

# The role of driving range in consumers' purchasing decision for electric cars in Italy

Marco Giansoldati\*§, Romeo Danielis§, Lucia Rotaris§, Mariangela Scorrano§

\*Corresponding author. Tel.: +39 040 5587076; fax: +39 040 567543.

E-mail address: mgiansoldati@units.it (M. Giansoldati).

§Dipartimento di Scienze Economiche, Aziendali, Matematiche e Statistiche "Bruno de Finetti"

Università degli Studi di Trieste, Via dell'Università, 1 − 34123 Trieste, Italy.

#### **Abstract**

The paper reports the results of a stated preference study, carried out in Italy in 2017, on consumers' preferences between an electric car (EC) and a petrol car. The focus is on the role of driving range. We find that the linear specification leads to lower willingness to pay (WTP) estimate for the driving range than the logarithmic, quadratic and EC-specific ones. The estimation of a mixed logit model leads to a coefficient of the EC-specific range attribute six times larger than the coefficient of the non-EC one. The jointly statistically significant covariates explaining the heterogeneity of the coefficient of the EC-specific driving range attribute are gender, number of cars owned by the family, and knowledge of cars. The implied WTP varies from 37 to 106 €/km, depending on the socioeconomic characteristics of the respondent. Simulative analysis shows that very relevant increases in the probability of buying an electric car (ranging from 28% to 68%) over a petrol one require jointly improvements in the fast charging network, driving range and financial incentives.

**Keywords**: electric cars; petrol cars; driving range; willingness to pay.

## 1 Introduction

Stated and revealed preference data and discrete choice modelling have been used extensively since the 1980s to evaluate the consumers' acceptance of electric cars (ECs) (Beggs and Carrell, 1980; Beggs et al. 1981; Calfee, 1985). All studies showed that driving range is one of the main choice determinants, but also one of the main limiting factors for ECs uptake because of their limited range

(Brownstone et al. 2000; Mabit and Fosgerau, 2011, Hess, et al. 2012). Recent surveys on the importance of driving range on purchase choice decisions are provided by Egbue and Long (2012), Coffman et al (2017), and Kim et al. (2017).

Different model specifications have been used to measure the impact of a 1-mile variation on a EC choice probability such as the linear, quadratic, logarithmic, piece-linear and EC-specific specification, resulting in quite different WTP estimations. Dimitropolous et al. (2013) review such studies and argue that non-linear specifications are superior to the linear ones. Other authors dispute such conclusion. For instance, Bahamonde-Birke and Hanappi (2016) find that their sample perceives gains in the driving range linearly and explain it with the inexperienced regarding the use of electric vehicles. Cherchi (2017) tests several non-linear specifications and finds that also in her case the linear specification is the one performing the best. To contribute to this debate we will compare the different specifications using our data collected in Italy in 2017.

It is also still widely researched how socio-economic, technological, mobility, geographical and infrastructural factors influence car purchase decisions and ECs' acceptance. All studies (e.g., Ziegler, 2012, and Link et al., 2012) find that economic and technological attributes such as purchasing price, annual operating cost, acceleration, driving range, motor power, charging time, are CO<sub>2</sub> emissions are crucial determinants, Socio-demographic variables such as sex, income, education are also found to play a role. Attitudinal, psychological, experience and environmental awareness variables are modeled and tested by Daziano and Chiew (2012), Daziano (2013) and Cherchi (2017), finding empirical evidence on their statistical significance. Vehicle ownership and mobility patterns of the respondents – such as number of car in the household, garage ownership, urban\intercity mobility, annual travel distance or percentage of longer trips – appear also to influence car choice (e.g. Valeri and Danielis, 2015). It is important to distinguish amongst car segments (small, medium, luxury or sports cars) and ownership types (private vs. company car) (Jensen et al., 2013). ECs' acceptance is, moreover, dependent on infrastructural and policy variables such as service\charging station availability, remission of parking fees, number of spaces reserved for ECs, free entry in environmental zones, access to dedicated bus lanes, and fiscal incentives (Ziegler, 2012; Link et al., 2012; Hackbarth and Madlener, 2013; Hoen and Koetse, 2014; Cherchi, 2017). Some studies investigate also differences among specific cities, states, and countries (Tanaka et al., 2014).

The studies carried out up to a decade ago suffered from the limitation that ECs were unknown or relatively new so that respondents had little or no direct experience with ECs' driving range, leading them to provide likely incorrect valuations. Nowadays, ECs' uptake is gradually expanding. ECs' driving tests are offered by most car manufactures and numerous blogs or video reports are available in the Internet documenting the pros and cons of ECs, with special attention to driving range limitation and charging issues. Scientific and economic development made it possible to increases ECs driving range, with some car models (e.g., the one released by Tesla Motors) gradually catching up with conventional cars range. Moreover, the charging infrastructure is rapidly developing, becoming more densely and evenly distributed over the territory and allowing faster charging rates (up to 350 kW). Consequently, we deemed it worthwhile to carry out a new survey, focusing our attention on the consumer's evaluation of the ECs' driving range in a discrete choice modeling framework, with the aim to assess its importance relative to other car features.

This paper contributes to the literature by: a) collecting and estimating recent Italian consumers' preference data regarding car choice; b) testing the statistical performance of alternative driving range specifications in the random utility model; c) evaluating the implicit WTP and comparing it with the results so far presented in the literature; d) estimating the main covariates that impact ECs' driving range; e) carrying out scenario analysis to assess the driving range impact of ECs uptake.

Apart from the various interesting methodological aspects tackled in the paper, we believe that the results obtained could be of value both to the automotive industry and to policy makers aiming at incentivizing ECs uptake due to their favorable environmental and energy efficiency.

# 2 Stated choice experiment and data collection

Disaggregate demand analysis based on the random utility theory is one of the most established approaches to estimate demand (McFadden, D., 1981; Ben-Akiva and Lerman, 1985; Train, 2002). The probability that an individual chooses the alternative with the highest utility, among a specific set of choice profiles, is estimated, and the main factors that influence her/his choice are identified. Assuming that the parameters in a utility function have a random nature, the mixed logit model allows for preference heterogeneity and permits to identify its main determinants (McFadden and Train, 2000).

The mixed logit model is estimated with data deriving from interviews administered in 2017 in the Friuli Venezia Giulia region, located in the north-east of Italy. Currently, the Region has a very low ECs uptake (less than 1%), despite recent financing incentive set up by the Regional Administration both to purchase ECs and to install charging stations. The number of charging station has been rapidly increasing in the last year but only 3 fast charging stations with 10 stalls (including 8 Tesla stalls) are currently available.

The interviews consisted in a questionnaire divided into two parts. In the first part the respondent was asked to supply socio-economic information, while in the second part was confronted with 10-12 stated choice scenarios. The socio-economic information includes: 1) personal information 2) car and garage ownership; 3) mobility habits; 4) car knowledge and attitude towards ECs. An example of choice scenario is illustrated in Figure 1. A decision was made to limit the number of attributes to 5 in order to avoid respondents' fatigue: brand, purchase price  $(\mbox{\ensuremath{\mathfrak{E}}})$ , annual operating cost (gasoline, insurance, tax, maintenance)  $(\mbox{\ensuremath{\mathfrak{E}}})$ , driving range (km), and the percentage of fuel service stations endowed with fast electric charging capability. For the same reason, the number of scenarios was also reduced from the initial 12 to 10, having tested insufficient respondents' attention during the last stages of the face-to-face interview.

Figure 1. Example of state preference choice proposed to the respondent

Attributes	VW Egolf kWh 35.8	Renault Clio
Powertrain:	Electric	Internal combustion
Purchasing price (€)	20,000	15,000
Driving range (km)	Km 150	Km 400
Annual operating cost (per 10,000 km)	2,500	5,000
% of service stations with fast charging infrastructures	30%	-

The 4 best-selling ECs in the Italian market were used in the choice scenarios: the VW E-Golf equipped with a 35.8 kWh battery, the Renault Zoe, the Nissan Leaf and the Daimler Smart forfour EQ, confronted with the petrol VW Golf, the Renault Clio, the Nissan Pulsar and the Daimler Smart forfour. Their picture was also provided. The Status Quo (SQ) attribute levels for each car were set equal to the Italian average values as reported in Table 1. They were varied as follows: i) four brands; ii) purchase price: -20%, SQ, +20%, +40%; iii) driving range: SQ, +20%, +40%; iv) annual operating cost: -20%, SQ, +20%; v) the percentage of fuel service stations endowed with fast electric charging capability: SQ, +30%. +50%. The SQ for the annual operating costs attribute are based on Danielis et al. (2018). An efficient experimental design strategy was used with 2 waves in order to minimize the asymptotic standard error (Bliemer and Rose, 2010, 2011; Huber and Zwerina,1996; Yu et al., 2009).

#### ----Table 1 about here-----

Three survey channels were used: Google-Forms (204 valid responses), 38 face-to-face interviews, and 110 collective paper-and-pencil interviews, of which 34 were discarded as lexicographic, for a total of 318 valid interviews. We tested whether the results were dependent on the channel used, finding no statistical difference.

# 3 Descriptive statistics of the sample

The sample of individuals we analyzed is quite heterogeneous and can be summarized as follows:

Socio-economic information:

- *Gender* (%): Males; 61.3%; Females; 38.7%;
- Age (%): From 18 to 30: 34.9%; From 30 to 60: 60.7%; More than 60: 4.4%;

- Level of education (%): Middle school: 4.7%; High school diploma: 44.0%; Undergraduate degree: 43.7%; Postgraduate degree: 7.5%;
- *Current employment* (%): Employee: 40.9%; Managerial employee: 10.7%; Entrepreneur: 13.5%; Student: 17.3%; Working-student: 2.5%; Retiree: 2.2%; Housewife: 2.8%; Unemployed: 2.2%; Other: 7.9%;
- *Net yearly household income* (%): Less than €30,000: 27.0%; Between €30,000 and €70,000: 47.2%; More than €70,000: 23.0%; Missing values: 2.8%;
- Place of residency (%): Urban: 74.2%; Non-urban: 25.8%.

#### Car and garage ownership:

- *No. of owned cars in the family (%)*: 0 cars: <1%; 1 car: 17.3%; 2 cars: 50.9%; 3 cars: 21.7%; 4 cars: 7.2%; 5 cars: 2.2%; 6 cars: <1%;
- Availability of a garage or car box (%): Yes: 81.4%; No: 18.6%.

## Car mobility habits:

- Average distance by car per trip (%): ≤10 km: 30.8%; 11-50 km: 52.2%; 51-100 km: 8.8%; >100 km: 5.7%; Missing values: 1.9%;
- *Number of yearly return trips by car over 400 km (%)*: ≤11: 83.0%; >11: 17.0%.

## Car knowledge and attitude towards ECs:

- Self-evaluated level of expertise with cars (%) (1=None, 7=Very high): 1: 10.4%; 2: 10.7%; 3: 17.0%; 4: 17.0%; 5: 27.4%; 6: 12.9%; 7: 4.7%;
- ECs knowledge (%) (our elaboration on respondents' knowledge on ECs' driving range and minimum time required for a full charge): Scarce: 50.9%; Good: 49.1%;
- *ECs' driving experience* (%): Yes: 18.3%; No: 81.7%;
- ECs' purchase intentions (%) (Reply to the following question: "Have you ever thought to buy an EC?" 1: "Yes", 2: "No, but I may think about it.", 3: "No. I do not think it is an option in the near future": Reply 1: 34.3%; Reply 2: 50.3%; Reply 3: 15.4%.

The most relevant feature of the sample for our analysis is that almost three quarters of the respondents live in urban areas and most of them own a garage. As for their ECs knowledge, half of them have a good knowledge, answering correctly to questions regarding ECs' range and charging time. However, only 18% had a direct driving experience. Surprisingly, most of them expressed an interest in buying an EC in the near future.

# 4 Driving range specification: comparison of functional forms

In our scenarios based on 8 car models currently available in the Italian market, ECs' driving range varies between 150 and 350 km, whereas petrol cars' range varies between 400 and 1,200 km. Four driving range specifications are possible according to the literature.

A first group of authors (e.g. Knockaert, 2010; Christensen et al. 2012; Tanaka et al., 2014) suggest a linear specification:

$$U = ASC + \beta_{range} driving range + \cdots$$

A second group of authors (Mabit and Fosgerau, 2011; Link et al., 2012; Hess et al., 2012; Dimitropoulos et al., 2013; Hackbarth and Madlener, 2016) claim that the lognormal specification is superior since its non-linearity is consistent with the fact that the range coefficient is expected to decline as the driving range increases. This relationship can be described either by a natural logarithm transformation of the driving range,

$$U = ASC + \beta_{range} \ln(driving range) + \cdots$$

or by adding the squared of the driving range to the linear term if an inversed U-shaped relationship between range and utility is assumed:

$$U = ASC + \beta_{range} driving \ range + \beta_{range^2} driving \ range^2 + \cdots$$

A third group of authors (e.g. Ziegler, 2012; Hoen and Koetse, 2014; Valeri and Danielis, 2015) use an EC-specific driving range specification:

$$\begin{cases} U_{ICEV} = ASC + \beta_r range + \cdots \\ U_{EC} = \beta_{EC\_r} range + \cdots \end{cases}$$

We tested all these four specifications with the addition of our four attributes (brand, purchasing price, annual operation cost, % of fuel stations with fast charging equipment), using a simple binary logit model. Table 2 reports the results.

The best performing model is the EC-specific one which shows the largest log-likelihood, whereas the worst performing model is the linear one.

The implied WTP for the non-linear specifications is computed in the intermediate reference point at 200 km, the difference between the maximum and the minimum EC range, as suggested by Dimitropoulos et al. (2013). It can be observed that the WTP with the linear specifications is equal to  $\epsilon$ 35 per km. The logarithmic and the quadratic specifications imply, respectively, a WTP equal to  $\epsilon$ 70 and  $\epsilon$ 62. The EC-specific range specification produces an estimate equal to  $\epsilon$ 76 for the EC and  $\epsilon$ 15 for the petrol cars. These results confirm that the linear specification results in lower WTP estimates for the EC driving range than the non-linear one, as argued by Dimitropoulos et al. (2013), as it averages among very different range levels. In absolute terms, however, our estimates are not in line with those obtained through a meta-analysis by Dimitropoulos et al. (2013). On the basis of a meta-analysis, they report a WTP for a 1-mile range variation ranging between \$66 and \$75, equivalent to  $\epsilon$ 34 and  $\epsilon$ 39 for a 1-km range variation using the current exchange rate (May 3<sup>rd</sup>, 2018). This difference might be due to the fact the Dimitropoulos et al. (2013)'s meta-analysis is also based on

studies published up to the year 2011, prior to the advent of electric cars and therefore suffers from underestimates due to lack of experience, as pointed out by Kurani et al. (1994) and Franke et al. (2012).

It can also be noted that the EC-specific specification results in WTP-estimates in line with the non-linear specifications estimated at 200 km. Given its high statistical performance and the fact that it clearly differentiates between EC- and non-EC driving range, in the following model we will adopt an EC-specific specification for our analysis of the main sources of heterogeneity in the driving range valuation.

# 5 Detecting covariates of the driving range via a mixed logit model

In order to take into account preference heterogeneity and explain its determinants we estimate a mixed logit model.

We tried numerous specification in search for the one with the largest set of significant parameters and the highest explanatory power. Our preferred specifications are shown in Equation 1 and 2 (for EC and non-EC, respectively), whilst the results obtained through 1,000 random draws for simulated probabilities are reported in Table 3.

```
U_{EC} = \beta_{CE}ASC + \beta_{PP}PurchasePrice + \beta_{RE}ECrange + \beta_{AOC}AnnualOperatingCost + \beta_{ECS}FuelStationWithFastCharging + \beta_{B_vw}Volkswagen + \beta_{B_k}Renault + \beta_{B_n}Nissan + \beta_{RE_MALE}ECrange x Gender + \beta_{RE_NO_CARS_F}ECrange x NumberOfCarsInFamily + \beta_{RE_EXPERT}ECrange x RespondentsCarExpertise + \beta_{ECS_URBAN}FuelStationWithFastCharging x Residency + <math>\varepsilon (1)
```

 $U_{\text{non\_EC}} = \beta_{\text{PP}} Purchase Price + \beta_{\text{RNE}} Non-E Crange + \beta_{\text{AOC}} Annual Operating Cost + \beta_{\text{B\_VW}} Volkswagen + \beta_{\text{B\_R}} Renault + \beta_{\text{B\_N}} Nissan + \varepsilon (2)$ 

Table 3. Results of the preferred mixed effects model specification

Variables	Coeff.	t-Ratio
Random parameters		
ASC*: EC $(\beta_{CE})^a$	-1.2927	-5.9
EC range (100 km) $(\beta_{RE})^a$	0.6499	3.2
Non-EC range (100 km) $(\beta_R)^a$	0.0953	6.0
% of fuel stations with fast charging stalls $(\beta_{ECS})^a$	0.0211	6.8
Non-random parameters		
Purchase price (€1,000) (β <sub>PP</sub> )	-0.0641	-5.4
Annual operating cost ( $\&$ 1,000) ( $\beta$ <sub>AOC</sub> )	-0.2370	-4.3

#### Working papers SIET 2018 – ISSN 1973-3208

Brand Volkwagen ( $\beta_{B_{-}VW}$ )	0.9416	11.1
Brand Renault ( $\beta_{B_{-}R}$ )	0.3524	4.4
Brand Nissan ( $\beta_{B_{-}N}$ )	0.3588	3.7
Heterogeneity sources		
EC range: Gender: Male ( $\beta_{RE\_MALE}$ )	-0.1272	-1.7
EC range: No. of owned cars in the family (1 to 6) ( $\beta_{RE\_NO\_CARS\_F}$ )	-0.1061	-3.2
EC range: Self-evaluated level of expertise with cars (1 to 7) ( $\beta_{RE\_EXPERT}$ )	0.0528	2.3
% of fuel stations with fast charging stalls: Place of residency: Urban ( $\beta_{ECS\_URBAN}$ )	0.0095	2.0
Ts ASC* EC	3.0412	10.6
Ts EC range	0.2591	1.2
Ts Non-EC range	0.1613	2.5
Ts % of fuel stations with fast charging stalls	0.0123	0.6
Adjusted R-squared no of observations	0.1536	
Number of observations	3298	
Log likelihood	-1924.85	

Source: our elaboration from survey data

*Notes*: \*ASC refers to the constant-specific attribute.

First, we identified the coefficients with the largest standard deviations indicating high preference heterogeneity. We find that this applies to the following attributes: constant-specific attribute, EC-range, non-EC range and % of fuel stations with fast charging stalls. Second, we tested different distributions that would fit the data and be consistent with our priors. We find that the constrained triangular distribution, imposing that the average to be equal to the spread of the distribution, therefore excluding coefficients value's contrary to our a-priori, fits the data quite well. Third, we tested which socio-economic variables explain the preference heterogeneity.

All attributes are significant and have the expected sign. It can be noted that the coefficient of the ECspecific range attribute is more than 6 times larger than the coefficient of the non-EC one. A strong preference for the VW cars relative to the Daimler Smart is also detected. Thanks to our socioeconomic data, we considered the following potential covariates with the EC-specific range attribute: gender, age, level of education, employment, household income, place of residency, number of cars owned by the family, availability of owned garage or car box, average distance by car per trip, number of yearly return trips by car over 400 km, ECs' driving experience, and knowledge of cars. Only the following ones are jointly statistically significant: gender, number of cars owned by the family, knowledge of cars. Their interpretation is the following. Men are more sensitive than women to the effect of the EC range, in line with the findings of Valeri and Danielis (2015). The larger the number of cars owned by the family members the lower the sensitivity of the sample to the EC range, a reasonable outcome since households who can rely on a larger number of vehicles are more likely to own one car able to travel longer distances. The higher the self-declared car knowledge the larger the sensitivity to the EC range. We also find that the place of residency is a significant covariate of the attribute % of fuel stations with fast charging stalls, meaning that respondents who live in a urban area are more sensitive to the density of electric charging stations, since they are less likely to own a private garage. No attempt has been made to explore the heterogeneity determinants of the non-EC range since this is not the focus of our investigation.

The implied WTP is presented in Table 3. The WTP would normally vary from 37 to 106 €/km, depending on the socio-economic characteristics of the respondent.

Table 4. Implied WTP of the mixed logit model

	WTP (€/km)
Male (coded: 1)	82
Female (coded: 2)	62
1-car family member (coded: 1)	85
2-car family member (coded: 2)	68
Car expert (level 1, coded: 1)	143
Car non-expert(level 5, coded: 5)	110
Lowest joint evaluation: Female, 2-car family, non-expert	37
Highest joint evaluation: Male, 1-car family, expert	106

## 6 Simulation

The parameters of the mixed logit are now used to perform a model simulation in order to estimate the variation in the probability of buying an EC versus a petrol car when the current base case values are altered.

The base case scenario derives from the SQ consisting in the current value (Table 1) and an assumed % of fuel stations equipped with fast charging stalls equal to 10% (a policy goal of the Regional Administration, higher than the current number).

The simulative scenarios considered are the following:

- S1) Increase from 10% to 50% of the % of fuel stations equipped with fast charging stalls
- S2) Increase from 10% to 100% of the % of fuel stations equipped with fast charging stalls
- S3) EC range increase by 25%
- S4) EC range increase by 50%
- S5) €5,000 subsidy on purchase price
- S6) Increase from 10% to 50% of the % of fuel stations equipped with fast charging stalls and EC range increase by 25%
- S7) Increase from 10% to 100% of the % of fuel stations equipped with fast charging stalls, EC range increase by 50% and  $\in$ 5,000 subsidy on purchase price

Table 5 reports the results, considering the 3 covariates resulting from the mixed logit estimation. It is to be read as follow. If the % of fuel stations equipped with fast charging stalls increases from the

base case scenario value of 10% to 50% (S1), women would be 3.6% more likely to buy an electric car than a petrol car, all other attributes held constant. It can be seen that cars experts (i.e, the respondents who self-evaluated their level of expertise with cars equal to 5 on a scale1 to 7) are the more reactive to all scenarios. The interpretation being that they value more than any other respondent type positive changes towards ECs. Comparing among scenarios, it can be observed that the assumed infrastructural improvements are more convincing than the assumed ECs range increases or purchasing price decreases. Very relevant changes in the probability preferring an electric car over a petrol one requires joint improvements in all dimension considered: fast charging network, driving range improvements and financial incentives.

## 7 Conclusions

This paper reports the results of a stated preference study, carried out in Italy in 2017, on consumers' preferences between an electric and a petrol car. The main focus of the analysis is to evaluate the role of the driving range in consumers purchasing decisions. We tested the statistical performance of alternative driving range specifications in the random utility model, evaluated the implicit WTP of our sample, and compared it with the results so far presented in the literature. Furthermore, we searched for the main covariates that explain ECs' driving range preference heterogeneity and carried out simulative analysis to assess the driving range impact on ECs uptake.

Although in Italy and in the Friuli Venezia Giulia Region the ECs uptake is yet very limited, the sample of our respondents knew and was interested in buying an EC. Most likely, information via various media and Internet on EC has reached large segments of the population and in many Italian locations charging stations are getting increased attention. However, informal and statistical evidence suggests that ECs' driving range limitations are still a main factor of concern, preventing people from buying ECs.

Having administered an admittedly-limited number of stated choice interviews, the preference data collected lead us to confirming Dimitropolous et al. (2013)'s statement that the linear specification of the driving range parameter in the utility function leads to a lower WTP estimate than the logarithmic, quadratic and EC-specific ones. We find a superior goodness of fit when using the EC range-specific specification relative to other ones, which leads to an implied WTP of a 1-km increase in the driving range equal to  $\epsilon$ 76 for the EC and  $\epsilon$ 15 for the petrol cars. Compared with estimates resulting from the meta-analysis performed by Dimitropolous et al. (2013) on up to 2011 stated preference studies equivalent to  $\epsilon$ 34 and  $\epsilon$ 39 for a 1-km range variation, our estimate let us conclude that a better knowledge of the ECs, in general, and their driving limitation in the day-to-day use, in particular, have reinforced consumers' concerns on ECs' range.

The use of the mixed logit model – in order to allow for and explain preference heterogeneity – results in a coefficient of the EC-specific range attribute 6 times larger than the coefficient of the non-EC one. The jointly statistically significant covariates explaining the heterogeneity of the coefficient of the EC-specific range attribute are gender, number of cars owned by the family, and knowledge of cars. Men are more sensitive than women to the effect of the EC range. The larger the number of cars owned by the family members the lower the sensitivity to the EC range. The higher the self-declared

car knowledge the larger the sensitivity to the EC range. Other potential covariate such as age, level of education, employment, household income, availability of owned garage or car box, average distance by car per trip, number of yearly return trips by car over 400 km were found not statistically significant. We also found that the place of residency is a significant covariate of the attribute % of fuel stations with fast charging stalls. The imply WTP for a 1-km increase in the EC driving range derived from this model varies from 37 to 106 €/km, depending on the socio-economic characteristics of the respondent, thus confirming the importance of this attribute in the car choice decisions of our sample.

Lastly, we have performed a simulative analysis that showed that infrastructural improvements increase the probability of opting for an EC instead of a petrol one even more than increasing the EC driving range or decreasing the EC purchasing price. Very relevant increases in the probability of buying an electric car (ranging from 28 to 68%) requires joint improvements in fast charging network, driving range and financial incentives.

These outcomes justify the formulation of at least two policy recommendations. Policy makers should set up incentives to provide a larger number of fast charging stations, possibly in the same location of current fuel stations, to send a clear signal that ECs enjoy public support. Increases in the driving range are urgently needed and will be rewarded by the consumers, since a 100 km driving range increase is valued up to €10,600. This could be accomplished through R&D efforts undertaken by private companies, with the support by the public sector through financial and fiscal incentives granted to academic\non-academic research institutes.

The estimates presented in this paper suffer from the common data uncertainties, related to the sample size and its representativeness. Moreover, since technological, economic and political developments might induce relevant changes in the car market, variations in the preference structure of the car buyers are possible and need to be closely monitored. Our future research envisions a new choice experiment on both a larger sample size and on an extended geographical (possibly international) dimension. We would also like to improve our understanding of the relationship amongst the density of electric charging stations, the individual-specific mobility needs and WTP for the EC driving range. A further research goal is to test whether there is a threshold driving range beyond which customers are comfortable with the EC driving range.

#### References

- Anderson S., Palma A.D., Thiesse J.F. (1992), *Discrete Choice Theory of Product Differentiation*. MIT Press, Cambridge.
- Bahamonde-Birke, F. J., Hanappi, T. (2016), "The potential of electromobility in Austria: Evidence from hybrid choice models under the presence of unreported information", *Transportation Research Part A: Policy and Practice*, 83, 30-41.
- Beggs S., Cardell S., Hausman J. (1981). "Assessing the potential demand for electric cars", *Journal of econometrics*, 17(1), 1-19.
- Beggs S., Cardell, S. (1980). Choice of smallest car by multi-vehicle households and the demand for electric vehicles, *Transportation Research Part A: General*, Volume 14, Issues 5–6, 389-404
- Ben-Akiva M., Lerman S. (1985), *Discrete choice analysis: theory and application to travel demand.* MIT Press, Cambridge.
- Bliemer M.C., Rose, J.M. (2010), "Construction of experimental designs for mixed logit models allowing for correlation across choice observations", *Transportation Research Part B: Methodological*, 44(6), pp. 720-734.

- Bliemer M.C., 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), pp. 63-79.
- Brownstone D., Bunch D., Train K (2000), "Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles" *Transportation Research Part B*, 34 (5), 315-338.
- Calfee J. E. (1985), "Estimating the demand for electric automobiles using fully disaggregated probabilistic choice analysis". *Transportation Research Part B: Methodological*, 19(4), 287-301.
- 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.
- Christensen L., Kveiborg O., Mabit S. L. (2010), The market for electric vehicles—What do potential users want. In Proceedings of the 12th world conference on transportation research (WCTR'10), Lisbon, Portugal, pp. 11-15.
- Coffman M., Bernstein P., Wee S. (2017), "Electric vehicles revisited: a review of factors that affect adoption", *Transport Reviews*, 37(1), 79-93.
- Danielis R., Giansoldati M., Rotaris L. (2018), "A probabilistic total cost of ownership model to evaluate the current and future prospects of electric cars uptake in Italy", *Energy Policy*, Vol. 119, August, pp. 268-281.
- Daziano R. A. (2013), "Conditional-logit Bayes estimators for consumer valuation of electric vehicle driving range", *Resource and Energy Economics*, 35(3), 429-450.
- Daziano R. A., Chiew E. (2012). "Electric vehicles rising from the dead: data needs for forecasting consumer response toward sustainable energy sources in personal transportation", *Energy Policy*, 51, 876-894.
- Dimitropoulos A., van Ommeren J. N., Koster P., Rietveld P. (2016), "Not fully charged: Welfare effects of tax incentives for employer-provided electric cars", *Journal of Environmental Economics and Management*, 78, 1-19.
- Egbue O., Long S. (2012), "Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions", *Energy policy*, 48, 717-729.
- Franke T., Neumann I., Bühler F., Cocron P., Krems J.F. (2012), "Experiencing range in an electric vehicle: understanding psychological barriers", *Applied Psychology* 61 (3), 368–391.
- Hackbarth, A., & Madlener, R. (2013), "Consumer preferences for alternative fuel vehicles: A discrete choice analysis", *Transportation Research Part D: Transport and Environment*, 25, 5-17.
- 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*, 39:593–625
- Hoen A., Koetse M. J. (2014), "A choice experiment on alternative fuel vehicle preferences of private car owners in the Netherlands", *Transportation Research Part A: Policy and Practice*, 61, 199-215.
- Huber J., Zwerina K. (1996), "The importance of utility balance and efficient choice designs', *Journal of Marketing Research*, 33, 307-317.
- Jensen A. F., Cherchi E., Mabit S. L. (2013), "On the stability of preferences and attitudes before and after experiencing an electric vehicle", *Transportation Research Part D: Transport and Environment*, 25, 24-32.
- Kim S., Lee J., Lee C. (2017), "Does driving range of electric vehicles influence electric vehicle adoption?" *Sustainability*, 9(10), 1-15.
- Knockaert J. (2010), *Economic and Technical Analysis of Road Transport Emissions*, Ph.D. Dissertation, Katholieke Universiteit Leuven, Faculty of Engineering, Department of Mechanical Engineering.

- Kurani K.S., Turrentine T., Sperling D. (1994), "Demand for electric vehicles in hybrid households: an exploratory analysis", *Transport Policy*, 1 (4), 244–256.
- Link C., Raich U., Sammer G., Stark J. (2012), "Modeling demand for electric cars-a methodical approach", *Procedia-Social and Behavioral Sciences*, 48, 1958-1970.
- Mabit S. L., Fosgerau M. (2011), "Demand for alternative-fuel vehicles when registration taxes are high", *Transportation Research Part D: Transport and Environment*, 16(3), 225-231.
- McFadden D. (1981), Econometrics Models of Probabilistic Choice, Structural Analysis of Discrete Data. MIT Press, Cambridge.
- McFadden D., Train K. (2000), "Mixed MNL models for discrete response", *Journal of Applied Econometrics*, 15, pp. 447-470.
- Tanaka M., Ida T., Murakami K., Friedman L. (2014), "Consumers' willingness to pay for alternative fuel vehicles: A comparative discrete choice analysis between the US and Japan", *Transportation Research Part A: Policy and Practice*, 70, 194-209.
- Train, K.E., 2002. *Discrete Choice Methods with Simulations*. Cambridge University Press, Cambridge.
- Valeri E., Danielis R (2015), "Simulating the market penetration of cars with alternative fuelpowertrain technologies in Italy", *Transport Policy*, 37, 44-56
- Yu J., Goos P., Vandebroek M. (2009), "Efficient choice-based designs for estimating panel mixed logit models", Presented at the Leuven Statistical Day.
- Ziegler A. (2012), "Individual characteristics and stated preferences for alternative energy sources and propulsion technologies in vehicles: A discrete choice analysis for Germany", *Transportation Research Part A: Policy and Practice*, 46(8), 1372-1385.

#### **Abbreviations**

EC: electric car

Non-EC: non-electric car

WTP: willingness to pay

ASC: constant-specific attribute

Working papers SIET 2018 – ISSN 1973-3208

Table 1. Status quo for the main attributes of the eight selected cars

	Daimler							
	Smart For		VW Egolf					Daimler Smart
Attributes	Four ED	VW Golf	kWh 35.8	Renault Clio	Renault Zoe	Nissan Pulsar	Nissan Leaf	For Four
Purchase price (€)	24,559	20,400	37,600	16,350	33,250	18,090	30,690	12,960
Driving range (km)	145	610	300	714	300	1,000	199	428
Annual operating cost (€)	1,791	3,396	1,666	2,908	1,679	2,859	1,750	3,049

Source: www.alvolante.it

Table 2. Comparison of alternative specifications – Estimates of binary logit models

	(1)		(2)		(3)		(4)		
	Linear		Logarithmic		Quadratic		EC-specific		
Variables	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	
Constant EC	-0.429285	-3.5	-0.167877	-1.2	-0.121491	-0.8	-0.957057	-5.5	
Generic range (100 km)	0.000527	4.2	0.491301	5.5	0.293542	4.2			
Generic range squared (100 km)					-0.014468	-3.5			
EC-specific range (100 km)							0.003020	5.0	
Non-EC range (100 km)							0.000607	4.8	
Purchase price (€)	-0.000015	-1.9	-0.000035	-3.7	-0.000038	-3.7	-0.000040	-4.1	
Annual operating costs (€)	-0.000120	-2.7	-0.000158	-3.4	-0.000174	-3.6	-0.000160	-3.4	
% of fuel stations with fast charging stalls	0.014470	6.2	0.016200	6.8	0.017000	7.0	0.016007	6.8	
Brand Volkswagen	0.552354	8.7	0.611958	9.3	0.615205	9.3	0.639495	9.5	
Brand Renault	0.156792	2.4	0.189553	2.9	0.190533	2.9	0.222449	3.3	
Brand Nissan	0.101037	1.4	0.157971	2.1	0.141927	1.9	0.218047	2.8	
Number of observations	3298		3298		3298		3298		
Adjusted R-squared	0.0283		0.0311		0.0307		0.0320		
Log-Likelihood	-2205.3		-2198.8		-2199.0		-2196.2		
Reference point (km)			200		200				
Generic WTP (€/km)	35		70		62				
EC WTP (€/km)							76		
Non-EC WTP (€/km)							15		

Source: our elaboration from survey data

Table 5. Percentage change in respondents' preference for ECs.

<b>S</b> 2	0.2				
	S3	S4	S5	<b>S</b> 6	S7
13.6%	0.8%	1.8%	1.0%	5.3%	28.3%
17.5%	1.5%	3.6%	1.4%	7.9%	38.9%
18.3%	1.7%	4.0%	1.5%	8.4%	40.7%
14.9%	1.0%	2.3%	1.2%	6.0%	31.6%
33.2%	7.4%	18.6%	3.4%	23.1%	68.6%
24.3%	3.3%	8.3%	2.1%	13.4%	54.7%
•	17.5% 18.3% 14.9% 33.2% 24.3%	17.5% 1.5% 18.3% 1.7% 14.9% 1.0% 33.2% 7.4%	17.5%       1.5%       3.6%         18.3%       1.7%       4.0%         14.9%       1.0%       2.3%         33.2%       7.4%       18.6%         24.3%       3.3%       8.3%	17.5%       1.5%       3.6%       1.4%         18.3%       1.7%       4.0%       1.5%         14.9%       1.0%       2.3%       1.2%         33.2%       7.4%       18.6%       3.4%         24.3%       3.3%       8.3%       2.1%	17.5%       1.5%       3.6%       1.4%       7.9%         18.3%       1.7%       4.0%       1.5%       8.4%         14.9%       1.0%       2.3%       1.2%       6.0%         33.2%       7.4%       18.6%       3.4%       23.1%         24.3%       3.3%       8.3%       2.1%       13.4%

Source: our elaboration from survey data and results of the mixed effect model specification reported in Table 3.