixed logit model” refers to the presence of two distributions (for the parameters

---

[1] We did not include the Tesla Model S and Model X, although they were among the most selling cars in 2018, since we chose to focus on the more popular small/medium car segment (UNRAE, 2019).

and the error term). An alternative term is random parameter logit (RPL) model, underling the fact that the preference parameters are not fixed across individuals.

Moreover, we took into account that revealed preference (RP) and stated preference (SP) data have complementary characteristics that can be exploited to enhance the understanding of the choice determinants. RP data are extremely reliable with regards to the actual choice, but not with regards to the attributes of non-chosen alternatives. Moreover, RP data are of little use when researchers need to forecast a market different from the existing one. SP data, on the contrary, being collected in a fully controlled experiment, are able to elicit preferences for non-existing attributes and alternatives. Furthermore, since the choice set is pre-specified, the researcher can avoid multicollinearity issues and extend the attributes' range. SP data, however, suffer from the hypothetical bias. Technically, RP and SP data can be merged by 'scaling' the utility function, as described in Bhat and Castelar (2002).

We report in Table 2the results of the RP/SP RPL model with the largest set of significant parameters and the highest explanatory power. We estimated the model with the Apollo package in R (Hess & Palma, 2019).

All the estimates confirm our expectations in terms of sign and are statistically significant. The scale parameter is not statistically different from 1, indicating no scale difference between the RP and SP data, implying that the two datasets can be jointly used. The parameters of *Purchase price* and *Fuel economy* are both negative and largely significant. As expected, the driving range is much more important for BEVs than for CVs. In fact, we find that the parameter of the *BEV Range* is about three times larger than that of the *Petrol car range*. The attribute describing the time required for a fast charge *(Low fast charging time)* has been coded as a dummy variable taking value 1 if charging time is equal to 25′ and 0 otherwise. Its parameter is positive, as expected, and highly significant. The *Max distance btw fast charging station*, as expected, has a negative sign. The possibility to charge at home, thus garage ownership, plays a role in increasing the interest towards BEVs. Mobility habits, specifically a low annual distance travelled, increase the probability of choosing a BEV. Relative to Smart Daimler, all other models/brands provide a higher relative utility.

Table 2
Results of the RP/SP RPL model specification.

	Estimate (Std. err.)
ASC_BEV (relative to CV)	0.057* (0.032)
Standard deviation of ASC_BEV	1.194*** (0.114)
Purchase price (10,000 €)	−1.472*** (0.124)
Standard deviation of Purchase Price	1.154*** (0.096)
Fuel economy (€/100 km)	−0.111*** (0.013)
BEV range (100 km)	0.513*** (0.054)
Standard deviation of BEV range	0.181*** (0.033)
Petrol car range (100 km)	0.153*** (0.018)
Standard deviation of Petrol car range	0.082*** (0.01)
Max distance btw fast charging station (km)	−0.011*** (0.002)
Free parking (hours: 1, 3, 24)	−0.003 (0.003)
Low fast charging time (25 min = 1; 40 or 55 min = 0)	0.737*** (0.093)
Home charging (yes = 1, no = 0)	0.069** (0.033)
Low annual distance travelled (less than 8 th/year = 1, otherwise = 0)	0.216** (0.089)
VW (relative to Daimler)	0.557*** (0.078)
Renault (relative to Daimler)	0.46*** (0.06)
Nissan (relative to Daimler)	0.451*** (0.065)
BMW (relative to Daimler)	0.423*** (0.071)
RP/SP scale parameter	0.935 (0.084)
Model diagnostics	
LL(0)	−15,255
LL(final, whole model)	−11,585
Adj. Rho-square (0)	0.239
AIC	23,218
BIC	23,410
LL(final, RP)	−584
LL(final, SP)	−10,798
Estimated parameters	24

Note: The t-statistic corresponding to the scale factor is computed with respect to a value of 1; a value of 1 indicates no scale difference in the RP and SP choice contexts.
***, **, * indicate significance at 1%, 5% and 10% respectively.

4. Simulation model

The simulation model comprises a demand and a supply module. The demand module is formulated as an ABM with interactive agents choosing between sticking to their conventional vehicle or switching to a BEV. They based their decision on the vehicles attributes (purchase price, driving range, fuel economy), on the possibility of home charging, on access to high speed charging and on their annual distance travelled. The brand/model coefficients are not implemented in the ABM. Car buyers are influenced by advertising and peer pressure, as explained below. The supply module is modelled as a dynamic process, with manufacturing plans formulated annually based on the relative profit margins, manufacturing costs subject to technological progress and economies of scale and monthly manufacturing production conditions on the existence of BEV demand. In the next subsections, we present a more detailed illustration of the two modules.

4.1. *Car demand module*

The core of the module is the agent who chooses a BEV or a CV. In our model, the agents are car buyers and not car owners. We can hence disregard to model choices such as using a car sharing service, substituting the car with a bicycle or with public transport, how long to hold a car, etc. and concentrate only on the choice of the propulsion system of the car. Based on Italian registration data (see for details SM 2.1), we have assumed that each month 150 thousand agents buy a car and that such a number remains constant over the years 2019–2030.[2] Only a number of them considers the possibility to include BEVs in their choice set. In our model (Fig. 2), such a number is influenced by the car manufacturing advertisement and by the social interaction (social media and word-of-mouth/interpersonal communications from BEV owners). The issue of properly modelling and assessing the choice set has played a very relevant role in the initial ABMs concerning BEV adoption since their market uptake and public knowledge were very limited. For instance, Shafiei et al. (2012) argue that consumers must be sufficiently familiar with BEVs to include them in their consideration set. To capture the formation of consumers' consideration set, they introduce the concept of consumer's willingness-to-consider a vehicle and model it as a function of social influences and market conditions; the attractiveness of each vehicle in the consideration set is a function of vehicles' attributes. Nowadays, BEVs knowledge and acceptance have made large strides so that we can assume that a large number of car buyers include BEVs in their choice set. Yet, their number is certainly influenced by advertisement and social interaction (more details in SM 2.3).

Car buyers, who include BEVs in their choice set, make their choice between a CV and a BEV depending on their preference structure, the vehicle's characteristics and their socio-economic characteristics. Adopting the preference structure reported above, the attributes considered are purchase price net of subsidy, driving range, fuel economy, garage ownership, annual distance travelled and fast charging time. Furthermore, the utility function contains an alternative specific constant (ASC) that accounts for all other variables influencing consumers' decisions. The vehicles' technical and economic attributes and the socio-economic composition of the car buyers are the ones prevailing in the Italian market in 2019, described in detail in SM 2.0. The

---

[2] The assumption that monthly car sales are exogenous and constant is, of course, a simplification introduced to avoid modelling and parametrizing car stock, which in turn would require accounting for scrapping, car imports, etc.

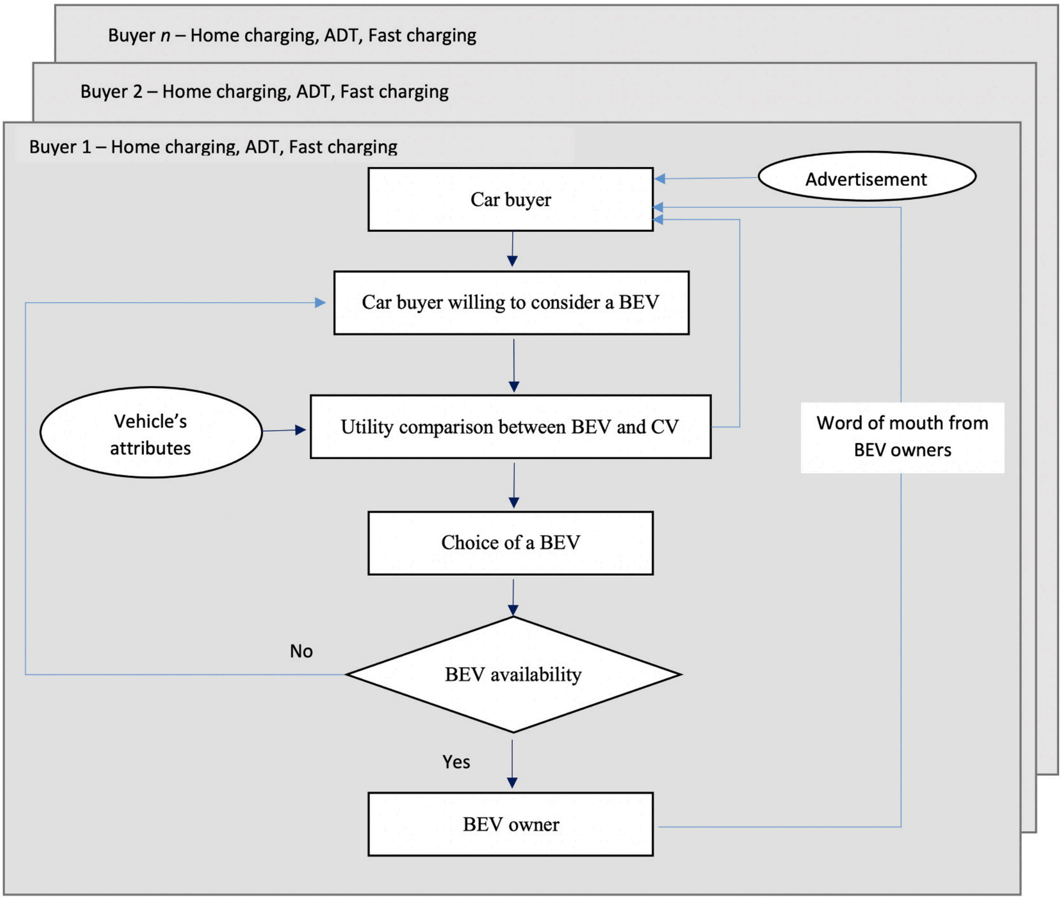


Fig. 2. Illustration of the agents' flow chart.

probability that a car buyer chooses a BEV is evaluated using the parameters of the RPL model, drawing from the Normal distribution. If a buyer chooses a BEV, s/he checks for its availability from the seller.[3] We assume that if the BEV is not available, s/he reconsiders her/his decision and delays the choice to a subsequent period. Similarly to previous studies (Gnann, Plötz, Kühn, & Wietschel, 2015; Kieckhäfer, Wachter, & Spengler, 2017; Klein et al., 2020), we focus on new vehicle sales. A simplifying assumption is that the agents' estimated preference structure is constant until 2030. It is a strong assumption since car buyers are likely to change their evaluation of the main attributes based on direct or indirect experience. Relaxing such an assumption would require modelling or making assumptions on future changes on the parameters of the utility function. At this stage and lacking the necessary empirical observations, we opted to hold them fixed. Such an assumption is likely to generate an underestimation of the BEV uptake.

4.2. *Car supply module*

We model car supply as a system dynamics process (Fig. 3).

The supply module is basically driven by exogenous (depicted by the diamond shape) technological progress and economies of scale, which gradually reduce manufacturing costs for both CVs and BEVs. Note that manufacturing costs, manufacturer suggested retail prices (MSRPs), BEV profits, BEV annual production plan, BEV stock, and utility are represented as stocks in the model, depicted by squares. The reduction of CVs' production costs is assumed to be small in the considered period, whereas based on historical trends and industry predictions, we assume a 22% cost decrease for BEVs, as illustrated in Fig. 4 (more details in the SM 3.0). Car manufacturers set MSRPs based on a mark-up principle, aiming for a normal profit, estimated to be about 7% for the CV industry (the impact of this assumption is tested in Section 5.3 via sensitivity analysis). In the case of BEVs, profits are below the normal level in the initial stage of production, catching up gradually and potentially overcoming those of CVs as technological progress and economies of scale reduce battery costs. In the model, we assume that, as the 7% threshold is realized, cost reductions are passed on to consumers via reduced BEV MSRP, thus increasing the utility associated with BEVs and spurring their demand (reinforcing effect). In turn, this leads car manufacturers to increase BEV production and invest in BEV manufacturing capacity.

The model is set up so that BEV production takes place only if there is demand. It stops when stocks are 20% larger than monthly demand (balancing effect).

The competitive mechanism envisioned in the supply module is rather simplified. It should be considered as a starting point, useful for the scope of this paper, to be improved in future modelling efforts. The limitations one should acknowledge are at least the following. Technological progress and economies of scale are exogenous. We assume that BEV production costs will decrease by 22% in the study period considered but do not model the main driving forces causing such a reduction. We model car production as an aggregate in a SD environment, while the auto industry consists of several large and small manufacturers located in the main developed countries, competing with each other and reacting to technological advances (e.g., lithium battery technology, solid-state batteries) and to policy incentives and regulation. Finally, we do not account for delays and/or bottlenecks in building the BEV production capacity (or upgrade the existing CV production facilities) and

---

[3] The model also contains a perception delay, accounting for the fact a person might need a few months to make a decision.

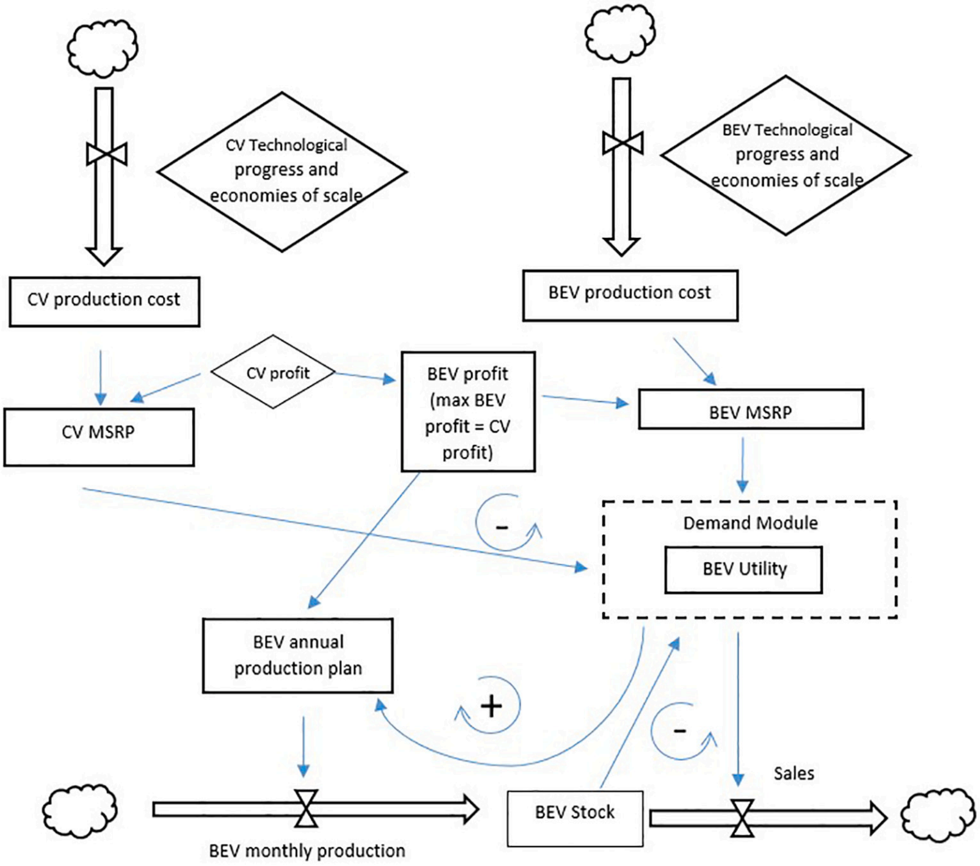


Fig. 3. Illustration of the car supply module.

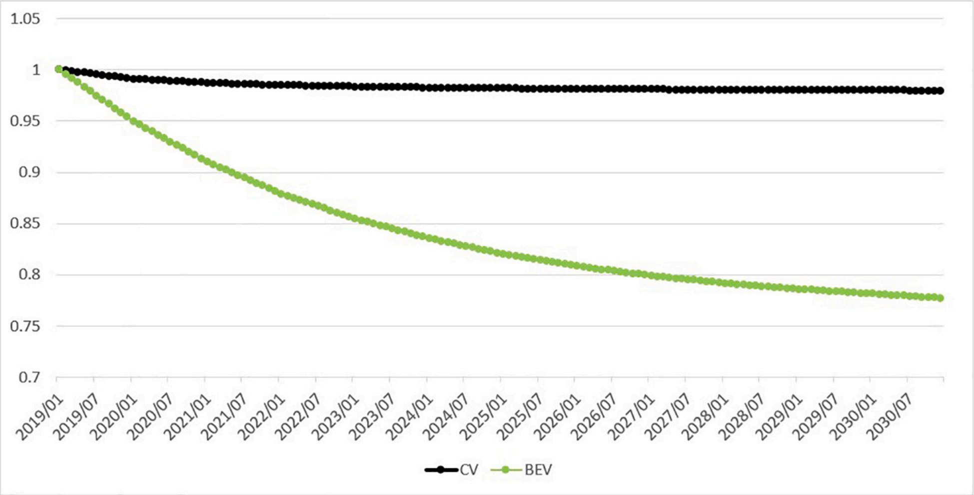


Fig. 4. Projected evolution of the BEV and CV manufacturing cost index over the 2019–2030 period (2019 = 1).

in developing the supply chain to extract the basic materials (lithium, nickel, cobalt, etc.) and to manufacture car batteries.

4.3. Implementation, parametrization, initialization, validation

One of the difficulties in developing and operationalizing the car market model is that it presents vehicles of various sizes, shapes and brands. To be consistent with the demand module and given the characteristics of the Italian car market (see SM 2.4), we consider only the small-to medium car segment. Table 3 describes the initial values of the main vehicles' attribute parameters. Some of the parameters are kept constant over the decade (although this is certainly a simplification), while others are adjusted to technological progress. Specifically, technological progress and economies of scale and competition among brands are assumed to generate MSRP reductions for both BEVs and CVs. In our model, the BEV MSRP drops from the €28,429 value in 2019 (see SM 3.3 for a detailed explanation of how such a MSRP is calculated) to the 2030 MSRP equal to €23,040, while it decreases in the same period

Table 3
Main economic parameters used in the reference scenario.

Parameter	2019
CV	
MSRP	€21,429
Driving range	1000 km
Fuel economy	8€/100 km
BEV	
MSRP	€28,429
Driving range	200 km
Fuel economy	3€/100 km
Purchase subsidy	€6000

from €21,429 to €20,920 for CVs. With reference to BEV driving range, we assume that it gradually increases over the decades from the current 200 km to 401 km.

Important parameters of the model reflect the impact of advertising on extending the set of propulsion systems considered to BEVs and the impact of social networks, specifically the word-of-mouth from BEV owners. The latter is captured by two parameters: contact rate and effectiveness. As no empirical data is available for parametrizing such a social network, we based on reasonable numerical assumptions to initialize the model. However, given their uncertainty we perform sensitivity analyses to evaluate their impact on the 2030 monthly BEV sales.

The SD/ABM is implemented using AnyLogic 8.7.6 (www.anylogic.com), a widely used Java-based software for SD, discrete event and ABMs.

4.4. *Model validation*

The validation of a SD/ABM is an important but challenging task. Many authors discussed it in detail and proposed various categorizations (a summary is presented in SM 5.0). Since our model comprised two main parts, the demand and the supply-side of the market, it is useful to discuss the validation issue both separately and jointly. Concerning the demand side, a strength of our model is that the car choice is firmly grounded on discrete choice modelling theory, which has been largely proved to be valuable to understand and model individuals' behavior. Based on the random utility model, it assumes an individuals' maximizing behavior based on preferences, information and attitudes. Such an approach should provide conceptual validity (Knepell & Arangno, 1993) and micro-face and macro-face validity (Rand & Rust, 2011) to our ABM. The large and representative dataset used to estimate the individuals' utility function adds empirical input validation (as defined by Rand & Rust, 2011) and data accuracy and adequacy (as requested by Knepell and Arangno (1993)).

With reference to the supply side, our model is aggregated and lacks some of the theoretical underpinnings provided, for instance, by Sun et al. (2019). Nonetheless, we attempted to assure macro-face validation using a system dynamics model capturing the main interactions in defining the production plans of alternative propulsion systems. Empirical input validation is provided by applying production cost function based on the most recent empirical evidence on technology trends.

As requested in the literature, the results of an ABM, in our case the interaction between demand and supply, needs to be history-friendly (Fagiolo, Windrum, & Moneta, 2006) in the sense that the results should be in line with ("in harmony with"; Carley, 1996) the empirical evidence. When a model is used for forecasting, validating the model requires in-sample and out-of-sample validation. Along the lines suggested by Buchmann et al. (2021), we attempted to provide historic data validation by splitting the historic data into two temporally separated parts, using the earlier data for calibration and the later data for validating the accuracy of the model. Such a task, however, could be only partially performed due to the fact that BEV uptake in Italy in significant numbers dates back only to the year 2019 so that there is no sufficient data for both calibration and validation.

Two further validation methods suggested in the literature are cross-model validation (Carley, 1996; Knepell & Arangno, 1993) and expert validation (Buchmann et al., 2021; Rand & Rust, 2011). We relied on the former by comparing the ABM results with those obtained in the discrete choice modelling framework assuming actual and expected value of the demand attributes. We find comparable results, although the fact that the latter methodology does not account for social interactions and supply adjustments prevents a full comparability of the two models. Similarly, Klein et al. (2020) performed a cross-model validation by checking whether monthly BEV market share by the Sawtooth Choice Market Simulator were similar to those obtained by the ABM, after disabling those variables that could be accounted for only in the ABM such as technological progress and communication.

Furthermore, we made sure by adjusting the data on social interaction that our estimates approximate the observed BEV sales up to the year 2021 (Fig. 5 – Observed vs estimated market share of BEV sales up to the year 2021.Fig. 5).

5. Simulation results: the reference scenario

5.1. *BEV uptake*

The model proceeds in monthly time steps. Table 4 reports the main indicators in 2019 (reference scenario) and in 2030.

In January 2019 the MSRP gap between BEVs and CVs amounts to €7000: the BEV MSRP is equal to €28,429 while the CV MSRP is €21,429. The €6000 BEV subsidy, granted in Italy since 2019,[4] almost compensate the price difference. Nonetheless, only few car buyers initially opt for BEVs, after considering the monetary (e.g. fuel economy, an important component of the total cost of ownership (Scorrano et al., 2020; Scorrano, Danielis, & Giansoldati, 2021; Scorrano, Mathisen, & Giansoldati, 2019)) and non-monetary factors (e.g. driving range (Giansoldati et al., 2018), attitudes (Giansoldati, Rotaris, Scorrano, & Danielis, 2020; Rotaris, Giansoldati, & Scorrano, 2021), advertisement, and WOM). In fact, a detailed analysis based on the Total Cost of Ownership model developed by Scorrano et al. (2020) reveals that, under typical conditions,[5] BEVs have a lower TCO/km than CVs (€0.34 vs €0.38). Adding to the monetary factors the non-monetary ones captured by the above-described logit model, BEVs level of utility is on average lower than that of CVs.

The model predicts that BEV sales start in August 2019 when the decreasing costs and the increasing driving range lead some consumers to buy a BEV. Gradually, the market share of BEV sales increases reaching in December 2030 52.4% of the market (Fig. 6).

In parallel, car manufacturers' yearly BEV production plans, based on BEV demand and relative profit margins, increase over time, starting from about 3 thousand in 2019 to more than 700 thousand in 2030 (Fig. 7). The model is set up so that when BEV stock tops BEV demand by more than 20% on a monthly basis, we assume that production stops.

---

[4] Since April 2019, the Italian government finances a purchase subsidy known as "Ecobonus". Up to the year 2020, BEVs, PHEVs and HEVs buyers were entitled to a discount ranging from €2000 to €6000. In 2021, the Ecobonus depended on CO_2 emissions: €6000–€10,000 for 0–20 g/km cars, €3500–€6500 for 21–60 g/km cars, €0–€3500 for 61–135 g/km cars. The maximum amount for each class is obtained when scrapping an old petrol or diesel car. Cars emitting more than 191 g/km are subject to a registration tax, ranging from €1100 to €2500.

[5] We estimated a TCO model with the following parameters: BEV MSRP equal to €23,040, CV MSRP equal to €21,429, resale value after 7 years holding period of €7000 for BEVs and €9900 for CVs, annual distance travelled of 10,000 km, fuel price equal to 1.64€/liter, electricity price equal to 0.21€/kWh, no subsidy. It results that the annual average TCO/km is equal to €0.34 for BEVs and €0.38 for CVs.

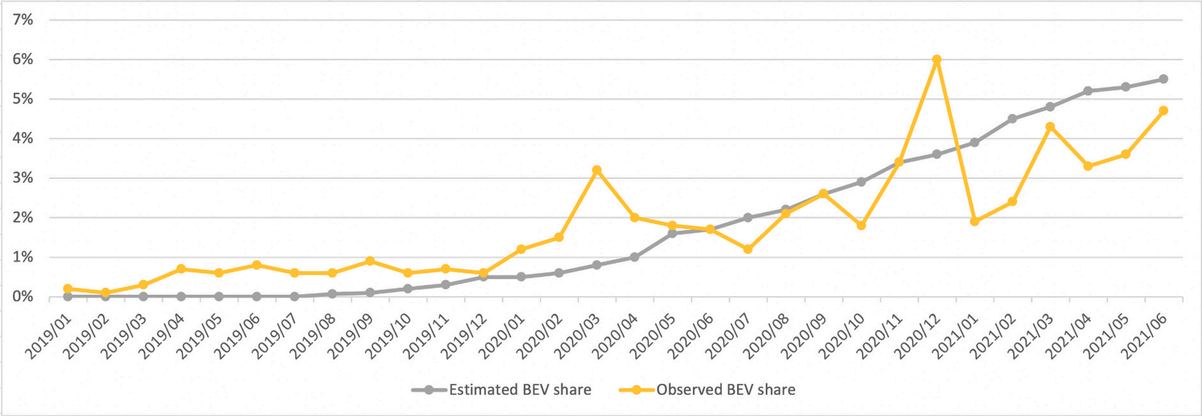


Fig. 5. Observed vs estimated market share of BEV sales up to the year 2021.

Table 4
Main indicators.

Parameter	2019	(December) 2030
CV		
MSRP	€21,429	€20,920
Driving range	1000 km	1000 km
Fuel economy	8€/100 km	8€/100 km
BEV		
MSRP	€28,429	€23,040
Driving range	200 km	401 km
Fuel economy	3€/100 km	3€/100 km
Purchase subsidy	€6000	€6000
Yearly demand	1752	895,350
Italian total BEV fleet	1752	4,841,202
Market share of monthly BEV sales	0.10%	52.4%

On the basis of the working of the model, the BEV uptake is due to these factors.

Technological progress reduces the cost of manufacturing BEVs relative to CVs, according to the assumptions illustrated in Fig. 4.

BEV profit margins are initially lower than CV profit margins (Fig. 8); however, as the BEV manufacturing costs decline, they overcome the latter. In our model, such event takes place already at the end of 2019. This allows BEV manufacturers to pass on the efficiency gains to the consumers, reducing the BEV MSRP. Consequently, BEV profit margins tend to those of the CVs and the BEV MSRP tend to the CV MSRP (Fig. 9). Net of subsidies, BEV MSRP is lower than CV MSRP starting from the end of 2020, thus spurring BEV uptake.

Next, we also assume that the BEV driving range increases in the period 2019–2030 from an average value of 200 km to 401 km, thus reducing the gap with the CVs whose driving range with a full tank is assumed equal to 1000 km.

In addition to these financial and technical factors, the increase of the BEV market share is caused in the model by the advertisement expenses (assumed proportional to BEV sales) and by the word-of-mouth effect.

As a result of these factors, our model predicts that in 2030 the Italian BEV market share will be equal to 52.4%. The BEV manufacturing costs are still higher than the CV ones (€21,660 vs. €19,530), resulting in a BEV MSRP €2120 higher than that of CV. However, assuming that €6000 subsidy is kept constant until 2030 (an assumption that we will relax below), BEVs are financially much more convenient than CVs.

Please note that during the simulation we have kept constant the preference structure of car buyers, a very strong and simplifying assumption, as discussed above, that is likely to cause an underestimation of the actual trends. Since relaxing such an assumption requires modelling the Italian consumers' preference evolution over time, a task that requires reliable data, we leave such a task for future research.

5.2. *BEV uptake by segment*

In order to appreciate how the socio-economic characteristics influence buying decisions, we disaggregate BEV sales by market segment according to the three major characteristics that proved significant in the econometric analysis: garage ownership, access to fast charging and

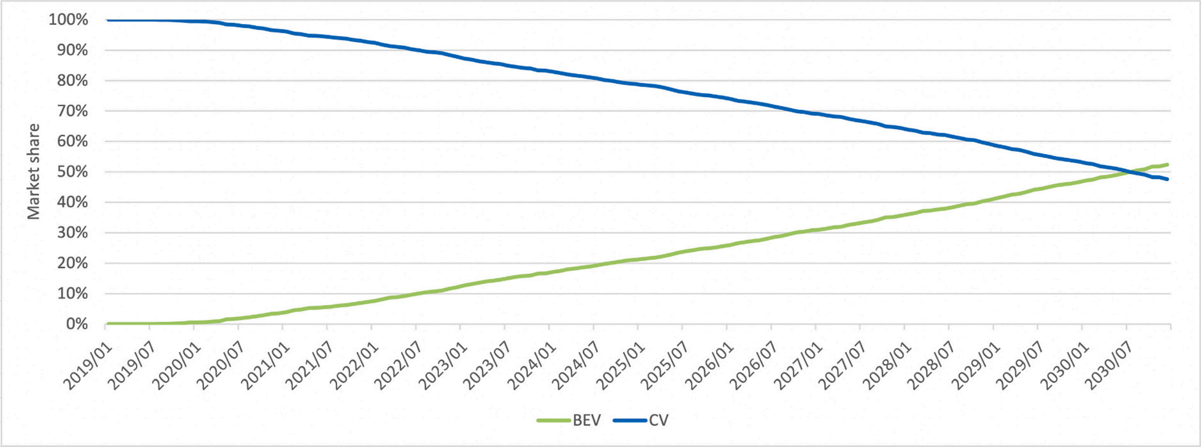


Fig. 6. Evolution of the CV and BEV market share in the small-to-medium car segment over the 2019–2030 period.

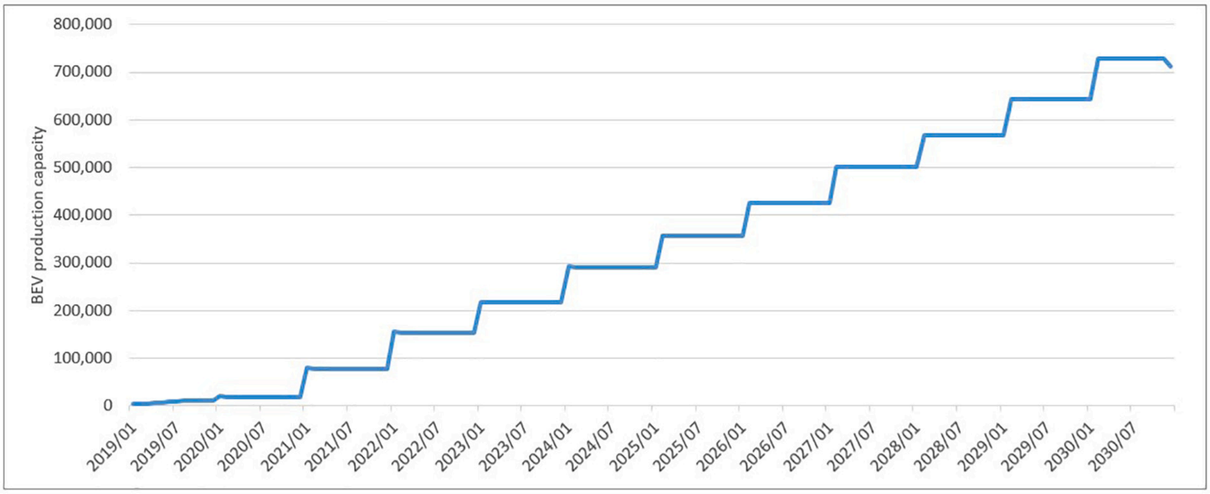


Fig. 7. Trend of BEV production capacity.

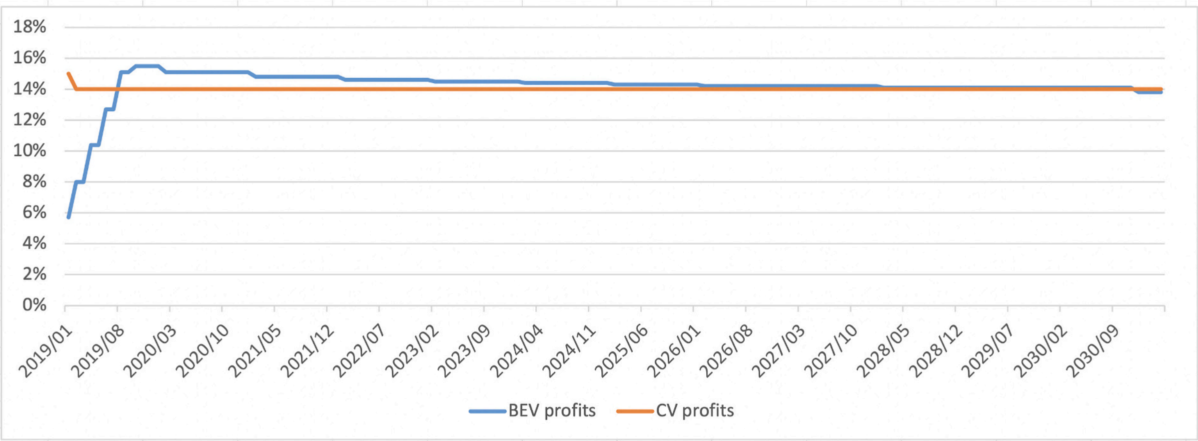


Fig. 8. Evolution of the CV and BEV profit margins.

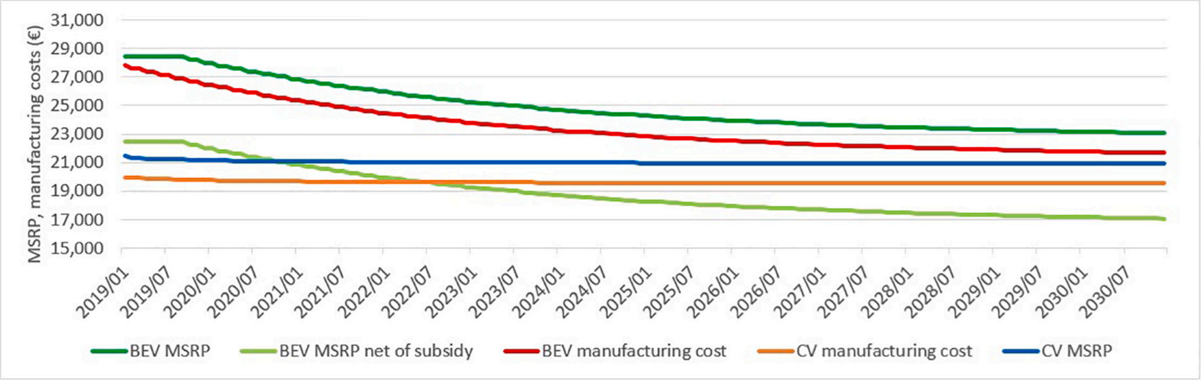


Fig. 9. Evolution of the CV and BEV manufacturing costs and MSRPs.

annual distance travelled. Based on the available Italian statistical data (ISTAT, 2011) and on information collected with the survey, we assume that 75.7% of the buyers own a garage or a private parking place that can be equipped with a wall box, 80% have easy access to fast charging during their trips and 60% drive more than 8000 km per year. Fig. 10 illustrates the results. Initial buyers belong to the market segment made up by people who own a garage, has access to fast charging and travels mainly in urban areas with a low ATD. Up to year 2021, garage ownerships seems to be a crucial characteristic of BEV buyers. After 2021, the market segments without garage start buying BEVs, especially those with a high annual distance travelled and who have access to fast charging, which gradually gain market relevance in terms of absolute number of BEV acquisitions.

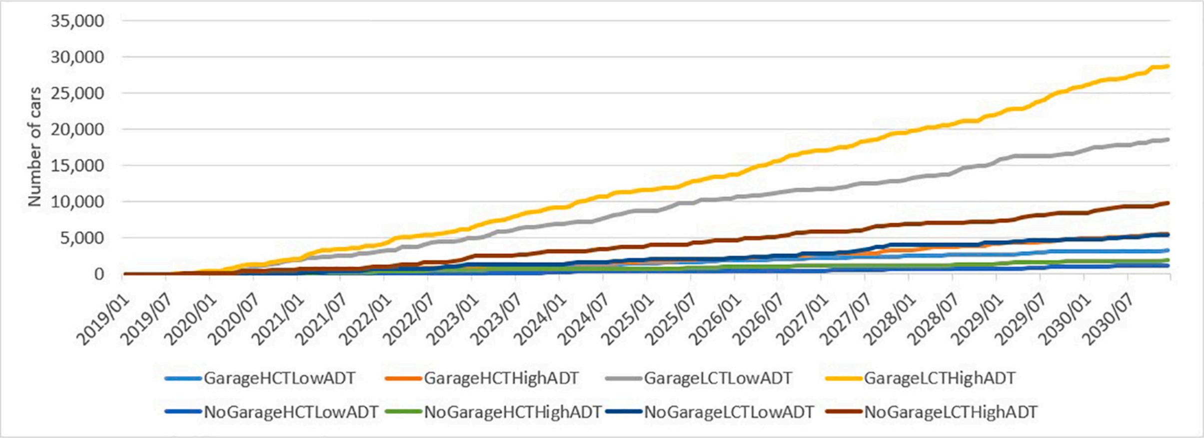


Fig. 10. Evolution of the BEV uptake by market segment over the 2019–2030 period (HCT: high charging time, LCT: low charging time).

5.3. *Sensitivity analysis: accounting for uncertainty*

Some of the parameters of the model are uncertain. Specifying the model assuming that at least three of them are distributed (contact rate as uniform(1,3); initial adoption rate as uniform(0.01, 0.05), normal profit as uniform (5%, 10%)), we obtain a 2030 market share of BEV sales varying between 27.3% and 73.9%, with a standard deviation of 0.123, distributed as illustrated in Fig. 11.

5.4. *Sensitivity analysis: the role of social network*

It is well-documented in the empirical literature that information is crucial in promoting the switch from CV to BEV (Wolf et al., 2015). With regards to Italy, Giansoldati et al. (2020) finds that information might derive from various formal and informal sources. ABMs are particularly suitable to incorporate in the simulation the role of social networks. They can be geographically-based, if the assumption is that spatial distance plays a crucial role (Buchmann et al., 2021) or a-spatial. Our model adopts the latter perspective and is based on two main assumptions: the contact rate and the adoption fraction. The former indicates the number of car drivers a new BEV owner comes into contact with in a given period of time; the latter how many people a driver is able to convince to include BEV into their consideration set. In our reference scenario, such parameters were set equal to 1 person/month with an initial adoption rate which gradually increases up to 1.5%. These two parameters determine the rate at which each BEV buyer sends a "buy" message to potential buyers to include BEVs into their choice set. In order to test the impact of our assumptions on the BEV market share, we performed a sensitivity analysis varying the contact rate from 1 to 4 and the initial adoption fraction from 0.01 to 0.1. We re-run the simulation 500 times (50 combinations times 10 replications with a random seed). The results are illustrated in Fig. 12. The *x*-axis reports the market share of BEV sales obtained in each simulation and the *y*-axis its frequency.

The sensitivity analysis indicates that a crucial factor determining the 2030 BEV market share is the number of individuals the BEV buyers come in contact with. As the number increases from 1 to 4, the BEV market share increases from about 26% to up of 90%. Our finding indicates that the social interaction plays a very important role in determining the BEV uptake, most likely even more crucial than the financial aspects, and underlines the need to carry out specific surveys regarding the social interaction parameters. To the best of our knowledge, only few papers have so far attempted to ground their SD/ABMs on empirical sound analysis of the social networks (e.g., Zhang et al., 2011[6]; Eppstein et al., 2011; Wolf et al., 2015; Buchmann et al., 2021).

6. Scenario analysis

6.1. *The impact of subsidies*

We use the model to perform a counterfactual analysis of the impact of the purchase subsidy. We set the subsidy at four different starting levels (€0, €3000, €6000, €10,000). We assume that subsidies last for the entire period of investigation, up to the year 2030.

As expected, higher subsidies lead to a faster BEV uptake (Fig. 13). However, the market share of BEVs in 2030 is not very different, varying between 45.3% and 56.9%. This finding suggests that, although a subsidy is necessary to accelerate BEV uptake, its amount should not be necessarily as generous as the one implemented in Italy or in other European countries, raising the question of what would be the optimal subsidy from a social point of view.

Next, we compare in Fig. 14 the impact on 2030 market share of BEV sales of constant (up to the year 2030) and declining subsidies. By a declining subsidy we mean that, starting from 2024, the subsidy is reduced by €2000 after each year. Such an assumption is not unrealistic since the countries' fiscal budget would be overburdened by the growing financial cost of the subsidies coupled with the declining tax revenues from the fuel tax. Real world examples of subsiding financial support can be found in the US and in the UK. The BEV market share is equal to 52.4% with a €6000 constant (up to the year 2030) subsidy and 50.0% with a declining subsidy. This finding reinforces the conclusion that the financial aspect might play a subordinate role to the social factors.

6.2. *Impact of a fuel carbon tax*

An interesting research question is whether introducing a fuel carbon tax on CVs could lead to a substantially different market equilibrium. We

---

[6] Zhang et al. (2011) asked respondents in the survey, how many owners of alternative fuel vehicles (AFVs) they have talked to and three questions about their domain-specific knowledge about AFVs (fueling, maintenance, and sticker price), which were measured on a 1–7 scale. They used this information to model the part worth of the utility function. Zhang et al. (2011) underlined that word of mouth acts as a social norm. They find a WOM adjustment factor ranging from −0.020 to 0.013.

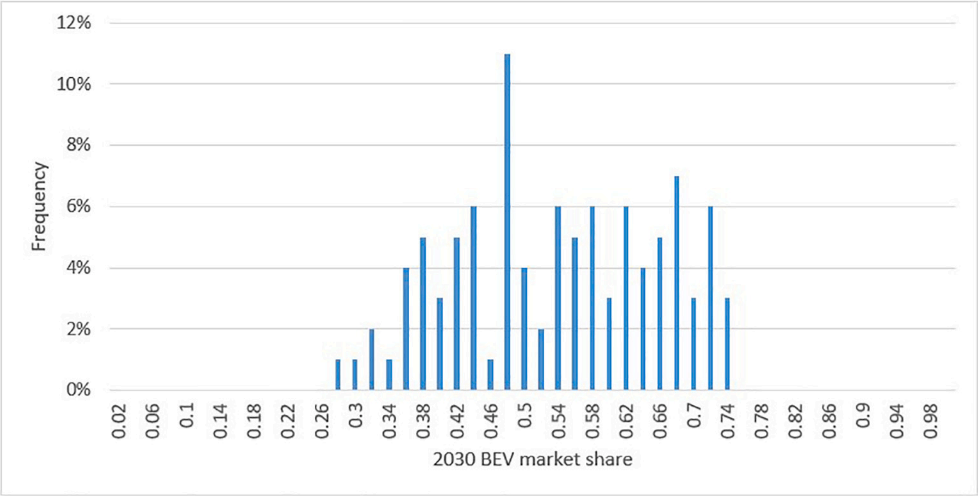


Fig. 11. Sensitivity analysis of the BEV market accounting for uncertainty.

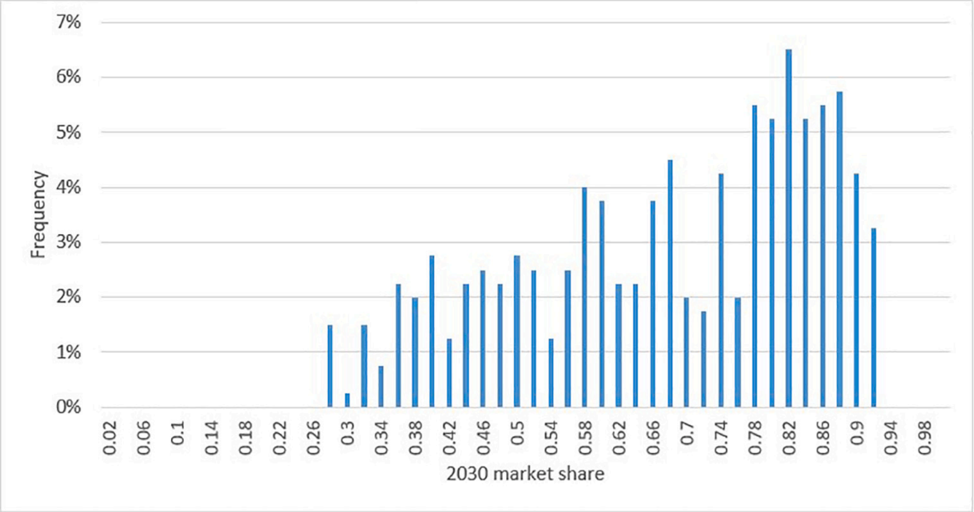


Fig. 12. Sensitivity analysis of the market share of BEV sales due to social network parameters.

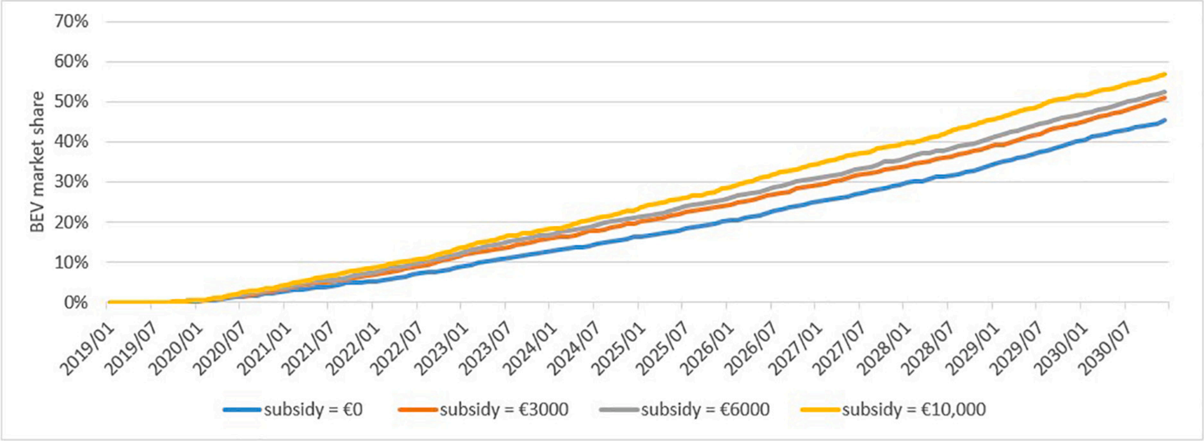


Fig. 13. Impact of different subsidies to the 2030 market share of BEV sales.

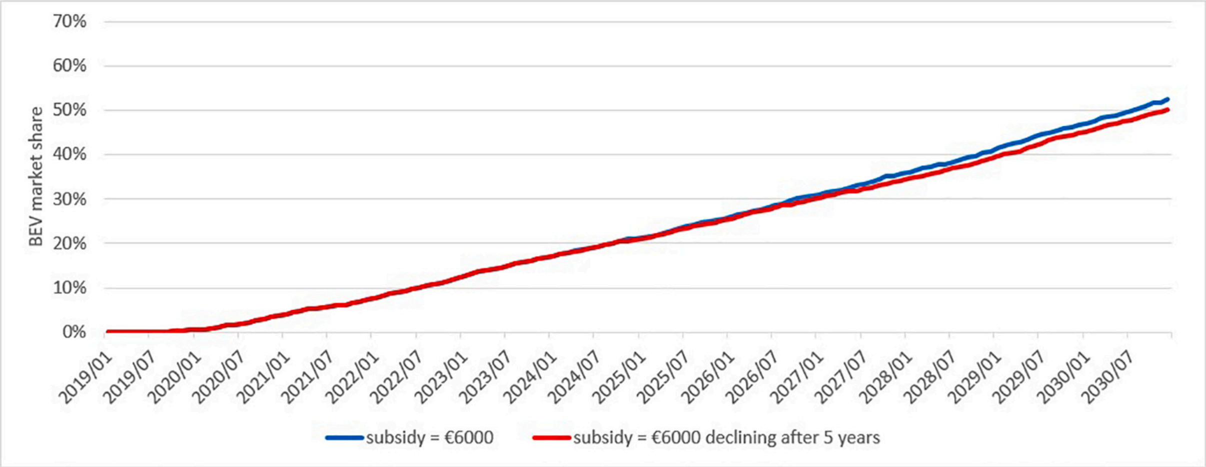


Fig. 14. 2030 market share of BEV sales with constant or declining subsidies.

started by considering what would be a plausible and politically acceptable carbon tax on vehicle fuel. On the basis on a study recently carried out in Italy by Rotaris and Danielis (2019), it results that Italians are willing to pay between €0.17 and €0.30 per liter as a vehicle pay for reducing CO_2. Such an amount corresponds to an increase in the CV fuel economy from 8 €/100 km assumed in the reference model to 9.3 €/100 km, as described in SM 4.0. Such a carbon tax would entail a monthly additional fuel cost for CV drivers equal to €10.82. We tested the impact of the introduction of such a fuel tax on BEV market share.

Not surprisingly, given the not substantial increase in fuel costs, we find that the impact on the BEV market share (Fig. 15) would be small. Although theoretically justified, since from a distribution point of view internalizing the source of pollution is preferable to subsidizing the less polluting vehicles, we do not find that it would lead to substantially different market equilibria (52.4% vs. 54.9%). An important caveat is that we do not account for the potential use of the carbon tax revenues to promote technological progress nor we discuss political acceptability issues.

7. Discussion and conclusion

The paper develops an interactive supply-demand model. The demand module is formulated as an ABM with interactive agents choosing between buying a conventional car or a fully electric one. They based their decision on utility maximization principles, taking into account the car's technical and financial attributes (MSRP, fuel economy, driving range), home charging availability, access to high speed charging and their annual distance travelled. The utility functions are parametrized on the basis of RP/SP data, assuming a RPL model. The choice of whether to consider BEVs as a potential substitute for CVs is influenced by advertising and social network.

The supply module is driven by exogenous technological progress and economies of scale, which gradually reduce manufacturing costs for both CVs and BEVs. The reduction of production costs is assumed to be smaller for CVs than for BEVs. Car manufacturers set MSRPs based on a mark-up principle, aiming for a normal profit. The supply module is modelled as a system dynamics process. Car manufacturers formulate their production plans annually based on the relative profit margins and manufacturing costs, subject to technological progress, economies of scale and BEV demand.

Since the discrete choice data refer to the small-to-medium car segment, the model is parametrized and implemented with reference only to that specific sector in Italy.

7.1. *Main findings*

The main findings are the following. We estimate that in the period 2019–2030 BEV sales will gradually increase. By the end of 2030, our model estimates that BEVs will represent more than 52% of new sales. A total fleet of almost 5 million BEVs will be on the Italian roads by 2030, i.

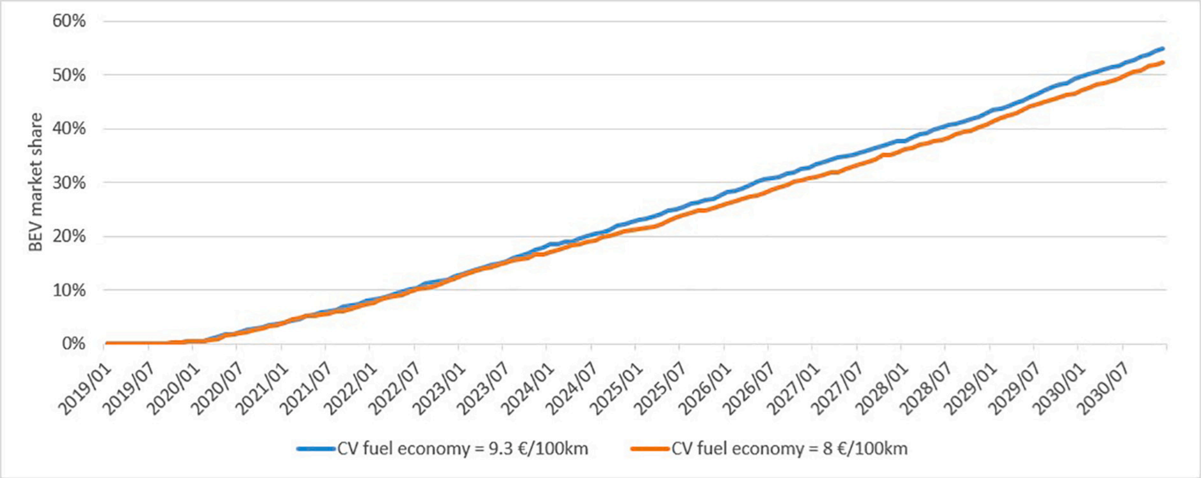


Fig. 15. Evolution of market share of BEV sales with and without fuel carbon tax.

e. about a sixth of the Italian car fleet. Initial buyers are mostly garage owners, who have also access to fast charging and travel short daily distances. At the end of the decade, however, long distance drivers, including those not owning a garage, will progressively buy BEVs.

Social networks play a major role in convincing car buyers to include BEVs in their choice set. Word-of-mouth and advertising induce a growing number of potential buyers to include BEVs in their choice set. Unfortunately, however, the survey we have performed did not allow us to ground social interaction model in firm empirical evidence.

Our estimates contain a certain degree of uncertainty, especially concerning the impact of social networks. A re-parametrization of the model allowing three important parameters (contact rate, adoption rate, normal profit) to be uniformly distributed, generated a 2030 BEV market share prediction varying between 27.3% and 73.9%.

Scenario analyses, performed to evaluate the impact of subsidies, lead us to conclude that, although BEV subsidies accelerate BEV uptake, their amount should not be necessarily as generous as the one implemented in Italy or in other European countries. We also found that a declining subsidy, instead of a constant (up to the year 2030) subsidy does not cause an excessive drop in the 2030 market share of BEV sales. Finally, we found that a politically acceptable fuel carbon tax, theoretically justified in distributional terms, would alter, although not substantially, the 2030 market share of BEV sales (52.4% vs. 54.9%).

7.2. *Comparison the previous results*

As suggested by Carley (1996), it is important to compare our findings, as much as possible, with those obtained by other researchers. Not all ABMs implemented with reference to BEVs are used to forecast BEV uptake. In fact, as argued by Gnann et al. (2015), the reviewed papers present a variety of research questions and results, which shed light on the factors that facilitate BEV uptake without necessarily providing projections for a specific date. The first study which presented an estimate of the market share that BEVs could reach in 2030 is Shafiei et al. (2012). They tested different scenarios and concluded that in Iceland the combination of high gasoline price, decreasing BEV price, dropping tax on BEVs and elimination of consumer concerns about recharging could lead to a BEV market share higher than 90%. A more recent study by Noori and Tatari (2016) provided a much more conservative estimate for the United States. They concluded that BEV market share of new sales by 2030 could be as high as 30%, but it would require mandating government subsidies for at least the first 10 years and encouraging the social acceptability of the BEVs via advertisement and other such means.

Gómez Vilchez and Jochem (2019) reported the results of three system dynamics studies (Pasaoglu Kilanc et al., 2016; Kieckhäfer et al., 2017; MIT, 2017) from which projections for the year 2030 can be derived. The projections are conservative; they range from approximately 12% to 21% but considering PHEVs and BEVs jointly. A very recent estimate for Germany based on an ABM is provided by Klein et al. (2020). They performed a scenario analysis for a 15 years' time span, with special focus on the role of home charging. They found that the relative competitiveness of BEVs vs. PHEVs depends on the rate of penetration of home charging in the population and on technological progress. Even in the most favorable scenario for BEVs including the rapid diffusion of charging network, they estimated that BEVs could reach within 15 years a maximum of 40% market share. Finally, Buchmann et al. (2021) developed an ABM to test whether the policy goal of 6 million BEVs could be obtained in Germany by 2030. They found that with the currently implemented set of policies it is very unlikely that the goal could be reached. They suggested the adoption of additional measures such as a carbon tax on fuel, more charging points, and higher direct subsidies.

In summary, apart from Shafiei et al. (2012), our estimates are in line, or slightly more in favor of the BEVs, with the previous literature.

A point of reference could also be drawn with the actual market penetration data. ACEA (2020) indicates that currently there are large differences among countries. Some European countries, notably Norway, Iceland and the Netherlands, have already, in 2020, market share of BEV sales well above 20%. The Southern and Eastern European countries are lagging behind. On the contrary, Italy has still a low BEV uptake, although rapidly growing over time (from 0.6% in 2019 to 2.4% in 2020). Germany, the largest European country, is also making huge progress in spurring BEV market share (from 1.8% in 2019 to 6.7% in 2020).

7.3. *Policy implications*

One of the main policy implications is that information and knowledge enhance BEV diffusion (Danielis et al., 2020), which, in turn, will enhance BEV acceptance and reinforce BEV uptake, probably reducing the misunderstandings or misperceptions underlined by Krause, Carley, Lane, and Graham (2013). Many obstacles still exist including charging times and costs, fire safety, charging issues for individuals without a private parking facility, battery disposal, resale value, and so on. Consequently, we deem important that all stakeholders playing a role in spreading information on BEVs (researchers, OEMs, policy makers, internet influencers, such as bloggers or YouTubers) continue on providing in-depth and reliable information on the BEVs technical, environmental and economic properties.

Another policy implication is that technological progress, especially with regard to batteries, has been and will most likely be in the next decade the driving force for BEV uptake. University and research centers, together with industries provided and will provide significant advance in the years to come (e.g., solid-state batteries). European and national governments have the responsibility to set up the incentives and the regulatory framework (e.g., the Dec 2020 EC Proposal for a Regulation on batteries and waste batteries; European Commission, 2020) for future developments.

With reference to the role of subsidies in allowing BEV uptake, several authors including the authors of this paper, demonstrated their importance to facilitate BEV adoption. In this paper, we have discovered that even if they do not last for the entire decade, thanks to other factors such as BEV knowledge and battery cost reductions, subsidies might be gradually reduced without hampering the market share that BEVs can achieve in 2030. Since subsidies represent a fiscal burden for the national budgets, such a finding is good news. However, a politically acceptable carbon tax on fuel does appear to alter but not significantly the achievable BEV market share.

7.4. *Improvements needed*

Our model has obviously many limitations and several improvements are possible. A crucial improvement would be to include PHEVs as an alternative to BEVs and CVs. Although some commentators regard them as a transitory technology, their current market share indicates that they are likely to play a relevant role in the coming decade. Since our RP/SP choice experiment did not present them as a choice option, we lacked information on their specific preference structure. Along the same lines, it would be interesting to distinguish between petrol, diesel and hybrid cars to reflect more closely the currently available technologies. Moreover, it would be useful to apply the model to higher car market segments, investigating the demand deriving from business or luxury car users.

With regards to the demand module, the current selection of attributes does not include other potentially relevant vehicle characteristics such as acceleration, maintenance & repair, insurance, battery substitution, resale price which have been found to play a role in car buyers' decisions (Coffman et al., 2017; Kumar & Alok, 2020). Furthermore, the demand module could be extended to include other aspects such as whether the car is used as the only car or as second family car, the geographical location of the car buyer, and her/his psychological and social attitudes. Moreover, dynamic preferences might be assumed and their impact on the market predictions could be evaluated. We made the simplifying assumption that the agents' estimated preference structure is constant until 2030. Admittedly, it is a very strong assumption since car buyers are likely to change their evaluation based on direct or indirect experience (Oliveira, Roth, & Dias, 2019).

A major limitation of the model is that the geographical and spatial aspects are not considered. However, they certainly play a major role since they determine where the car is mainly used (e.g. rural or urban trips), the access to the charging network and the availability of private parking space. Space is also essential in some ABMs to characterize the social networks (Wolf et al., 2015).

With reference to the supply module, we opted for an aggregate system dynamics approach. However, the competitive mechanism envisioned in the supply module is simplified and technological progress and economies of scale are exogenous to the model. It would be important in a new research effort to investigate the use of an ABM to model supply as well, along the lines suggested by Gómez Vilchez and Jochem (2019). It is also necessary to account for specific car manufacturers' electrification plans (e.g. Tesla, VW, Toyota; Vouzavalis, 2020) and to include their research and development expenses and strategies. Another possibility is to include in the model dealers as interactive agents.

Finally, another important agent currently not investigated in detail is made up by the regulatory bodies at supranational, national and local levels, who play a relevant role via standards and fines (e.g., European Union emission standards and fines, Regulation (EU) 2019/631 (European Commission, 2019)), subsidies and taxes (Ecobonus, https://ecobonus.mise.gov.it/) and parking regulations.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rtbm.2021.100736.

References

Abbas, K. A., & Bell, M. G. H. (1994). System dynamics applicability to transportation modeling. *Transportation Research Part A, 28*(5), 373–390. https://doi.org/10.1016/0965-8564(94)90022-1

ACEA, E. A. M. A. (2020). ACEA. http://www.acea.be.

Adepetu, A., & Keshav, S. (2017). The relative importance of price and driving range on electric vehicle adoption: Los Angeles case study. *Transportation, 44*(2), 353–373. https://doi.org/10.1007/s11116-015-9641-y

Ahkamiraad, A., & Wang, Y. (2018). An agent-based model for zip-code level diffusion of electric vehicles and electricity consumption in new York City. *Energies, 11*(3). https://doi.org/10.3390/en11030640

Ben-Akiva, M., & Lerman, S. (1985). *Discrete choice analysis: Theory and application to travel demand*. MIT Press.

Bhat, C. R., & Castelar, S. (2002). A unified mixed logit framework for modeling revealed and stated preferences: Formulation and application to congestion pricing analysis in the San Francisco Bay area. *Transportation Research Part B: Methodological, 36*(7), 593–616. https://doi.org/10.1016/S0191-2615(01)00020-0

Bliemer, M. C. J., & Rose, J. M. (2011). Experimental design influences on stated choice outputs: An empirical study in air travel choice. *Transportation Research Part A: Policy and Practice, 45*(1), 63–79. https://doi.org/10.1016/j.tra.2010.09.003

Brown, D. G., Riolo, R., Robinson, D. T., North, M., & Rand, W. (2005). Spatial process and data models: Toward integration of agent-based models and GIS. *Journal of Geographical Systems, 7*(1), 25–47. https://doi.org/10.1007/s10109-005-0148-5

Brown, M. (2013). Catching the phever: Simulating electric vehicle diffusion with an agent-based mixed logit model of vehicle choice. *JASSS, 16*(2). https://doi.org/10.18564/jasss.2127

Buchmann, T., Wolf, P., & Fidaschek, S. (2021). Stimulating E-mobility diffusion in Germany (EMOSIM): An agent-based simulation approach. *Energies, 14*(3), 656. https://doi.org/10.3390/en14030656

Caiani, A., Godin, A., Caverzasi, E., Gallegati, M., Kinsella, S., & Stiglitz, J. E. (2016). Agent based-stock flow consistent macroeconomics: Towards a benchmark model. *Journal of Economic Dynamics and Control, 69*, 375–408. https://doi.org/10.1016/j.jedc.2016.06.001

Carley, K. M. (1996). Validating computational models. In *Working Paper, 0793 (September)* (pp. 1–24).

Cherchi, E. (2017). A stated choice experiment to measure the effect of informational and normative conformity in the preference for electric vehicles. *Transportation Research Part A: Policy and Practice, 100*, 88–104. https://doi.org/10.1016/j.tra.2017.04.009

Cho, Y., & Blommestein, K. V. (2015). Investigating the adoption of electric vehicles using agent-based model. In *Portland international conference on management of engineering and technology, 2015-Septe* (pp. 2337–2345). https://doi.org/10.1109/PICMET.2015.7273206

Choi, J. (2016). Agent based model for estimating HEVs market: Focusing on the case of Korea. *Science, Technology and Society, 21*(2), 227–249. https://doi.org/10.1177/0971721816640625

Coffman, M., Bernstein, P., & Wee, S. (2017). Electric vehicles revisited: A review of factors that affect adoption. *Transport Reviews, 37*(1), 79–93. https://doi.org/10.1080/01441647.2016.1217282

Cui, X., Ridge, O., Bethel, O., Road, V., Liu, C., Kim, H. K., … Bhaduri, B. L. (2010). A multi agent-based framework for simulating household PHEV distribution and electric distribution network impact. In *, 1250. TRB comittee on transportation energy (ADC70)* (p. 21).

Danielis, R., Rotaris, L., Giansoldati, M., & Scorrano, M. (2020). Drivers' preferences for electric cars in Italy. Evidence from a country with limited but growing electric car uptake. *Transportation Research Part A: Policy and Practice, 137*, 79–94. https://doi.org/10.1016/j.tra.2020.04.004

EEA. (2019). Electric vehicles from life cycle and circular economy perspectives TERM 2018. In *Transport and environment reporting mechanism (TERM) report*. https://.eea.europa.eu accessed 23 January 2020.

EEA. (2019b). *Greenhouse gas emissions from transport in Europe*. https://www.eea.europa.eu/data-and-maps/indicators/transport-emissions-of-greenhouse-gases/transport-emissions-of-greenhouse-gases-12#:~:text=In 2017%2C 27%25 of total,by 2.2%25 compared with 2016.

Eppstein, M. J., Grover, D. K., Marshall, J. S., & Rizzo, D. M. (2011). An agent-based model to study market penetration of plug-in hybrid electric vehicles. *Energy Policy, 39*(6), 3789–3802. https://doi.org/10.1016/j.enpol.2011.04.007

Ernst, A., & Briegel, R. (2017). A dynamic and spatially explicit psychological model of the diffusion of green electricity across Germany. *Journal of Environmental Psychology, 52*, 183–193. https://doi.org/10.1016/j.jenvp.2016.12.003

European Commission. (2019). *CO_2 emission performance standards for cars and vans (2020 onwards) | climate action*. European Commission. https://ec.europa.eu/clima/policies/transport/vehicles/regulation_en.

European Commission. (2020). Proposal for a regulation on batteries and waste batteries. https://ec.europa.eu/environment/waste/batteries/pdf/Proposal_for_a_Regulation_on_batteries_and_waste_batteries.pdf.

Fagiolo, G., Windrum, P., & Moneta, A. (2006). Empirical validation of agent-based models: A critical survey. In *Economic policy (issue may)*. www.econstor.eu.

Fiorello, D., Fermi, F., & Bielanska, D. (2010). The astra model for strategic assessment of transport policies. *System Dynamics Review, 26*(3), 283–290. https://doi.org/10.1002/sdr.452

Folcik, V., & Orosz, C. G. (2006). An agent-based model demonstrates that the immune system behaves like a complex system and a scale-free network. In *SwarmFest 2006*.

Ford, A. (1995). Simulating the controllability of feebates. *System Dynamics Review, 11*(1), 3–29. https://doi.org/10.1002/sdr.4260110103

Forrester, J. (1961). *Industrial dynamics*. MIT Press.

Giansoldati, M., Danielis, R., Rotaris, L., & Scorrano, M. (2018). The role of driving range in consumers' purchasing decision for electric cars in Italy. *Energy, 165*, 267–274. https://doi.org/10.1016/j.energy.2018.09.095

Giansoldati, M., Rotaris, L., Scorrano, M., & Danielis, R. (2020). Does electric car knowledge influence car choice? Evidence from a hybrid choice model. *Research in Transportation Economics, 80*. https://doi.org/10.1016/j.retrec.2020.100826

Gnann, T., Plötz, P., Kühn, A., & Wietschel, M. (2015). Modelling market diffusion of electric vehicles with real world driving data - German market and policy options. *Transportation Research Part A: Policy and Practice, 77*, 95–112. https://doi.org/10.1016/j.tra.2015.04.001

Gómez Vilchez, J. J., & Jochem, P. (2019). Simulating vehicle fleet composition: A review of system dynamics models. In *, vol. 115. Renewable and sustainable energy reviews*. https://doi.org/10.1016/j.rser.2019.109367

Greene, D., Hossain, A., Hofmann, J., Helfand, G., & Beach, R. (2018). Consumer willingness to pay for vehicle attributes: What do we know? *Transportation Research Part A: Policy and Practice, 118*, 258–279. https://doi.org/10.1016/j.tra.2018.09.013

Haer, T., Botzen, W. J. W., de Moel, H., & Aerts, J. C. J. H. (2017). Integrating household risk mitigation behavior in flood risk analysis: An agent-based model approach. *Risk Analysis, 37*(10), 1977–1992. https://doi.org/10.1111/risa.12740

Harrison, G., Thiel, C., & Jones, L. (2016). Powertrain technology transition market agent model (PTTMAM). In *JRC technical reports*. https://www.academia.edu/download/48139216/PTTMAM_Technical_Report_FINAL_online.pdf.

Hensher, D. A. (2006). How do respondents process stated choice experiments? Attribute consideration under varying information load. *Journal of Applied Econometrics, 21*(6), 861–878. https://doi.org/10.1002/jae.877

Heppenstall, A. J. J., Crooks, A. T., See, L. M., & Batty, M. (2012). Agent-based models of geographical systems. In *Agent-based models of geographical systems*. https://doi.org/10.1007/978-90-481-8927-4

Hess, S., Fowler, M., Adler, T., & Bahreinian, A. (2012). A joint model for vehicle type and fuel type choice: Evidence from a cross-nested logit study. *Transportation, 39*(3), 593–625. https://doi.org/10.1007/s11116-011-9366-5

Hess, S., & Palma, D. (2019). Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. *Journal of Choice Modelling, 32*. https://doi.org/10.1016/j.jocm.2019.100170

ISTAT. (2011). *Popolazione residente - Censimento 2011: Superficie delle abitazioni occupate da persone residenti*.

Jochem, P., Gómez Vilchez, J. J., Ensslen, A., Schäuble, J., & Fichtner, W. (2018). Methods for forecasting the market penetration of electric drivetrains in the passenger car market. *Transport Reviews, 38*(3), 322–348. https://doi.org/10.1080/01441647.2017.1326538

Kangur, A., Jager, W., Verbrugge, R., & Bockarjova, M. (2017). An agent-based model for diffusion of electric vehicles. *Journal of Environmental Psychology, 52*, 166–182. https://doi.org/10.1016/j.jenvp.2017.01.002

Kieckhäfer, K., Wachter, K., & Spengler, T. S. (2017). Analyzing manufacturers' impact on green products' market diffusion – The case of electric vehicles. *Journal of Cleaner Production, 162*, S11–S25. https://doi.org/10.1016/j.jclepro.2016.05.021

Klein, M., Lüpke, L., & Günther, M. (2020). Home charging and electric vehicle diffusion: Agent-based simulation using choice-based conjoint data. *Transportation Research Part D: Transport and Environment*, 88. https://doi.org/10.1016/j.trd.2020.102475

Knepell, P. L., & Arangno, D. C. (1993). *Simulation validation*. IEEE Computer Society Press. https://ieeexplore.ieee.org/iel3/69/5754/x0325907.pdf.

Krause, R. M., Carley, S. R., Lane, B. W., & Graham, J. D. (2013). Perception and reality: Public knowledge of plug-in electric vehicles in 21 U.S. cities. *Energy Policy, 63*, 433–440. https://doi.org/10.1016/j.enpol.2013.09.018

Kumar, R. R., & Alok, K. (2020). Adoption of electric vehicle: A literature review and prospects for sustainability. In *, vol. 253*. *Journal of cleaner production*. https://doi.org/10.1016/j.jclepro.2019.119911

Liao, F., Molin, E., & van Wee, B. (2017). Consumer preferences for electric vehicles: A literature review. *Transport Reviews, 37*(3), 252–275. https://doi.org/10.1080/01441647.2016.1230794

McCoy, D., & Lyons, S. (2014). Consumer preferences and the influence of networks in electric vehicle diffusion: An agent-based microsimulation in Ireland. *Energy Research and Social Science, 3*(C), 89–101. https://doi.org/10.1016/j.erss.2014.07.008

McFadden, D. L. (1973). Conditional Logit analysis of qualitative choice behavior — Economics E-journal. *Frontiers in Econometrics, 105*. http://elsa.berkeley.edu/reprints/mcfadden/zarembka.pdf.

Michalek, J. J., Papalambros, P. Y., & Skerlos, S. J. (2004). A study of fuel efficiency and emission policy impact on optimal vehicle design decisions. *Journal of Mechanical Design, 126*(6), 1062–1070.

MIT. (2017). Driving the future: alternative fuel vehicle market simulator. https://forio.com/app/mit/afv-test.

Mueller, M. G., & de Haan, P. (2009). How much do incentives affect car purchase? Agent-based microsimulation of consumer choice of new cars-part I: Model structure, simulation of bounded rationality, and model validation. *Energy Policy, 37* (3), 1072–1082. https://doi.org/10.1016/j.enpol.2008.11.002

Nieuwenhuijsen, J., de Correia, G. H. A., Milakis, D., van Arem, B., & van Daalen, E. (2018). Towards a quantitative method to analyze the long-term innovation diffusion of automated vehicles technology using system dynamics. *Transportation Research Part C: Emerging Technologies, 86*, 300–327. https://doi.org/10.1016/j.trc.2017.11.016

Ning, W., Guo, J., Liu, X., & Pan, H. (2019). Incorporating individual preference and network influence on choice behavior of electric vehicle sharing using agent-based model. *International Journal of Sustainable Transportation, 14*(12), 917–931. https://doi.org/10.1080/15568318.2019.1656310

Noori, M., & Tatari, O. (2016). Development of an agent-based model for regional market penetration projections of electric vehicles in the United States. *Energy, 96*, 215–230. https://doi.org/10.1016/j.energy.2015.12.018

Oliveira, G. D., Roth, R., & Dias, L. C. (2019). Diffusion of alternative fuel vehicles considering dynamic preferences. *Technological Forecasting and Social Change, 147*, 83–99. https://doi.org/10.1016/j.techfore.2019.06.002

Pablo-Martí, F., Santos, J. L., & Kaszowska, J. (2015). An agent-based model of population dynamics for the european regions. *Emergence: Complexity and Organization, 17*(2). doi:10.emerg/10.17357.2d9791afc384e40b47f02d089976c627.

Palmer, J., Sorda, G., & Madlener, R. (2015). Modeling the diffusion of residential photovoltaic systems in Italy: An agent-based simulation. *Technological Forecasting and Social Change, 99*, 106–131. https://doi.org/10.1016/j.techfore.2015.06.011

Pasaoglu Kilanc, G., Harrison, G., Jones, L., Hill, A., & Thiel, C. (2016). A system dynamics based market agent model simulating future powertrain technology transition: Scenarios in the EU light duty vehicle road transport sector. *Technological Forecasting and Social Change, 104*, 133–146.

Querini, F., & Benetto, E. (2014). Agent-based modelling for assessing hybrid and electric cars deployment policies in Luxembourg and Lorraine. *Transportation Research Part A: Policy and Practice, 70*, 149–161. https://doi.org/10.1016/j.tra.2014.10.017

Ramsey, D. M., Kowalska-Pyzalska, A., & Bienias, K. (2018). Diffusion of electric vehicles: An agent-based modelling approach. In *Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics): Vol. 11290 LNCS* (pp. 118–135). https://doi.org/10.1007/978-3-662-58464-4_11

Rand, W., & Rust, R. T. (2011). Agent-based modeling in marketing: Guidelines for rigor. *International Journal of Research in Marketing, 28*(3), 181–193. https://doi.org/10.1016/j.ijresmar.2011.04.002

Rindfuss, R., Entwisle, B., Walsh, S., Li, A., Badenoch, N., Brown, D., Deadman, P., Evans, T., Fox, J., Geoghegan, J., Gutmann, M., Kelly, M., Linderman, M., Liu, J., Malanson, G., Mena, C., Messina, J., Moran, E., Parker, D., … Verburg, P. (2008). Land use change: Complexity and comparisons. *Journal of Land Use Science, 3*(1), 1–10. https://doi.org/10.1080/17474230802047955

Rotaris, L., & Danielis, R. (2019). The willingness to pay for a carbon tax in Italy. *Transportation Research Part D: Transport and Environment, 67*, 659–673. https://doi.org/10.1016/j.trd.2019.01.001

Rotaris, L., Giansoldati, M., & Scorrano, M. (2021). The slow uptake of electric cars in Italy and Slovenia. Evidence from a stated-preference survey and the role of knowledge and environmental awareness. *Transportation Research Part A: Policy and Practice, 144*, 1–18. https://doi.org/10.1016/j.tra.2020.11.011

Scorrano, M., Danielis, R., & Giansoldati, M. (2020). Dissecting the total cost of ownership of fully electric cars in Italy: The impact of annual distance travelled, home charging and urban driving. *Research in Transportation Economics, 80*. https://doi.org/10.1016/j.retrec.2019.100799

Scorrano, M., Danielis, R., & Giansoldati, M. (2021). Electric light commercial vehicles for a cleaner urban goods distribution. Are they cost competitive? *Research in Transportation Economics*. https://doi.org/10.1016/j.retrec.2020.101022

Scorrano, M., Mathisen, T. A., & Giansoldati, M. (2019). Is electric car uptake driven by monetary factors? A total cost of ownership comparison between Norway and Italy. *Economics and Policy of Energy and the Environment, 2*. https://doi.org/10.3280/EFE2019-002005

Shafiei, E., Thorkelsson, H., Ásgeirsson, E. I., Davidsdottir, B., Raberto, M., & Stefansson, H. (2012). An agent-based modeling approach to predict the evolution of market share of electric vehicles: A case study from Iceland. *Technological Forecasting and Social Change, 79*(9), 1638–1653. https://doi.org/10.1016/j.techfore.2012.05.011

Shepherd, S. P. (2014). A review of system dynamics models applied in transportation. In *, vol. 2*. *Transportmetrica B* (pp. 83–105). Taylor and Francis Ltd. https://doi.org/10.1080/21680566.2014.916236. Issue 2.

Silvia, C., & Krause, R. M. (2016). Assessing the impact of policy interventions on the adoption of plug-in electric vehicles: An agent-based model. *Energy Policy, 96*, 105–118. https://doi.org/10.1016/j.enpol.2016.05.039

Sterman, J. (2000). *Business Dyanmics: Systems thinking and modeling for a complex world*. McGraw-Hill.

Struben, J., & Sterman, J. D. (2008). Transition challenges for alternative fuel vehicle and transportation systems. *Environment and Planning. B, Planning & Design, 35*(6), 1070–1097. https://doi.org/10.1068/b33022t

Sullivan, J. L., Salmeen, I. T., & Simon, C. P. (2009). PHEV market place penetration an agent based simulation. In *University of Michigan Transport Research Institute (Issue July)*.

Sun, X., Liu, X., Wang, Y., & Yuan, F. (2019). The effects of public subsidies on emerging industry: An agent-based model of the electric vehicle industry. *Technological Forecasting and Social Change, 140*, 281–295. https://doi.org/10.1016/j.techfore.2018.12.013

Tesfatsion, L. (2002). Agent-based computational economics: Growing economies from the bottom up. In *, vol. 8*. *Artificial life* (pp. 55–82). https://doi.org/10.1162/106454602753694765. Issue 1.

Thies, C., Kieckhäfer, K., & Spengler, T. S. (2016). Market introduction strategies for alternative powertrains in long-range passenger cars under competition. *Transportation Research Part D: Transport and Environment, 45*, 4–27. https://doi.org/10.1016/j.trd.2015.05.002

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge university pres.

UNRAE. (2019). UNRAE - Unione Nazionale Rappresentanti Autoveicolo Esteri. http://www.unrae.it/dati-statistici/immatricolazioni.

Valeri, E., & Cherchi, E. (2016). Does habitual behavior affect the choice of alternative fuel vehicles? *International Journal of Sustainable Transportation, 10*(9), 825–835. https://doi.org/10.1080/15568318.2016.1163445

Valeri, E., & Danielis, R. (2015). Simulating the market penetration of cars with alternative fuelpowertrain technologies in Italy. *Transport Policy, 37*, 44–56. https://doi.org/10.1016/j.tranpol.2014.10.003

Vouzavalis, A. (2020). *Capturing car market dynamics in the transition towards electric mobility in an agent-based simulation model*. University of Twente.

Wang, H., Mostafizi, A., Cramer, L. A., Cox, D., & Park, H. (2016). An agent-based model of a multimodal near-field tsunami evacuation: Decision-making and life safety. *Transportation Research Part C: Emerging Technologies, 64*, 86–100. https://doi.org/10.1016/j.trc.2015.11.010

Wojnarová, R. (2017). *Agent-based analysis of market potential for electric vehicles in the Czech Republic*. Charles University. https://dspace.cuni.cz/handle/20.500.11956/91440.

Wolf, I., Schröder, T., Neumann, J., & de Haan, G. (2015). Changing minds about electric cars: An empirically grounded agent-based modeling approach. *Technological Forecasting and Social Change, 94*, 269–285. https://doi.org/10.1016/j.techfore.2014.10.010

Wu, G., Inderbitzin, A., & Bening, C. (2015). Total cost of ownership of electric vehicles compared to conventional vehicles: A probabilistic analysis and projection across market segments. *Energy Policy, 80*, 196–214. https://doi.org/10.1016/j.enpol.2015.02.004

Wurzer, G., Kowarik, K., & Reschreiter, H. (2015). Agent-based modeling and simulation in archaeology. *Advances in Geographic Information Science, 7*.

Yang, W., Zhou, H., Liu, J., Dai, S., Ma, Z., & Liu, Y. (2015). Market evolution modeling for electric vehicles based on system dynamics and multi-agents. In *Proceedings - 2015 international symposium on smart electric distribution systems and technologies, EDST 2015* (pp. 133–138). https://doi.org/10.1109/SEDST.2015.7315196

Yang, W., Xiang, Y., Liu, J., & Gu, C. (2018). Agent-based modeling for scale evolution of plug-in electric vehicles and charging demand. *IEEE Transactions on Power Systems, 33*(2), 1915–1925.

Zhang, T., Gensler, S., & Garcia, R. (2011). A study of the diffusion of alternative fuel vehicles: An agent-based modeling approach. *Journal of Product Innovation Management, 28*(2), 152–168. https://doi.org/10.1111/j.1540-5885.2011.00789.x

Zhuge, C., Wei, B., Dong, C., Shao, C., & Shan, Y. (2019). Exploring the future electric vehicle market and its impacts with an agent-based spatial integrated framework: A case study of Beijing, China. *Journal of Cleaner Production, 221*, 710–737. https://doi.org/10.1016/j.jclepro.2019.02.262