A meta-analysis of the importance of the driving range in consumers' preference studies for battery electric vehicles

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Abstract

We perform a meta-analysis of the studies that evaluate the importance attributed by the consumers to the driving range of the Battery Electric Vehicles (BEVs). The paper updates and extends the paper by Dimitropoulos et al. (2013), including primary studies up to the year 2018. It tests whether the conclusions drawn by Dimitropoulos et al. (2013) still hold true given the many changes that occurred in the last years concerning BEVS' uptake in the market, growing consumers' direct and indirect experience with electric cars, vehicles' increased range, and growing diffusion of the charging infrastructure. We carried out two analyses: a) the estimation of the summary effect size of the driving range utility coefficient, and b) a meta-regression of the willingness to pay for a 1-km increase in the BEVs' driving range. The main findings are that: a) the importance attributed to the BEV's range by the consumers has not decreased; b) there is a very large dispersion of the estimates around the mean values, implying that there is a large heterogeneity due to differences in respondents' needs, vehicle segments and modelling techniques. The meta-regression allowed us to further explore and test statistically these conclusions.

Keywords: Battery Electric Vehicles, driving range, preference studies, consumer valuation, stated preferences

1. Introduction

As argued in a recent paper by Liu and Cirillo (2017), the automotive industry is going through a phase of rapid transformation, as environmental awareness, new regulations, and the need to diminish greenhouse gas emissions make alternative fuel vehicles more competitive. This evolving technological and economic context determines deep changes in firms' investment decisions, in vehicle characteristics, and in consumer decisions. Within this broad topic, the paper focuses on the analysis of how the driving range (i.e. the maximum distance that a vehicle can travel with a fully-charged battery) affects the decision of whether to buy or not an electric car. Hereafter we will use the common acronym BEV, Battery Electric Vehicle, although most of the studies we will review deal mainly with passenger cars[2].

Many studies have concluded that the driving range is one of the most important factors determining the acceptances of a BEV to the consumers. A recent example is Coffman et al. (2017). Liu et al. (2017) present an extensive review of the socio-economic, psychological, infrastructural and mobility factors that affect BEV's adoption. Various approaches are possible to analyze the importance of the driving

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[2] The terms 'car' and 'vehicle' will be used interchangeably throughout this paper. The definition of the term vehicle comprises all body types of light duty vehicles, including vans, pick-up trucks and sport utility vehicles but excludes two- and three-wheelers, as well as heavy-duty vehicles.

range for the consumer. Franke et al. (2017), for instance, perform a field trial, collecting data on range satisfaction before vehicle handover and after one, six and twelve weeks of BEV usage. Jensen and Mabit (2017) explore the issue of range limitation by analyzing real electric vehicle trip data. Skippon et al. (2016) propose a randomized controlled trial to study how use experience influences drivers' willingness to consider a BEV. Jung et al. (2015) analyze the impact of the precision of range estimates and state-of-charge on drivers' attitudes towards BEVs. At macro level, Kim et al. (2017) analyze the impact of range on the market share of electric vehicles through panel data analysis based in 31 countries. Fernández-Antolín et al. (2016) approach the issue from the policy point of view, finding that the most effective scenario corresponds to a decrease in price and an increase in driving range.

This paper examines a different stream of literature. It focuses on studies that evaluate the importance of the driving range by eliciting consumers' stated or revealed preferences via interviews and market data. They are part of a larger set of studies trying to understand how consumers make their car purchasing decisions. Within this literature, the driving range is an attribute of the consumer's utility function, whose importance can be quantitatively estimated. Many papers have taken this approach. Daziano and Chiew (2012), for instance, pointed out the many facets and challenges of these type of studies. A variety of model specifications have been used to analyze the data, mostly belonging to the logit family but also extended to the hybrid models, with an interest to capture the effect of social influences and latent attitudes (Kim, 2014).

The most recent meta-analysis of the studies investigating consumer preferences for the driving range is the one published by Dimitropoulos et al. (2013)[3]. The main motivation of their study it that the limited driving range of BEVs is hampering their large-scale adoption[4]. Such a motivation is in our opinion to a large extend still valid. They find that consumers are willing to pay, on average, between 66 and 75 US$ for a 1-mile increase in driving range. The primary studies they surveyed are based on stated choice and contingent ranking data collected in the period 1978-2011, before the BEVs commercial penetration in the market. One of the main motivation of our study is to find out whether the conclusions drawn by Dimitropoulos et al. (2013) still hold true and which new insights can be derived from more recent studies. Our meta-analysis is based on 35 primary studies, 18 of which published after the year 2011.

Many technological and economic developments have taken place in the BEVs market after 2011. Most importantly, BEVs have emerged from the prototype phase and entered the market with successful cars such as the Nissan Leaf (December 2011), the Tesla Model S (June 2012), and, in Europe, the Renault Zoe (December 2012). It is estimated that worldwide in 2017 more than 2 million highway-capable, light-duty, pure electric vehicles are on the roads. Technological innovation (mainly, the lithium-ion battery) and large investments in battery production have radically improved the technical properties of the battery. As a result, while in 2013 most BEVs had an EPA-certified driving range of less than 100 miles[5], in 2017 several BEVs have a range higher than 100 miles[6]. Furthermore, the large investments in car battery production have succeeded in decreasing the cost of the battery packs from $1,000 per kWh in 2010 to the estimated $209 per kWh in 2017 (Bloomberg, 2017). The combination of

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[3] A more recent contribution that makes use of a meta-analysis, but to estimate the demand for electric cars in Italy is provided by Giansoldati et al. (2017) who consider driving range plus a broader set of attributes i.e. purchase price, fuel efficiency, annual operating costs, emissions, acceleration and charging time.

[4] Dimitropoulos et al. (2013) include also other alternative fuel vehicles (AFVs) in their meta-analysis, although they recognize that AFVs suffer less a driving range constraint and more a fuel availability limitation.

[5] In 2013, the most popular BEVs in the market were the Nissan Leaf 22 kWh with 84 miles of range, the BMW i3 with 81 miles, the Kia Soul EV with 93 miles. An exception was the Tesla model S (70D) that had a range of 240 miles but a twice as high sticker price.

[6] For instance, the 2017 Chevrolet Bolt (238 miles), the BYD e6 (187 miles), the 2018 Nissan Leaf (151 miles), the 2017 VW e-Golf (125 miles), the Hyundai Ioniq Electric (124 miles), the 2017 Ford Focus Electric (115 miles) and all the Tesla models, including the recent Tesla Model 3 (220 miles), sometimes with a sticker price lower than 40 thousand dollars.

BEVs with larger battery packs (higher driving range) and decreasing battery pack costs has resulted in a slightly declining average sticker price per driving range.

Because of the growing BEVs' market penetration and media coverage, more and more consumers have direct or indirect experience with BEVs. As already suggested by Kurani et al. (1994) and more recently confirmed by Franke et al. (2012) and Franke and Krems (2013), the lack of experience with BEVs might have resulted in consumers having not well-developed preferences, leading them to overstate their willingness to pay (WTP) for an additional mile of driving range. A further element that might influence the importance attributed to BEVs driving range is the deployment of denser charging networks, which is gradually taking place in most countries. As underlined by Dimitropoulos et al. (2013), the combination of personal experience and the diffusion of a fast-charging networks, together with increasing power of the charging stations to up to 350 kWh, are likely to impact the role played by the driving range in the purchasing decisions[7].

A further element that plays a role in the assessment of the driving range is the day-to-day experience with charging technology, the knowledge of the various charging alternatives (home charging, fast charging, and destination charging) and their relative costs, and the increased familiarity with the BEVs software regarding range management and the localization of charging stations.

For all these reasons, we feel it is worth re-analyzing the role played by the BEVs driving range in the car purchasing decisions. Such a role might differ among countries, due to different annual\daily distance travelled and meteorological or urban density aspects; among individuals, due to different travel patterns; or among locations, depending on the density of the BEV's charging infrastructure.

In order to assess the consumers' valuation of the driving range, we perform a meta-analysis of the existing studies. As stated by van den Bergh et al. (1997), meta-analysis helps achieving several goals, including: a) summarizing or averaging, possibly using weights, relationships or indicators in similar studies; b) comparing outcomes of different methods applied to similar questions; c) apprehending common elements in different studies; and d) tracing factors that are responsible for differing results across similar studies.

The findings of this paper are interesting at various levels. The car manufacturing industry has the crucial task of developing the right BEVs models for the various market segments. Since there is an inevitable trade-off between driving range and sticker price, auto manufacturers need to make strategic decisions about what BEVs to build in terms of car type (small, large, SUV, etc.) and battery size, and how much production capacity to allocate to each model. Up to few years ago, there was a widespread opinion that BEVs, due to their technical characteristics (short range, zero local air and noise emissions), would be only small urban cars. The opposite has been true. The most successful BEVs so far have been the Tesla Model S and X, which are large, luxury sedans or SUVs, intended mostly for intercity trips. However, the BEV market might develop into two main segments: one consisting of high trim, sporty or large, 200-300 mile-range cars (Tesla Model S and X, Chevrolet Bolt, Porches E mission, Jaguar I-Pace, and so on) and one of small, 100 miles-range, urban cars (Renault Zoe, Smart Electric drive).

The policy makers have also an interest into knowing how consumers value the driving range. Motivated by social goals such as reduced air pollution at local and global level, they are generally willing to play a role in setting the incentives for the BEVs penetration supporting specific segments. Some countries (e.g., Germany[8]) link monetary incentives with the size\price of the BEV, with a preference for the small, affordable models, to avoid the risk of subsidizing wealthy car buyers.

[7] The popular term used to reflect the importance attributed to the BEVs driving range is that of "range anxiety", that is the fear of remaining with an empty battery during a trip, or, less dramatically, the limited possibility to make long trips.

[8] In the case of Germany, a controversy aroused because the government set a 60-thousand-euro max price cap, affecting mainly the cars produced by Tesla Motor Inc.

Finally, researchers might benefit from the results of our paper since we discuss what is known and what is not yet known, what is controversial and what is not, what needs to be further researched and how to best set up the field research.

From a technical point of view, apart from the timeframe of the primary papers, there are two main differences with the meta-analysis performed by Dimitropoulos et al. (2013). The first one is that we will restrict our analysis to the papers that include BEVs in their choice set and disregard other alternative fuel vehicles, since for the latter the driving range limitations are less stringent. The second one is that we will not only perform a meta-regression on the implied WTP for driving range of each primary study in order to assess how time, geography, model type and range specification influence the WTP, but we will also compute the summary effect size of the driving range on the BEVs utility, using the methodology suggested by Borestein (2009).

The paper consists in 6 sections. In Section 2 we illustrate the search strategy, the inclusion criteria and the selected papers. In Section 3 we explain how the driving range is modelled in the utility function. In Section 4 we present the resulting summary effect size for each specification. In Section 5 we discuss the results of a meta-regression of the WTP for the BEVs' driving range derived from each study. Section 6 concludes and discusses the policy implications.

2. Meta-analysis: search strategy, inclusion criteria and selected papers

Meta-analysis is "the statistical analysis of a large collection of results from individual studies for the purpose of integrating the findings" (Glass, 1976). Since it was first introduced in the 1970s, meta-analysis has been applied in many fields (medicine, psychology, economics and so on). By investigating the relationship between the dependent variable and an independent variable (expressed either as risk ratio, odds ratio, or correlation, depending on the science), meta-analysis provides a systematic synthesis and evaluates how specific aspects of primary papers affect the results obtained.

The main merits attributed to the results obtained via a meta-analysis study are that, while a single study might lack statistical power due to a small sample size, when many primary studies are combined the statistical power is increased and the precision of the estimate is improved. Moreover, meta-analysis can answer questions not posed by single studies or might help resolve the disputes when diverse or even conflicting results are found in the primary studies (Higgins and Green, 2008).

Meta-analysis, however, suffers from potential limitations (Ioannides, 2016) due to assumption of standardized effects (primary studies might have different degrees of randomization), social dependence (researchers influence one another), publication bias (the censoring of studies with non-significant results), subjective selection, and varying conditions across studies (different protocols).

A meta-analysis usually involves the development of a search strategy on the potential literature containing information on the relationship among the dependent and independent variables of interest, the definition of the inclusion criteria and a systematic review of each primary study in order to understand if and how a study should be included.

2.1 Search strategy

The literature on BEVs is multidisciplinary and rapidly growing. First, we sourced the papers from the available databases, including papers published in academic journals and books, unpublished working papers, discussion papers, conference presentations, and policy reports. Initially, we searched Google and Google Scholar in order to have a general overview and, then, restricted our search to the Scopus and Web of Science databases. Both databases permit the use of wildcards or Boolean operators so that we could perform the search strategy illustrated in Table 1.

Table 1 – Search strategy results

Search terms	**Number of results Scopus**	**Number of results WOS**
Electric AND vehicle*	176500	32887
Electric AND vehicle* AND range	31532	4758
Electric AND vehicle* AND "driving range"	1492	2107
Electric AND vehicle* AND range AND preference*	873	87
Electric AND vehicle* AND "driving range" AND preference*	132	45
Electric AND vehicle* AND "driving range" AND "consumer* preference*"	56	25
First selection based on three criteria: empirical data on consumers' preferences; inclusion of BEVs; specify driving range as an attribute	23	
Snowballing effect	17	
Final set	35	

We started with a broad search, looking for studies that contained the word "electric vehicle*" in the main text, and then refined it by adding further words that would lead to papers that might report results on consumers' preference for BEVs. The initial numbers of papers were very large, but they decreased rapidly as the words "driving range" (the term "range", having several meanings was not very effective) and "preference*" are added. They further reduced to 81 (56+25) when the word "consumer* preference*" was added.

2.2 Inclusion criteria

We examined the abstracts and methodology of the identified 81 papers to decide whether a study was eligible for our meta-analysis. We used three inclusion criteria. The study should:

a) analyze consumers' preferences on the basis on empirical data;
b) include both BEVs and ICEVs, to allow the comparison among the attributes of the two propulsion systems;
c) specify the driving range as an attribute and report its coefficient, regardless of its specification;

A limited number of papers (23) satisfied these criteria. Most of the excluded papers did not collect preference data, performing either technological simulations, or policy discussion or reviewing the literature. One of the studies (Huang, 2015) was not available to us. Some of the papers did not include both BEVs and ICEVs, considering PHEVs only or alternative fuel vehicles in general. Some papers did not include driving range as an attribute of the choice decision process. The careful reading of the 23 selected studies allowed us to add 17 further papers that satisfy our criteria (snowballing effect). A final check proved that 5 papers (Beggs et al, 1980; Nixon and Saphores, 2011, Oliveira et al., 2015; Krause et al., 2016; Junquera et al. 2016) could not be used for the meta-analysis because the consumers' attitude towards the driving range was not measured in terms of miles (or km) [9].

[9] Beggs et al. (1980) estimates the disutility of BEVs with 50 miles of range versus a gas powered car with 200 miles of range. Nixon and Saphores (2011) could not be included because the range difference between an alternative fuel vehicle (instead of a BEV specifically) and a gas vehicle is measured. Oliveira et al. (2015) compare two techniques, choice-based conjoint analysis and multicriteria decision analysis, to evaluate preferences for electric vehicles in Portugal, but did not report the numerical results needed for our meta-analysis. Junquera et al. 2016 measure the disutility of allowing less than 100 km or the frequency of trips longer than 200 km. Krause et al. (2016) measure range parity as a dichotomous variable assuming the value equal to 1 when the range is 300 miles.

2.3 Selected papers

Table 9 lists the 35 primary studies selected, Column 2 reports the alternative propulsion systems considered by each study. The year of the survey ranges from 1977 up to 2017. Since the BEVs entered the market in significant numbers only in the year 2010, only 13 out of 35 primary studies potentially reflect a direct or indirect day-to-day experience on BEVs' characteristics.

The selected studies cover 12 countries: USA, Canada, Belgium, Spain, Portugal, Norway, Denmark, Austria, the Netherlands, Germany, Italy, and Japan. Regretfully, no Asian countries are included, not even China where BEVs are currently gaining market acceptance[10].

The sample size is usually quite small, ranging from 51 to 4202 respondents, reflecting on the one hand the scientific rather than commercial nature of these studies and, on the other hand, the fact that collecting preference data at individual level is quite costly and time consuming, especially before the web age.

With regards to the modelling technique, some studies limit themselves to the estimation of the multinomial logit (MNL) model. Other studies use more advanced specification such as joint Stated Preference (SP)\Revealed Preference (RP) MNL, nested logit model, preference space model, conditional logit model, cross-nested logit model, random regret model, error component MNL). More recent studies make use of random parameters specifications such as the mixed logit, probit, invariant stochastic effects model, correlations between alternatives model, independent multinomial probit and explore preference heterogeneity issue via latent class models, behavioral mixture models, and hybrid choice models.

Dimitropoulos et al. (2013) performed their meta-analysis on 33 primary studies. We share with them 20 studies (indicated in Table 9) and add 13 new ones. Some other studies used by Dimitropoulos et al. (2013) were not included in our set of primary studies when not relevant (BEVs were not in the choice set), when they used the same dataset with results already reported in other studies, or when not available. Further information included in Table 9 is discussed in the next Sections.

3. Specification of the driving range attribute in the utility function

In the selected papers the driving range attribute enters the utility function describing the consumers' preferences together with other attributes related to the vehicle's characteristics. Some attributes enter the utility functions of all the propulsion systems considered and can be labeled "generic". Others refer to specific propulsion systems and can be labeled "alternative-specific". The former is usually the case of purchase price, annual operating cost, and acceleration. The latter is the case, for instance, of charging time, usually considered only for BEVs since recharging a battery takes much longer than refueling a conventional vehicle.

In the primary studies reviewed, the driving range attribute appears both as generic or as alternative-specific attribute. Since the driving range of the BEVs varies between 57 to 335 miles, whereas that of ICEVs and HEVs varies between 200 and 600 miles[11] depending on tank size, car efficiency and driving conditions, in some studies the driving range is modelled as BEV-specific attribute.

The generic linear specification of driving range used in many studies (Beggs et al., 1981; Golob et al., 1997; Ewing and Sarigöllü, 1998; Dagsivik et al., 2002; Hesse et al., 2006; Knockaert, 2010; Christensen et al., 2012; Chorus et al., 2013; Tanaka et al., 2014) could be written as follows:

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

[10] Huang (2015) - Discrete Choice Analysis on Demand for Electric Vehicles was not accessible to us.

[11] We do not consider in this review PHEVs since they allow a total mileage closer to the ICEVs than to the BEVs.

while the BEV-specific specification, also quiet frequently used (Tompkins et al., 1998; Ramjerdi and Rand, 1999; Hackbarth and Madlener, 2013; Jensen et al., 2013; Hoen and Koetse, 2014; Valeri and Danielis, 2015; Bahamonde-Birke and Hanappi, 2016; Dimitropoulos et al., 2016; Cherchi, 2017), can be written as

$$\begin{cases} U_{ICEV} = ASC + \beta_{range} range + \cdots other\ attributes \\ U_{BEV} = \qquad\qquad \beta_{BEV\_range} range + \cdots other\ attributes \end{cases}$$

Bahamonde-Birke and Hanappi (2016) justify their choice on the basis of the empirical evidence. They find that it was not possible to reject the hypothesis of linearity (tested via a Box–Cox transformation) and explain it with the inexperience in the use of electric vehicles. Cherchi (2017) tests several non-linear specifications but finds that the best one is a linear utility with specific coefficients for BEVs and ICEVs (Internal Combustion Engine Vehicles). This implies that they are linear within each propulsion system.

Although the logit family models are linear-in-parameters, the data can be entered nonlinearly, for instance, as natural logarithm transformation of the driving range, if one believes that the marginal utility of the driving range decreases as the absolute value of range increases. Hence, the specification becomes:

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

It allows the researcher to estimate a generic driving range coefficient across propulsion systems. A large group of authors (Calfee, 1985; Train and Weeks, 2005; Mabit and Fosgerau, 2011; Link et al., 2012; Hess et al., 2012; Dimitropoulos et al., 2013; Daziano, 2012, 2013; Daziano and Chiew, 2013; Hackbarth and Madlener, 2016) finds the lognormal specification both theoretically convincing and empirically superior. Dimitropoulos et al. (2013) conclude that there is evidence that the WTP for the driving range not only diminishes as the range increases, but that it also declines at a decreasing rate. This leads them to suggest that the driving range should enter consumer's utility function non-linearly. Other authors (Bunch et al., 1993; Brownstone et al., 2000) use the quadratic specification:

$$U = ASC + \beta_{range1}(driving\ range) + \beta_{range2}(driving\ range^2) + \ldots..\ other\ attributes$$

A final group of authors (Ewing and Sarigöllü, 2000; Hidrue et al., 2011, Parsons et al., 2011; Rasouli and Timmermans, 2016, Junquera et al., 2016, Krause et al., 2016) test the piecewise linear specification specification, also defined effects-coded approach (Dimitropoulos et al., 2013):

$$U = ASC + \beta_{range1}(1st\ driving\ range\ segment) + \beta_{range2}(2nd\ driving\ range\ segment) + \ldots..\ other\ attributes$$

More recently, Giansoldati et al. (2018) test all the above specifications comparing them in terms of goodness of fit and estimate the implied WTP.

The choice of the specification has important consequences. Firstly, we explore them by estimating the summary effect size, and then we perform a meta-regression of the WTP for a 1-km driving range increase.

4. Estimating the summary effect size

Using the methodology described by Borenstein (2009), we started by identifying the coefficients of the driving range from each primary study and by transforming them in the "per kilometer" metric, since they are presented in two units of distance, miles and kilometers, and usually in hundreds of miles or kilometers. We selected the base case coefficient reported in each primary study, disregarding its interactions with socio-economic and mobility variables. The latter is discussed in Section 4.6.

Meta-analyses could be based on two statistical models: the fixed-effect model or the random-effects model. Under the fixed-effect model, it is assumed that there is one true effect and that all differences in observed effects are due to sampling error. By contrast, under the random-effects model the true effect is assumed to vary from study to study. It is largely acknowledged that the random-effects model is the more proper one in social sciences where the samples are drawn from populations having different socio-economic and territorial characteristics. Hence, only the results deriving from the random-effects model are reported below.

In a random-effects model, the observed effect Y_i for any study is given by the grand mean μ, the deviation of the study's true effect from the grand mean ς_i, and the deviation of the study's observed effect from the study's true effect ϵ_i. That is,

$$Y_i = \mu + \varsigma_i + \varepsilon_i$$

To predict how far the observed effect Y_i is likely to fall from μ in any given study we need to consider both the variance of ς_i and the variance of ϵ_i. In an actual meta-analysis, rather than starting with the population effect and making projections about the observed effects, one makes use of the collection of Y_i to estimate the overall mean, μ. In order to obtain the most precise estimate of the overall mean (to minimize the variance) a weighted mean is computed, where the weight assigned to each study is the inverse of the study's variance[12]. The significance of the effect size is measured by the Z-test, whilst the precision of the pooled effect size is estimated considering the 95% confidence intervals.

4.1 The generic linear range specification

Table 2 reports the data drawn from the 10 studies who applied the linear specification. As above described, we have adjusted the original base-case coefficients to the same unit of measurement, which is a 1-km driving range.

[12] See Borenstein (2009) for a thorough description of the methodology.

Table 2 – Driving range coefficients: linear specification (per km)

Authors	*Parameter*	*St. Err.*	*Lower Limit*	*Upper Limit*	*Weights*
Beggs et al. (1981)	0.0025	0.0003	0.0019	0.0031	12.6%
Golob et al. (1997)	0.0009	0.0003	0.0003	0.0016	12.4%
Ewing and Sarigöllü (1998)	0.0024	0.0006	0.0012	0.0036	9.7%
Dagsivik et al. (2002)	0.0019	0.0006	0.0007	0.0030	9.7%
Hesse et al. (2006)	0.0035	0.0015	0.0005	0.0065	3.5%
Knockaert (2010)	0.0026	0.0005	0.0016	0.0036	0.0%
Christensen et al. (2012)	0.0017	0.0002	0.0014	0.0020	10.5%
Chorus et al. (2013)	0.0014	0.0002	0.0011	0.0017	13.7%
Tanaka et al. (2014)	0.0004	0.0000	0.0003	0.0005	13.7%
Giansoldati et al. (2018)	0.0005	0.0001	0.0003	0.0008	14.1%
Summary Effect with the random effect model	0.0017		0.0011	0.0024	

All studies report a positive and highly significant coefficient. The values are comparable but vary from a minimum of 0.0004 to a maximum of 0.0035.

Table 9 illustrates the studies using a generic linear specification are quite heterogeneous. Some studies focus on the comparison among gasoline and electric vehicles only, while others include various fuel types. Chorus et al. (2013), for instance, consider the choice among petrol/diesel, hybrid, plug-in hybrid, fuel cell, flexifuel, and electric vehicles. Various model specifications of the logit family are used: multinomial logit, ordered logit, mixed logit, utility maximization and regret minimization paradigms. The range attribute levels presented in the scenarios vary from 50 to 400 miles. The surveys methods changed over the years: from face-to-face interviews, to postal ones, to web-based questionnaires. The surveys were performed in the USA (California), in Canada, in Japan and in Europe (Belgium, Norway, Denmark, the Netherlands, and Italy). The sample size of the primary studies is quite small: it varies from 200 to 4,202 respondents.

Based on these studies, we have estimated the summary effect with the random effects model. The weights with which the studies enter in the estimation of the summary effect size are reported in the last column. We find a summary effect for the generic range equal to 0.0015, with a relatively small 95%-significance interval varying from 0.0012 of 0.0024.

4.2 The BEV-specific range specification

Table 3 reports the data drawn from the 11 studies who used the BEV-specific range specification.

Table 3 – BEV driving range coefficients: linear specification (per km)

Authors	*Parameter*	*St. Err.*	*Lower Limit*	*Upper Limit*	*Weights*
Tompkins et al. (1998)	0.0014	0.0004	0.0005	0.0023	9.90%
Ramjerdi and Rand (1999)	0.0041	0.0012	0.0018	0.0064	9.07%
Ziegler (2012)[13]	0.0015	0.0005	0.0005	0.0025	9.87%
Hackbarth and Madlener (2013)	0.0015	0.0005	0.0005	0.0025	9.87%
Jensen et al. (2013)	0.0078	0.0025	0.0029	0.0127	6.68%
Hoen and Koetse (2014)	0.0063	0.0005	0.0053	0.0073	9.86%
Valeri and Danielis (2015)	0.0105	0.0026	0.0055	0.0155	6.62%
Bahamonde-Birke (2016)	0.0053	0.0005	0.0043	0.0063	9.84%
Dimitropoulos et al. (2016)	0.0107	0.0006	0.0096	0.0119	9.79%
Cherchi (2017)	0.0151	0.0014	0.0124	0.0178	8.72%
Giansoldati et al. (2018)	0.0030	0.0006	0.0018	0.0042	9.77%
Summary Effect with the random effect model	0.0058		0.0036	0.0080	

This group of studies is also quite heterogeneous. The studies include various propulsion systems such as alcohol, compressed natural gas and liquid propane gas. The brand or the specific model type is not usually specified, with the exception of Valeri and Danielis (2015). Econometric specifications include also the hybrid model. The range levels presented in the scenarios vary from 75 to 300 miles. The surveys methods comprise face-to-face, personal interviews, and web-based. The surveys were administered in the USA and in several European countries. The sample size varies between 121 to 1711 respondents. We find a summary effect for the generic range equal to 0.0058, with a 95%-significance interval varying from 0.0036 of 0.0080.

4.3 The logarithmic range specification

Table 4 reports the data drawn from the eight studies[14] that use the logarithmic specification.

[13] Zigler (2012) models range as a BEV-specific attribute but models purchasing price as a logarithmic variable.

[14] The following studies are not included. Daziano (2012) did not report the coefficient value, while Daziano (2013) is similar to Daziano and Chiew (2013)’s estimate.

Table 4 – Driving range coefficients: logarithmic specification

Authors	*Parameter*	*St. Err.*	*Lower Limit*	*Upper Limit*	*Weights*
Calfee (1985)	0.269	0.018	0.266	0.272	13.07%
Train and Weeks (2005)	0.727	0.130	0.711	0.744	13.06%
Mabit and Fosgerau (2011)	1.750	0.105	1.374	2.126	9.28%
Hess et al. (2012)	0.285	0.184	0.216	0.354	12.89%
Link et al. (2012)	0.790	0.127	0.740	0.840	12.98%
Daziano and Chiew (2013)	0.608	0.095	0.534	0.683	12.86%
Hackbarth and Madlener (2016)	0.494	0.141	0.415	0.573	12.84%
Giansoldati et al. (2018)	0.491	0.089	0.452	0.530	13.01%
Summary Effect with the random effect model	0.637		0.425	0.850	

From Table 9 it can be seen that some studies focused on the comparison between gasoline and electric vehicles only, others included various fuel types. Hess et al. (2012), for instance, consider the choice among standard gasoline, flex fuel/E85, clean diesel, compressed natural gas, hybrid-electric, plug-in hybrid-electric, and full electric vehicles. Various model specifications of the logit family are used: multinomial logit, mixed logit, and probit models. The range levels vary from 70 to 625 miles. The surveys methods include face-to-face interviews as well as postal and web-based questionnaires. The surveys were performed in the USA (California), in Canada, and in Europe (Austria, Germany, Denmark and Italy). The sample size is quite small: it varies from 51 to 3,274 respondents.

The summary effect size is equal to 0.637, with the 95% interval lying between 0.425 and 0.850.

4.4 The quadratic specification

The quadratic specification has been used in 3 primary studies but with different model specifications. Because of the limited number, we opted for using them all to estimate the summary effect. Table 5 reports the results.

Table 5 – Driving range coefficients: quadratic specification (per km)

Authors	*Parameter*	*St. Err.*	*Lower Limit*	*Upper Limit*	*Weights*
First term					
Bunch et al. (1993): Base coeff. Base fuel segmentation	0.0163	0.0135	0.0192	0.0192	14.2%
Bunch et al. (1993): Base coeff. personal segmentation	0.0158	0.0122	0.0194	0.0194	13.7%
Brownstone et al. (2000): SP/MNL	0.0031	0.0017	0.0044	0.0044	14.9%
Brownstone et al. (2000): SP/MXL	0.0111	0.0050	0.0171	0.0171	11.8%
Brownstone et al. (2000): RP/MNL	0.0154	-0.0047	0.0356	0.0356	3.6%
Brownstone et al. (2000): RP/SP MNL	0.0079	0.0044	0.0113	0.0113	13.8%
Brownstone et al. (2000): RP/SP MNL	0.0062	0.0032	0.0092	0.0092	13.8%
Giansoldati et al. (2018): MNL	0.0029	0.0016	0.0043	0.0043	14.1%
Summary Effect with the random effect model	0.0099		0.0055	0.0143	
Second term					
Bunch et al. (1993): Base coeff. Base fuel segmentation	-0.0027	0.0003	-0.0034	-0.0020	12.9%
Bunch et al. (1993): Base coeff. personal segmentation	-0.0017	0.0004	-0.0024	-0.0009	12.5%
Brownstone et al. (2000): SP/MNL	-0.0002	0.0002	-0.0005	0.0001	15.7%
Brownstone et al. (2000): SP/MXL	-0.0011	0.0005	-0.0021	-0.0001	10.4%
Brownstone et al. (2000): RP/MNL	-0.0016	0.0011	-0.0038	0.0006	4.1%
Brownstone et al. (2000): RP/SP MNL	-0.0007	0.0002	-0.0012	-0.0003	14.7%
Brownstone et al. (2000): RP/SP MNL	-0.0006	0.0002	-0.0010	-0.0002	14.7%
Giansoldati et al. (2018): MNL	-0.0001	0.0000	-0.0002	-0.0001	15.0%
Summary Effect with the random effect model	-0.0011		-0.0016	-0.0006	

There is a considerable difference in the coefficients among the studies and model specifications. The summary effect size for the first term of the quadratic equation is equal to 0.0099, but with a large confidence interval (0.0055-0.0143). The second term has a more limited confidence interval.

4.5 The piecewise linear specification

The piecewise linear specification, also defined effects-coded, has been applied with different kink points in each study (Ewing and Sarigöllü, 2000; Hidrue et al., 2011; Parsons et al., 2011; Rasouli and Timmermans, 2013, Junquera et al., 2016, Krause et al., 2016) so that it is not possible to estimate a summary effect size.

4.6 Driving range covariates

The utility function specification of the discrete choice models analyzing consumers' preferences for BEVs' range can include several type of variables:

- Socio-demographic variables such as sex, income, and education;
- attitudinal, psychological, experience and environmental awareness variables;
- variables indicating vehicle ownership and mobility patterns of the respondents or respondents' family, such as number of cars of the household, garage ownership, urban\intercity mobility, annual travel distance or percentage of longer trips;
- Variables describing the car market segment (small, medium, luxury or sports cars) or the car ownership (private car vs. company car);
- Infrastructural (e.g. service\charging station availability) and policy variables;
- Geographical and territorial variables referring to specific cities, states or countries;

Concerning the socio-demographic variables, Valeri and Danielis (2015) find that older drivers are more sensitive to the BEV's driving range than younger drivers are. The negative impact of age on the stated choice of an electric vehicle is also found in previous literature (Ewing and Sarigöllü, 1998; Potoglou and Kanaroglou, 2007; Ziegler, 2012; Hackbarth and Madlener, 2013). It is therefore quite well established that younger individuals are more inclined to purchase BEVs. With regards to gender, the literature is unclear. Bunch et al. (1993), Mabit and Fosgerau (2011), and Jensen et al (2013) report that females have a significantly higher sensitivity to the driving range attribute. Ziegler (2012) finds that in Austria there is no statistically significant difference between men and women in the propensity for BEVs' range. Dagsivik et al. (2002) and Valeri and Danielis (2015) conclude that women are less sensitive than men to the BEVs' range. With reference to the role played by respondents' income, as Bahamonde-Birke and Hanappi (2016) clearly explain, in stated choice surveys these questions are answered with reluctance or only partially by respondents (obviously, especially if the survey is carried out face-to-face). This implies that is quite hard to collect reliable information and, hence, some experiments do not include the income variable in the model specification. Moreover, income tends to be correlated with the number of car available to the household. Hess et al. (2012) and Valeri and Danielis (2015) find that higher income respondents are more sensitive to the BEV's driving range. On the contrary, Bahamonde-Birke and Hanappi (2016), having tried to disentangle the complex relationships between income and the other socio-economic variables, report a lower price sensitivity of the wealthy respondents when buying a BEV.

Concerning the attitudinal, psychological, experience and environmental awareness variables, Bahamonde-Birke and Hanappi (2016) find that environmental attitudes positively impact the preferences for BEVs in Austria. Experience with BEVs is also as a crucial factor. Jensen et al. (2013) states that the importance attached to driving range almost doubles after individuals have tried a BEV. Cherchi (2017) investigates the impact of normative conformity measured in terms of social adoption, social-signalling and injunctive norms. She finds that social conformity effects are highly significant and their impact in the overall utility can be high enough to compensate also quite a low driving range for BEV or significant differences in purchase prices.

Concerning the variables indicating vehicle ownership and mobility patterns, there is abundant evidence on their impact on the BEVs acceptance. As expected, drivers with a higher share of city trips (more than 60%) are more willing to buy a BEV (Hackbarth and Madlener, 2013). Beggs et al. (1981) and Bunch et al. (1993) find that commuters have a high driving range sensitivity. Bunch et al. (1993), Ewing and Sarigöllü (2000), and Hoen and Koetse (2014) study the impact of the annual travel distance and find, as expected, that the higher the annual distance travelled the higher is the sensitivity to the BEV's ranges. Bunch et al. (1993) study also the impact of refueling habits, finding that refueling on shopping trip increases the range sensitivity.

Concerning the variables indicating the car market segment, Jensen et al. (2013) and Hackbarth and Madlener (2013) find that the preference for BEVs is higher for smaller car classes than for larger car classes. This apparently contrasts with the success of the luxury Tesla cars, but is consistent with the growing diffusion of BEVs in the small, urban car segment (e.g., Smart Electric). The driving range sensitivity is, however, higher for sports cars and compact pickups (Bunch et al., 1993).

Infrastructural and policy variables play certainly a role in determining BEVs' acceptance. Many paper investigate this issue (Ziegler, 2012; Link et al., 2012; Hackbarth and Madlener, 2013; Hoen and Koetse, 2014; Cherchi, 2017). However, the impact of charging infrastructure on range is not frequently studied. An exception is Hoen and Koetse (2014) that investigate the impact of having the possibility to recharge at home.

Finally, Tanaka et al. (2014) makes a comparison between the US and Japan regarding the WTP for the driving range, finding no differences (21.5 $/mile). On the contrary, the meta-analysis conducted by Dimitropoulos et al. (2013) finds evidence that Americans value the driving range substantially more than European and Japanese drivers.

4.7 Comparing the summary effects

The comparison across alternative specifications shows that the summary effect size of the driving range is positively related to the overall utility. The estimate of the marginal effect of an additional kilometer of driving range differs, however, across specifications. Figure 1 provides a visual representation.

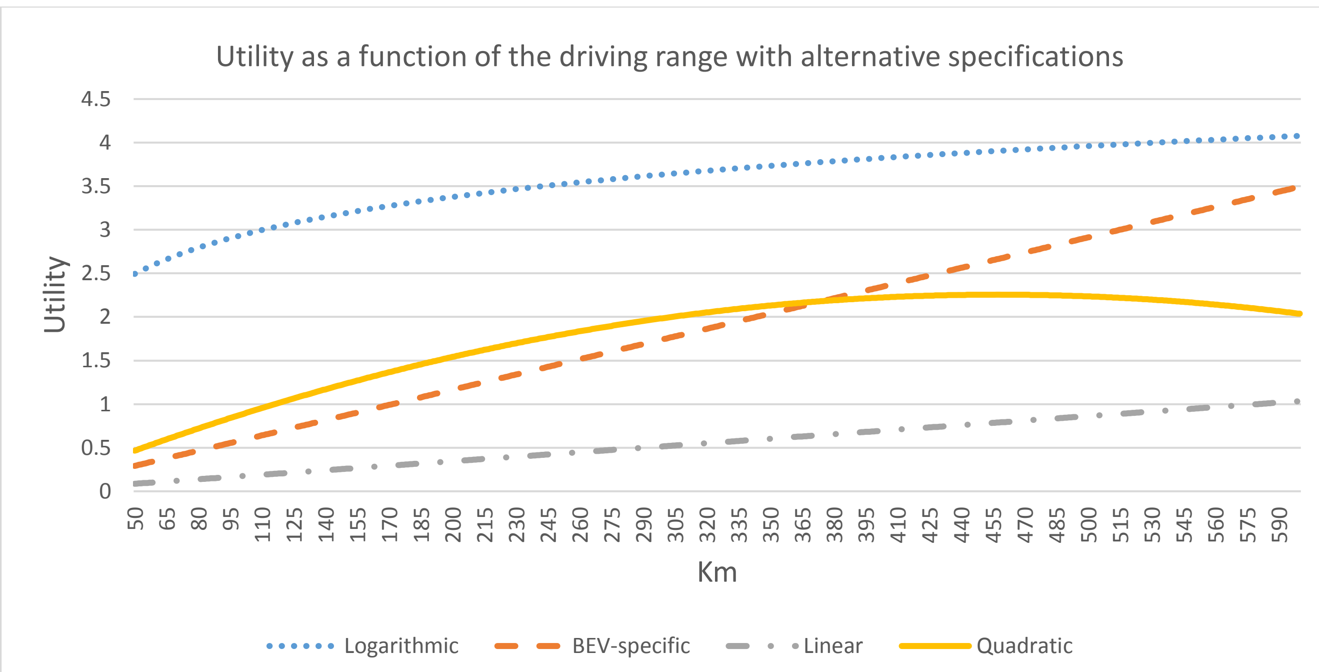

Figure 1 – Utility as a function of the driving range (in km) for alternative driving range specifications.

From Tables 2 to 5 it can be derived that the marginal utility of a 1-km driving range increase is, on average, 3.38 times higher when the range attribute is specified as generic than when it is modeled as BEV specific (0.0017 vs. 0.0058). The marginal utility associated to the non-linear specifications depends on the assumed reference levels. It can be calculated that the derivative of the logarithmic specification equals that of BEV-specific one when the driving range is equal to 109 km. It equals that of the linear one when the reference level is 370 km[15]. The quadratic specification equals that of the BEV-specific one when the reference range is equal to 190 km and to the linear one when the reference range is equal to 370 km.

The implications of these results are the following. According to a recent document by the International Council on Clean Transportation (2018, figure 4, page 10), the average battery capacity of electric vehicles in 2014 was about 22-26 kWh, allowing a driving range of about 140 km (assuming the Nissan Leaf combined efficiency of 18.9 kWh per 100 km). If we assume 140 km a reference range level, the resulting marginal utilities would be: linear (0.0017), BEV-specific (0.0058), logarithmic (0.0046), quadratic (0.0069). Consequently, the linear specification would attribute the least importance to the driving range, while the quadratic one the highest importance. The same source shows that the average battery capacity of electric vehicles has increased in 2017, but quite differently among countries. It is estimated to be equal on average to 65 kWh in the US (the Tesla effect), to 39 kWh in Europe and to 27 kWh in China. By applying the US value and assuming an energy efficiency of 20.09 kWh per 100 km (as reported for the Tesla Model S), the resulting driving range is 325 km. Assuming this value as reference range, the marginal utilities in the four specifications are the following: linear (0.0017), BEV-specific (0.0058), logarithmic (0.0020), quadratic (0.0028). The BEV-specific specification leads to the highest range importance, whereas the other three specifications are lower.

To summarize, different specifications leads to difference marginal utilities of the driving range, depending also on the reference range levels. For low driving range values (below 200 km), the summary effect size derived from linear specification tends to underestimate the marginal utility relative to the other specifications. For higher driving range values (above 300 km), the summary effect size derived from BEV-specific specification tends to overestimate the marginal utility relative to the other specifications.

The above analysis is mainly based on the base-case coefficients. But because of the heterogeneity among studies in terms of model types, year of the survey, country, range specification and various socio-economic factors, it is very relevant to test how these factors influence the importance attributed by the consumers to the driving range.

5. Meta-regression of the WTP for the BEV driving range

In order to search for common patterns among studies with different range specifications, we develop a common metric. Similarly to Dimitropoulos et al. (2013), we adopt as a metric the WTP for a marginal change of the driving range. Differently from Dimitropoulos et al. (2013), we have not estimated the alternative metric of the compensating variations, since in their case such alternative metric did not lead to significantly different results. The first task is to estimate for each primary study the implied WTP stemming from the driving range and purchasing price coefficients. Only in some cases the authors provided the WTP for the driving range. The WTP is the ratio of the marginal utility of the driving range and purchase price:

$$WTP = -\left(\frac{\partial U}{\partial R}\Big/\frac{\partial U}{\partial P}\right)$$

where U is a stochastic utility function, encompassing the driving range of the vehicle, R, its purchase price, P, and other variables. When the range and price are linearly specified (generic linear or BEV-

[15] The formula to be used to calculate the range that equates the marginal utilities of the logarithmic specification and that of the BEV specification is $\frac{\beta_{log}}{X}\Big/\beta_{BEV}$, where X is the driving range in km. Similarly, for range that equates the marginal utilities between the logarithmic specification and the linear specification, $\frac{\beta_{log}}{X}\Big/\beta_{Lin}$.

specific linear), the WTP equals $-(\beta_R/\beta_P)$. On the contrary, when the driving range is non-linearly specified[16] (logarithmic or quadratic) the WTP is equal to $-\left(\frac{\beta_R}{R}/\beta_P\right)$ for the logarithmic specification and to $-(\beta_{R1}+2\beta_{R1}R/\beta_P)$ for the quadratic specifications. Consequently, a reference level R must be defined. Following Dimitropoulos et al. (2013), we selected the mean of the driving range and the purchase price attribute used in the SP experiment, which, however, might vary substantially among primary studies.

As the estimates differ by year and by currency, in order to compare them one needs to standardize them to the same unit. We selected the Purchasing Power Parity-adjusted 2017 Euro for a 1-km range increase, in order to account for intertemporal and international differences in consumers' purchase power. We performed the standardization using indicators drawn from the OECD and IMF data series.

5.1 Descriptive statistics on the WTP for the driving range

The 35 primary studies provided us with 128 WTP estimates. We reported the number of WTP estimates drawn from each study and their average, maximum and minimum value in the last columns of Table 9. Figure 2 provides a graphical representation of their distribution by WTP value. It can be seen that they are quite disperse, ranging from few Euro\km to more than 100 €/km, depending on the range specification, model type, year of the survey and market segment.

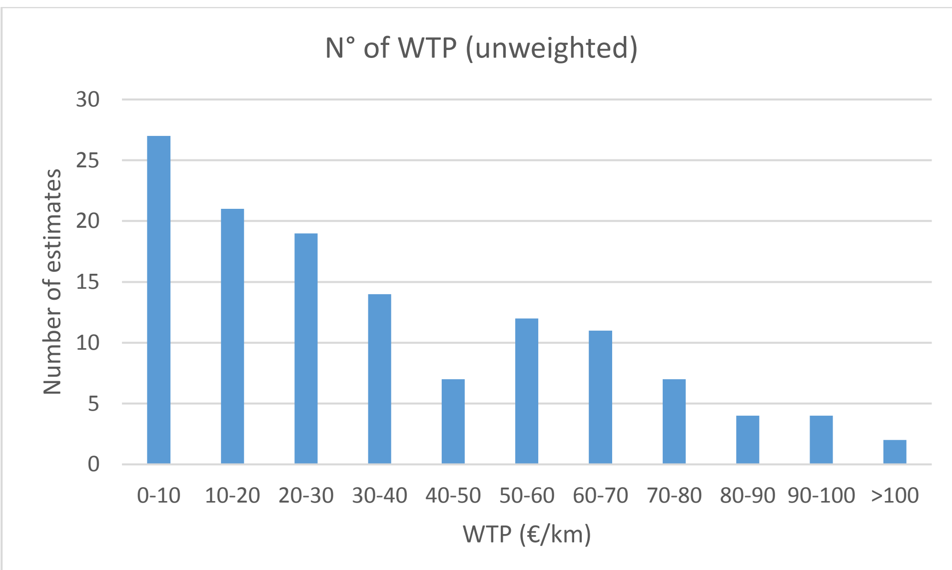

Figure 2 – Number of WTP estimates per WTP value

[16] We will not describe the equations when the purchasing price is specified non-linearly, since they obviously imply the derivative of the formula describing the price attribute.

Table 6 – Summary statistics on WTP mean values under different weighting schemes

Year of the survey	*Unweighted mean*	*Weighted average by the inverse of n° of WTP estimates in the dataset*	*Weighted average by the inverse of n° of WTP estimates in the dataset times the sample size*
Up to the year 2000 (St. Dev)	32.8 (31.9)	19.4 (34.7)	22.6 (32.1)
Between the years 2000 and 2010 (St. Dev)	26.1 (17.3)	24.5 (26.8)	23.9 (32.1)
After the year 2011 (St. Dev)	41.3 (30.3)	42.7 (31.5)	33.0 (36.6)
Grand mean (St. Dev)	*34.4 (27.9)*	*30.0 (28.3)*	*27.4 (28.8)*

value

Table 6 reports some mean values, grouped by time period, unweighted or weighted using as weights a) the inverse of the number of estimates drawn from each dataset and b) the sample size over the number of estimates drawn from each paper (SS/n), similarly to Dimitropoulous et al. (2013). Recall that Dimitropoulous et al. (2013)'s unweighted WTP estimate is equal to 66 to 70 PPP-adjusted 2005 US$ per mile. Using the OECD and IMF data, such value correspond to a PPP-adjusted 2017 EUR per km equal to 32.20 and 36.59 €/km[17], respectively. Our estimates are in line with Dimitropoulous et al. (2013)'s when the unweighted WTP is considered, while the unweighted ones are lower. It is also interesting to note that the WTP estimates for the primary studies conducted after the year 2011 are higher than those estimated in the previous periods. Contrary to Kurani (1994)'s expectations but in line with Jensen et al. (2013), respondents appear to increase the importance that they attribute to the driving range as their experience increased.

Note also that the standard deviations around the mean values and, consequently the 95% confidence intervals are very large. Dimitropoulous et al. (2013) finds also large confidence intervals, but, in our case, they include also the zero value. The large variation in the WTP estimates around the mean values require therefore a meta-regression analysis.

5.2 Meta-regression results

In order to perform a meta-regression, we have identified the following variables:

- WTP for a 1-km increase in 2017 EUR: dependent variable;
- Type of econometric model used, clustered into 3 groups: a) NML_NL (SP, RP and joint SP\RP multinomial logit, nested logit, preference space model, conditional logit, cross-nested logit, random regret, error component multinomial logit), b) Mixed Logit (SP, RP and joint SP\RP mixed logit, probit, invariant stochastic effects model, correlations between alternatives model, independent multinomial probit), and c) LC_H (latent class models, behavioral mixture model, hybrid choice model);

[17] We use the value US real effective exchange rate for the US$ equal to 109.31 and 117.45 for the year 2005 and 2017, respectively (http://data.imf.org/regular.aspx?key=61545862), and the value 0.73 for the PPP value between the EUR and the dollar (https://data.oecd.org/conversion/purchasing-power-parities-ppp.htm#indicator-chart).

- Year of the survey, grouped into a) up to the year 2000, b) between the years 2000 and 2010, and c) after the year 2010, when the current BEVs where introduced into the market;
- Range specification, grouped in a) Non-Linear (piecewise, logarithmic, quadratic), b) Generic, and c) BEV-specific;
- BEV driving range levels used in the SP hypothetical scenarios. Different studies, over the years, assumed different maximum BEV range levels, depending on the technological developments. We grouped them into three classes: a) less than 150 km, b) between 150 and 400 km, and c) more than 400 km.
- Gender: male or female;
- N° of cars in the household: a) single-car household, and b) multi-car household;
- Age: grouped into a) less than 60 years old, and b) older than 60 years;
- Country where the data were collected, grouped into a) EU_ J (Europe and Japan, with Europe including Germany, Denmark, The Netherlands, Italy, and Austria) and b) non_EU_J (USA and Canada)

Estimates for other segmentations were also available (vehicle size, travel distance, commuting trips, before\after experiencing BEV use, specific US states such as California or Michigan, income groups), but insufficiently numerous to be used as an explanatory variable.

Since variance heterogeneity is likely to exist in the estimates, we estimated a linear pooled data random effect-size model[18]. The pools reflected the number of WTP estimates that were derived from each dataset. We tested three specifications: an unweighted pooled data random effect-size model and two weighted pooled data random effect-size models, using the weights described in Section 5.1. We tested also a further regression method, based on the generalized least square regression, obtaining very similar results[19].

[18] As stated by Dimitropoulous et al. (2013), the dataset does not form a panel, but rather a sample of pooled data (Florax, 2002).

[19] Generalized least squares regression are to perform linear regression when there is a certain degree of correlation between the residuals in a regression model. In these cases, ordinary least squares and weighted least squares can be statistically inefficient, or even give misleading inferences. Also Dimitropoulous et al. (2013) do not obtain substantially different outcomes using the weighted ordinary least square and the generalized least squares technique.

Table 7 – Results of the meta- regression model with all variables (full model)

	Unweghited		Weighted a) (N° estimates)		Weighted b) (N° of estimates and sample size)	
Variable	Coefficient	t - ratio	Coefficient	t - ratio	Coefficient	t - ratio
Model type: with reference to MNL_NL						
Mixed	-2.10	-0.41	-2.65	-0.53	-2.10	-0.41
Hybrid	3.63	0.58	5.56	0.78	3.63	0.58
Year of survey: with reference to Before the year 2000						
Years 2000-2010	-8.81	-1.27	-0.38	-0.05	-8.81	-1.27
After the year 2010	5.85	0.83	9.46	1.05	5.85	0.83
Range specification: with reference to Generic						
Non-Linear	14.86**	2.54	11.87*	1.89	14.86**	2.54
BEV-specific	14.14**	2.11	14.31*	1.88	14.14**	2.11
BEV Range in the scenarios: with reference to less than 150 km						
Between 150 and 400 km	-6.70	-0.79	-3.33	-0.36	-6.70	-0.79
More than 400 km	-30.09***	-4.25	-24.28***	-3.18	-30.09***	-4.25
Socio-economic and geographical variables: dichotomous variables						
Gender: female	-3.21	-0.34	-10.22	-1.24	-3.21	-0.34
N° cars in household: multi-car	-15.36	-0.97	-21.12*	-1.81	-15.36	-0.97
Age: more than 60 years old	-1.38	-0.12	-2.66	-0.27	-1.38	-0.12
Country: USA and Canada	-8.83	-1.57	-9.95	-1.29	-8.83	-1.57
Constant	41.02***	3.67	34.15***	2.80	41.02***	3.67
Observations	128		128		128	
R-squared	0.478		0.430		0.478	

Table 8 – Results of the meta- regression model with fewer explanatory variables (parsimonious model)

	Unweighted		Weighted a) (N° estimates)		Weighted b) (N° of estimates and sample size)	
Variable	Coeff.	t - ratio	Coeff.	t – ratio	Coeff.	t - ratio
Year of survey: with reference to Before the year 2000						
Years 2000-2010	9.38	1.21	11.41	1.57	7.63	1.01
After the year 2010	20.83***	2.64	22.65***	3.01	18.81**	2.50
Range specification: with reference to Generic						
Non-Linear	17.08**	2.46	13.37**	2.00	14.84**	2.14
BEV-specific	23.90***	2.91	20.42**	2.54	21.40***	2.62
Maximum BEV Range in the scenarios: continuous variable						
Max BEV range	-0.04***	-3.40	-0.03***	-3.09	-0.03***	-3.34
Constant	21.18**	2.53	19.93***	2.64	23.13***	3.00
Observations	128		128		128	
R-squared	0.337		0.322		0.334	

We report the results of two models: a full model with all explanatory variables (Table 7) and a parsimonious model with a selection of the explanatory variables (Table 8). By jointly reading the results presented in Table 7 and Table 8, these conclusions can be drawn.

The model type (MNL_LN, Mixed, Hybrid_LC) does not significantly affect the WTP.

It is confirmed that range specification is crucial for the estimation of the WTP: nonlinear (piecewise, logarithmic, quadratic) specifications lead on average to a 14.86-19.45 €\km higher estimate than the generic one, and, similarly, the BEV-specification to a 14.14-19.39 €\km higher estimate relative to the generic one.

The BEVs' driving range assumptions presented to the respondent during the SP exercises impact their WTP for the range. The higher the BEVs range assumed the lower their WTP for an additional km of driving range. Of course, the scenarios should be realistic and be based on the current BEV ranges offered in the market. As they become higher, the less important is understandably the consumers' WTP, proving its non-linearity. This result stems both from Table 7, where 3 BEVs driving range reference classes are used (less than 150 km, between 150 and 400 km, and more than 400 km), and from Table 8, where range enters the regression as a continuous variable. Note that in Table 7, 400 km appears to be a threshold: the ranges between 150 and 400 km are not valued more than those below 150 km, while when they are higher than 400 km the WTP drops by 30 €/km.

The "After the year 2010" variable, relative to the "Before the year 2000" variable, is weekly significant and with a positive sign in one of the specifications (when the range is coded as continuous variable). Such result does not confirm, the opinion expressed by Kurani et al. (1994) according to whom the lack of experience might lead to an overestimate of the WTP for driving range. More in line with Franke et al (2017) and with Jensen et al. (2013), in the parsimonious model (Table 8), the importance of the driving range seems to have increased as customers acquired more direct and indirect experience with BEVs.

Unexpectedly, no statistically significant difference among WTP estimates seems to exist between USA and Canada on the one hand and the European countries and Japan on the other hand, although travel distances and travel habits are quite different between these two groups of countries.

With regards to the socio-economic and geographical variables, only in one specification the variable "owning more than one car in a household" leads to a 90% statistically significant lower WTP. The lack of significant results with regards to the socio-economic covariates confirm what already stated by

Dimitropoulous et al. (2013), i.e. the impact of the socio-economic and geographical variables on the WTP for the BEVs driving range is not often and consistently studied.

6. Conclusions and policy implications

One of the main motivation of our study was to assess whether the conclusion drawn by Dimitropoulos et al. (2013) still hold true and what new insight can be derived from more recent studies given the many changes that occurred in the last years concerning the BEVs' uptake in the market, the growing consumers direct and indirect experience with BEVs, the increased driving range of the BEVs, and the growing diffusion of the charging infrastructure. While Dimitropoulos et al. (2013) could use only primary studies based on surveys carried out in the period 1977-2009, we added papers based on surveys carried out up to the year 2017.

We carried out two meta-analysis exercises: the estimation of the summary effect size of the driving range coefficient, and a meta-regression of the WTP for a 1-km increase in the BEVs' driving range.

As far as the summary effect size is concerned, the primary studies used five different driving range attribute specifications (generic, BEV-specific, logarithmic, quadratic and piecewise linear). We have been able to estimate four summary effect size estimates, as it was not possible to identify the one for the piecewise linear specification. The main finding is that different specifications leads to different marginal utilities. For low driving range values (below 200 km), the summary effect size derived from linear specification tends to underestimate the marginal utility relative to the other specifications. For higher driving range values (above 300 km), the summary effect size derived from BEV-specific specification tends to overestimate the marginal utility. Consequently, it is advisable that researchers estimate different driving range specifications and compare the results in terms of parameters and WTPs. Great attention should be paid to use realistic range levels in specifying the SP hypothetical scenarios.

In order to search for common patterns among studies, we used the "WTP for a 1-km increase in the BEVs' driving range" metric. We find that an average the WTP varies between 27.4 and 34.4 €/km at 2017 prices, which is a slightly lower estimate than that obtained by Dimitropoulos et al. (2013). This result contains two important messages. The first is that on average, the importance attributed to the BEV's range by the consumers has not decreased, notwithstanding the above-discussed favorable changes to the BEVs technology, costs and charging infrastructure explained. The second is that there is a very large dispersion of the estimates around the mean values, implying that there is a large heterogeneity due to differences in respondents' needs, vehicle segments and modelling techniques.

The meta-regression allowed us to further explore and test statistically these conclusions. The econometric model used (MNL, Mixed logit, Hybrid) does not significantly affect the WTP estimate. On the contrary, it confirmed that the generic range specification leads to an underestimation of the WTP relative to the nonlinear and BEV-specific ones of about 14-19 €/km. We find that the BEVs' driving range assumptions presented to the respondents during the SP exercises negatively affect their WTP for the BEV-range. Interestingly, over the years the WTP estimates do not decline, contrary to what expected by Kurani et al. (1994), and confirming the findings by Jensen et al. (2013) that drivers attribute more importance to the BEVs' driving range after experiencing them. There is some statistical evidence that a threshold might exist above which the BEVs' driving range becomes less important. We recorded a significant WTP drop after 400 km, but more empirical evidence is needed to confirm this result. Finally, we did not find consistent statistical evidence from the primary studies on the impact of the various socio-economic, territorial or infrastructural covariates. More work needs to be done at this regard as well, in particular concerning the charging infrastructure and the mobility needs, as underlined by Dimitropoulos et al. (2013).

With reference to the policy implications, the starting point is that the BEV's driving range is still perceived as a major issue. According to our estimates, a 100 km driving range improvement is valued on average about 2,700-3,400 EUR. Stated differently, this is the discount that would convince a consumer to buy a BEV instead of a conventional car, ceteris paribus, if the BEVs' driving range is 100 km lower than that of a conventional car[20]. An important policy implication for the policy makers is that there is still a pressing need to improve batteries, making them less costly and also more efficiency in terms of weight, volume and energy density. As experience in the past, technological progress for batteries depends on public research funding and industry efforts in pursuing the industrialization of the scientific breakthroughs. Much progress has been achieved in the last decades; more progress is however needed if BEVs' uptake is considered important from a societal point of view.

Although it has not clearly emerged from the primary studies, the improvements in the charging infrastructures are most likely crucial to overcome the "range anxiety". Policy makers should consequently put more effort to encourage their diffusion (also in less densely populated areas), to enhance interoperability, to issue clear parking regulation in the charging areas, and to increase their power in order to reduce charging times. The proper interplay between policy makers (at national or local level) and industry is crucial to speed up investment in the public and private charging to set the stage for BEV's diffusion.

Although there are some studies evaluating the importance attributed to the BEVs' driving range among car market segments (Bunch et al., 1993, Jensen et al.,2013; Hackbarth and Madlener, 2013), we were not able to answer via meta-analysis the question we raise regarding the existence of two distinct car market segments (long range intercity cars vs. short range city cars). More research is needed in order to provide the automotive industry with this crucial information.

Finally, carrying out this study we have become aware of the several issue that one encounters when carrying out a meta-analysis. We highlight them as suggestions to those that will undertake future research efforts in the analysis of the consumers' preferences in car choice. It is essential that the primary studies describe in detail the respondents' sample, the year of the survey, the hypothetical scenarios presented to the respondents and the attribute levels used (and their coding). It also would be important that the authors derive their own WTP estimates for the non-monetary attributes and analyze them. With special reference to the driving range attributes, our suggestion is to test different specifications, to estimate their WTP selecting the appropriate reference levels and to explore and document the relevant covariates, including infrastructural, trip purpose, and charging habits variables.

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[20] On the contrary it is well documented that BEVs still have a higher total cost of ownerships that conventional vehicles (e.g., Giansoldati et al., 2018)

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Appendix

Table 9 – List of studies and their characteristics.

Authors	Propulsion system	Year of the survey	Country	Survey Method	N° of Respond.	Model Type	Range Levels	Range specification	Reference range (km)	N° WTP estimates	Average WTP €/km	Max WTP €/km	Min WTP €/km
Beggs et al. (1981) §	GV, BEV	1980	USA	telephone	193	OL	GV: 200, BEV: 50 (miles)	Generic		2	9.3	10.0	8.6
Calfee (1985) §	GV, BEV	1980*	USA	paper	51	MNL	GV: 150, BEV: 70 (miles)	Logarithmic	110	1	2.4	2.4	2.4
Bunch et al. (1993) §	GV, AFV, BEV	1991	California	mail	692	NL	GV: 300, AFV: 150, BEV: 75 (miles)	Quadratic	188	13	66.8	96.8	28.0
Golob et al. (1997) §	GV, NGV, MV, BEV	1994	California	CATI, mail	2023	MNL	GV: 250-350; BEV: 60-150; NGV: 80-275; MV: 150-250 (miles)	Generic		1	27.1	27.1	27.1
Tompkins et al. (1998) §	CV, CNGV, LPGV, BEV, PHEV, AV	1995	USA	CATI, mail	1711	MNL	up to 300 (miles)	BEV-specific		1	22.4	22.4	22.4
Ewing and Sarigöllü (1998) §	GV, AFV, BEV	1994	Montreal, Canada	mail	881	MNL	GV: 300, AFV: 300, BEV-100-300 (miles)	Generic		5	3.5	7.9	1.8
Ramjerdi and Rand (1999) §	AFV, BEV	1994	Norway	mail	945	NL	BEV: up to 300 (miles)	BEV-specific		2	27.9	31.0	24.7
Ewing and Sarigöllü (2000) §	GV,AFV,BEV	1994	Canada	mail	881	MNL	GV: 300, AFV: 300, BEV-100-300 (miles)	Piecewise		2	13.4	18.6	8.3
Brownstone et al. (2000) §	GV, CNGV, MV, BEV	1994	California	CATI, mail	2857	RP/SP MNL and RPL	All: 50-570 (miles)	Quadratic	310	5	1.9	3.3	1.0
Dagsivik et al. (2002) §	GV, BEV, HEV	2000*	Norway	n.a	642	MNL	BEV: 100-500 (km)	Generic		6	5.2	7.8	0.7
Train and Weeks (2005) §	GV, BEV, HEV	2000	California	n.a	500	preference space	BEV: 60	Logarithmic	310	2	57.8	63.7	51.9
Hesse (2006) §	GV, BEV, HEV	2000*	California	n.a	500	RPL	BEV: 60	Generic		1	23.1	23.1	23.1

Knockaert (2010) §	AFV, LPGV, BEV, FCV	2008	Belgium	CATI	209	MNL, NL, RPL	DV GV: 500, LPGV, BEV, AFV: 200-500; (km)	Generic		2	22.8	24.3	21.4
Christensen et al. (2010) §	BEV, CV	2008	Denmark	web-based	1348	MNL	BEV: 80-200 (km)	Generic		1	13.0	13.0	13.0
Hidrue et al. (2011) §	BEV, GV	2009	US	web-based	3029	MNL	BEV: 75-300 (miles)	Piecewise Linear		1	20.2	20.2	20.2
Mabit and Fosgerau (2011) §	CV, FCV, HEV, BDV, BEV	2007	Denmark	web-based	2146	RPL	CV: 575-950; BEV: 300-1425; HEV: 200-1400; BDV: 300-1424 (km)	Logarithmic	862	1	14.3	14.3	14.3
Parsons et al. (2011) §	BEV, GV	2009	USA	web-based	3029	MNL	BEV: 200 (miles)	Piecewise		3	20.1	26.1	12.1
Hess et al. (2012) §	HEV, PHEV, BEV, CNGV, GV, DV, FFV	2008	California	telephone	3274	CNL	BEV: 30-60; CNG: 150-300 (miles)	Logarithmic	134	1	32.0	56.1	15.2
Link et al. (2012)	GV, BEV, HEV	2011	Austria	telephone	220	MNL	BEV: 300 (km)*	Logarithmic	300	1	55.0	55.0	55.0
Ziegler (2012)	GV, DV, HEV, FCV, BFV, BEV	2007	Germany	CAPI	598	Probit	All: 100-1000 (km)	Logarithmic	550	4	12.0	14.4	9.4
Daziano (2012)	ICV, BEV, HV	2000*	Canada	n.a.	500	RPL	BEV: 60-200 (miles)	Logarithmic	209	1	26.5	26.5	26.5
Chorus et al. (2013)	GV, DV, HEV PHEV, FCV, FFV, BEV	2011	The Netherlands	web-based	616	Utility max, rando m regret min	BEV: 75-350, DV: 350-550 (km)	Generic		2	61.7	63.0	60.3
Daziano and Chiew (2013)	ICV, BEV, HV	2000*	California	n.a.	616	RPL	BEV: 60-200 (miles)	Logarithmic	209	1	24.4	24.4	24.4
Hackbarth and Madlener (2013)	CNGV, HEV, PHEV, BEV, BV, FCEV, GV, DV	2011	Germany	web-based	711	MNL, RPL	BEV: 100-700; other: 400-1000 (km)	BEV-specific		4	24.7	33.5	16.1
Jensen et al. (2013)	BEV, GV	2012	Denmark	web-based	369	HM	BEV: 160 (km)	BEV-specific		4	60.1	97.9	33.6
Rasouli and Timmermans (2013)	BEV, GV	2012	The Netherlands	web-based	726	RPL	All: 100 -550 (km)	Piecewise		5	20.5	51.2	8.1
Daziano (2013)	CV, BEV, HEV	2000*	California	n.a.	500	RPL	BEV: 60-200 (miles)	Logarithmic	209	5	47.5	70.0	37.1

Hoen and Koetse (2014)	GV, BEV, HEV	2011	The Netherlands	online questionnaire	1903	MNL, RPL	BEV: 75-350; other:250-550 (km)	BEV-specific		7	53.6	83.4	27.3
Tanaka et al. (2014)	BEV, PHEV, GV	2012	US	web-based	4202	ECM L	BEV: 100-400; PHEV: 700-1000; GV: 400-700 (miles)	Generic linear		6	0.5	0.6	0.4
Valeri and Danielis (2015)	DV, GV, CNGV, LPGV, HEV, BEV	2013	Italy	face-to-face	121	MNL, RPL	current,+40%;	BEV-specific		5	31.8	49.7	16.5
Bahamonde-Birke (2016)	CV, PHEV, HEV, BEV	2013	Austria	web-based	1449	RPL	BEV: 400*	BEV-specific		3	76.1	83.1	72.5
Hackbarth and Madlener (2016)	NGV, HEV, PHEV, BEV, BV, FCEV, ICEV	2011	Germany	web-based	711	MNL	BEV: 100-700; other: 400-1000 (km)	Logarithmic	711	6	46.6	123.1	9.4
Dimitropoulos et al. (2016)	PHEV, BEV, HEV, ICEV	2013	The Netherlands	web-based	756	MNL, LC	BEV: 100-500: PHEV: 500-900; ICEV-HEV: 600-900 (km)	BEV-specific		4	27.8	52.9	16.7
Cherchi (2017)	BEV, ICEV	2015	Denmark	web-based	2363	HM	BEV: up to 270 km	BEV-specific		1	33.9	33.9	33.9
Giansoldati et al. (2018)	BEV, ICEV	2017	Italy	web-based, face-to-face, paper	318	MNL, RPL	BEV: up to 350 km	All specifications	200	8	63.0	114.4	33.5

Legend:
*uncertain value, not mentioned in the paper;
Propulsion systems: AFV (alternative fuel vehicle), AV (alcohol vehicle), BDV (bio-diesel vehicle), BFV (Bio-Fuel vehicle), BEV (battery-only electric vehicle), CNGV (compressed natural gas vehicle), CV (conventional vehicle), DV (Diesel vehicle), FFV (flexible-fuel vehicle), FCV (Fuel cell vehicle), GV (Gasoline vehicle), HEV (Hybrid electric vehicle), HFCV (Hydrogen fuel cell vehicle), LPGV (liquid petroleum vehicle), MV (methanol vehicle), PHEV (plug-in electric vehicle), REEV (range extended electric vehicle).
Model types: OL (ordered logit), MNL (multinomial logit), NL (nested logit), RPL (random parameter logit or mixed logit), ECML (error component multinomial logit), HM (Hybrid choice model), CNL (cross nested logit model), CA (conjoint analysis), MCDA (multicriteria decision analysis), LC (latent class);
^ data to be used for WTP estimate not available.