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Consumer Valuation of Driving Range: A Meta-Analysis

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Abstract

We perform a meta-analysis of studies investigating consumers' preferences for electric and other alternative fuel vehicles to provide insights into the way consumers trade off driving range for capital costs. We find that consumers are willing to pay, on average, between 47 and 64 US$ for a one-mile increase in vehicle's range. The short driving range of most currently available electric vehicles entails that they should be offered at prices around half the price of their conventional counterparts in order to be considered competitive alternatives, ceteris paribus. In line with intuition, but in contrast to most specifications employed in primary studies, we find evidence that consumers' marginal willingness to pay (WTP) is decreasing in driving range. The wide divergence in the estimates of welfare measures among the examined studies can be mainly attributed to differences in the study design, the location at which the study was conducted and the size of the study's sample. Provided that a large scale introduction of electric vehicles is a policy aim, our findings support the continuation of R&D efforts directed towards the reduction of battery costs and the development of advanced battery technologies permitting higher driving ranges than the ones currently achievable by most commercially available electric cars.

Keywords: Electric vehicles; Meta-analysis; Driving range; Willingness to pay.

JEL Classification codes: R41, D12, Q41, Q42

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1. Introduction

Growing concerns over climate change and local air pollution, increasing oil prices, as well as car industry's efforts to recover from the global economic crisis, appear as the main factors that trigger a renewed global interest in electric cars.[1] However, there are some factors which hamper the large-scale adoption of battery-powered electric vehicles (BEVs). In addition to the substantially higher prices that consumers have to pay in order to acquire them, other factors which have been persistently discussed in the economic literature include the limited range they can travel on a fully charged battery, the long time needed for a battery recharge and the high costs required for the development of an extensive charging infrastructure (e.g., Beggs et al., 1981; Tompkins et al., 1998; Dagsvik et al., 2002).

Over the last decades, a number of studies that examine consumers' preferences for cars have emerged, to provide insights into the potential market for battery-electric cars and other alternative fuel vehicles (AFVs). The vast majority of these studies employ stated preference (SP) techniques to reveal households' and fleet managers' preferences for AFVs (e.g., Bunch et al., 1993; Golob et al., 1997; Mabit and Fosgerau, 2011). Most of these studies consider driving range - the maximum distance that a vehicle can travel on a full tank or a fully-charged battery - as a determinant of consumers' preferences for cars. The empirical results of these studies typically suggest that short range is indeed an important factor in consumers' vehicle choices and a notable reason for consumers' scepticism towards BEVs and other AFVs.

In the existing literature there is no agreement on how important increases in vehicle range are for the adoption of electric cars. There is substantial variation in consumers' estimated willingness to pay (WTP) for increased range across the examined studies. This paper addresses this issue on the basis of a meta-analysis of 31 discrete choice and contingent ranking studies of consumers' preferences for AFVs. Based on the analysis of 132 usable WTP estimates derived from these studies, we find that consumers are willing to pay, on average, 47 to 64 US dollars for a one-mile increase in the vehicle's range.[2] This translates into a compensating variation (CV) of 2,900 to 3,500 US dollars for a change in driving range from 100 miles - the current driving

[1] The terms 'car' and 'vehicle' are used interchangeably throughout this paper. The definition of the term comprises all body types of light duty vehicles, including vans, pick-up trucks and sport utility vehicles. Two- and three-wheelers, as well as heavy-duty vehicles, are not in the scope of the analysis.

[2] WTP and CV values are presented in PPP-adjusted 2005 US$.

range of most commercially available BEVs - to 150 miles. Our findings also suggest that, ceteris paribus, 100-mile-range cars should be 44-57% cheaper than conventional cars in order to be considered as competitive alternatives.

We provide insights into the variation of WTP and CV among studies by means of several meta-regression models. We show that this variation can be mainly attributed to differences in: (i) the methodology used in the reviewed studies, (ii) the country in which the study was carried out, and (iii) the size of the survey sample employed. We also propose that utility specifications allowing the expression of WTP for range as a decreasing function of vehicle's range can describe consumers' actual behaviour more realistically than utility specifications considering a constant marginal utility of range.

Overall, our study of the SP literature on consumers' preferences for AFVs implies limited prospects for vehicles with a driving range at the level of most currently commercialized BEVs, unless they are offered at prices substantially lower than their conventional counterparts. Hence, it provides strong support for the financing of R&D efforts directed towards the reduction of EV battery costs and the development of advanced battery technologies permitting higher driving ranges.

The remainder of the paper is organised as follows. Section 2 presents an overview of the literature studying consumers' preferences for AFVs, with a focus on driving range. Section 3 unravels the main contributions and limitations of meta-analysis in transportation research. Section 4 reviews the methodology employed to collect relevant studies and provides summary statistics of the WTP and CV for driving range. Section 5 discusses the empirical findings of several meta-regression models aiming to explain the variation in WTP and CV estimates in the existing literature. Section 6 concludes.

2. Preferences for AFVs and willingness to pay for driving range

The application of stated preference techniques for the investigation of consumers' preferences for alternative fuel vehicles (AFVs) has been of interest to economists for more than three decades (e.g., Morton et al., 1978; Ewing and Sarigöllü, 1998; Dagsvik and Liu, 2009), while the field seems to be recently gaining some popularity also in marketing science (e.g., Eggers and Eggers, 2011; Zhang et al., 2011). Stated preference (SP) methods have been identified from the beginning (Beggs et al., 1981) to be prominent candidates for the elicitation of consumers' preferences for AFVs as these methods can be used to study the market potential of alternatives that do not yet exist.

Characteristics theory of value (Lancaster, 1966) provided the theoretical basis of stated preference methods, while random utility theory (McFadden, 1974) established the econometric foundations for their development and application. SP methods consider goods as bundles of attributes and individuals as utility maximising economic units. In the current context, individuals are invited to engage in a hypothetical purchase of a car and maximise their utility by selecting their preferred vehicle from a set of alternative options (discrete choice method) or by ranking the options presented to them (contingent ranking method). These options are presented as bundles of attributes, whose levels are varied among alternatives. In the context of vehicle choice, these attributes may, for instance, comprise fuel type, car body type, acquisition and operating costs, performance characteristics and environmental impact.

The stated choices or rankings resulting from such experiments are analysed on the basis of discrete choice or rank order models, such as the multinomial logit or the ordered logit model. Under specific assumptions, these models allow the computation of the effects of changes in the attribute levels on the probability of an alternative being chosen, as well as the estimation of welfare measures associated with changes in the attribute levels. A further elaboration of the theory underlying the development, use and application of stated preference methods is beyond the scope of this paper. Louviere et al. (2000), Hensher et al. (2005) and Greene and Hensher (2010) provide a solid and comprehensive review of relevant methods.

The first attempts of using discrete choice or contingent ranking methods to quantify consumers' preferences for electric vehicles took place in the USA and Australia shortly before and after the second energy crisis of the 1970s (Morton et al., 1978; Beggs et al., 1981; Hensher, 1982; Calfee, 1985). These early studies use the results of surveys addressed to relatively small and non-representative samples and focus solely on electric cars as an alternative to petrol-fuelled vehicles.[3] They examine individuals' trade-offs between vehicles' purchase price, operating costs and driving range, while ignoring consumers' sensitivity to variations in fuel availability and refuel time. US studies of this period survey only multi-vehicle households, as they expect them to be more tolerant to the strong range limitations imposed by the BEVs of that

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[3] Hensher (1982) is a notable exception here. It is the only study drawing on an experiment asking decision makers' to rank order 27 electric cars, varying only in their attribute levels.

time period, due to the availability of at least one extra car at their disposal.[4] Their main conclusion is that EVs' short driving range and long recharge time can indeed account for strong impediments to their consumer adoption.

Californian environmental legislation stimulated the revisit of this issue during the 1990s (e.g., Bunch et al., 1993; Segal, 1995; Brownstone et al., 1996; Golob et al., 1997; Greene, 1998). In the middle of that decade, stated preference surveys on electric and other alternative fuel vehicles were also conducted in Australia (Hensher and Greene, 2001), Canada (Ewing and Sarigöllü, 1998) and Norway (Ramjerdi et al., 1996; Dagsvik et al., 2002). One of the noteworthy deviations of these later studies lies with their consideration of other alternative fuel vehicles, apart from BEVs. The fuel options introduced include compressed natural gas (CNG), liquefied petroleum gas (LPG) and biofuels, while hybrid and flex-fuel vehicles are often taken under consideration as well. The 1990s studies have also added some novel elements in regard with the attributes examined in the choice or ranking setting consumers are confronted with. These attributes are particularly relevant for AFVs and concern refuel duration and timing, the availability of refuel infrastructure and air emissions. The majority of these studies find that all the aforementioned attributes are significant determinants of consumers' vehicle choice, although probably not ones of primary importance.

Some of the 1990s studies go further to acknowledge that consumer's evaluation of driving range is not independent from the levels of refuel time and availability of fueling infrastructure presented to them (e.g., Segal, 1995; Ewing and Sarigöllü, 1998). For instance, if the refueling of AFVs took only a few minutes and the density of fueling infrastructure was high, the importance of the driving range attribute would probably be much lower. The practical acknowledgement of the relationship between these three attributes in consumers' minds would imply a non-linear formulation of the utility function, including interaction terms between driving range, refueling duration and fueling infrastructure availability. Surprisingly, however, none of the examined studies mentions explicitly testing for interaction effects among these attributes. We use the meta-analysis to look for signs of such non-linearities.

A third wave of studies, this time more evenly distributed across geographical regions, follows in the 2000s. Consumers' preferences for AFVs are also investigated in other European

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[4] On average, BEVs were assumed to have a driving range of 50 miles in these early studies.

countries, such as Belgium (Knockaert, 2010), Denmark (Jensen, 2010; Mabit and Fosgerau, 2011), Germany (Achtnicht et al., 2008; Eggers and Eggers, 2011), Ireland (Caulfield et al., 2010), the Netherlands (Molin et al., 2007, Molin & Brinkman, 2009, Molin et al., submitted) and the UK (Batley and Toner, 2003; Batley et al., 2004), as well as in Eastern Asian developing economies, such as China (Dagsvik and Liu, 2009) and South Korea (Ahn et al., 2008). A number of additional studies are also conducted in California (e.g., Adler et al., 2003; Axsen et al., 2009; Nixon & Saphores (2011)) and Canada (e.g., Horne et al., 2005; Potoglou and Kanaroglou, 2007; Mau et al., 2008). Expectations for strong developments in the hydrogen fuel cell (HFC) technology resulted oftentimes in the inclusion of HFC vehicles in the choice experiments presented in these recent studies (e.g., Achtnicht et al., 2008; Mau et al., 2008; Mabit and Fosgerau, 2011).

The majority of the aforementioned studies consider driving range as a vehicle attribute possibly affecting consumers' car choices. Especially among studies considering a BEV option, only the study by Achtnicht et al. (2008) does not include driving range in the attribute set. Empirical evidence from these studies suggests that vehicle range is an important determinant of decision makers' choice between petrol-fuelled vehicles and AFVs. A closer look at the primary results, however, reveals that the implicit trade-off between vehicle's range and purchase price varies substantially among studies, ranging from a few US dollars to a few hundreds of US dollars per additional mile. This implicit trade-off is the effect size of interest in this study. The measures we will employ to capture this trade-off are the willingness to pay for a one-mile increase in driving range and the compensating variation from a reference level of 100 miles to 150 and 350 miles.

The willingness to pay (WTP) for a marginal incremental change of driving range is defined as the ratio of the marginal utilities of the driving range and purchase price attributes:

$$WTP = -(\partial \mathrm{U} / \partial R) / (\partial \mathrm{U} / \partial P) \,, \qquad (1)$$

where U is the individual's stochastic utility function, encompassing the driving range of the vehicle, R, its purchase price, P, and a vector of other variables. When the utility function is linear in the purchase price and driving range variables (and no interactions among these two variables and other variables are considered), the WTP equals the ratio of the estimated coefficient of driving range, β_R, to the one of purchase price, β_P:

$$WTP = -(\beta_R / \beta_P)\,. \qquad (2)$$

WTP estimates stemming from studies considering a non-linear in vehicle range or purchase price utility specification are dependent upon the reference level at which the analyst calculates the WTP. This reference level is usually the mean level of the driving range or the purchase price attribute employed in the SP experiment, which can vary substantially among primary studies. This caveat of the WTP measure can be particularly problematic for the comparison of WTP values stemming from studies employing different utility specifications with respect to driving range or purchase price. A related measure which circumvents this problem is compensating variation.

Compensating variation (CV) reflects the change in the economic welfare of an individual caused by a change in the level of an attribute of a commodity. It is defined as the monetary compensation required after a change in the attribute level to restore the individual to the same utility level she was before the change occurred. A simple mathematical illustration of the concept, in the current context, is provided in Equation (3):[5]

$$\mathrm{U}(R_0, Y) = \mathrm{U}(R_1, Y - CV)\,, \qquad (3)$$

where R_0 is the reference level of the driving range attribute, R_1 is the driving range level after the change has occurred and Y is the income of the economic unit of interest. The compensating variation for a change in driving range from R_0 to R_1 can be calculated as the definite integral of the WTP, as defined in Equation (1):

$$CV = \int_{R_0}^{R_1} \left(-\frac{\partial\,\mathrm{U}/\partial R}{\partial\,\mathrm{U}/\partial P}\right) \mathrm{d}R\,. \qquad (4)$$

When the utility function is assumed to be linear in driving range, CV simply equals the product of marginal WTP and the considered change in driving range.

An investigation of car manufacturers' vehicle specifications reveals that the driving range of most currently available commercial BEVs is around 100 miles (Daziano, 2011). We compute CV on the basis of two departures from this reference level: a 50-mile increase, which

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[5] See also Louviere et al. (2000), p. 340.

seems to be feasible in the short term for BEVs, and an increase to 350 miles, a driving range level similar to the one of an average conventional car.

Before proceeding with the introduction of the meta-analysis approach, it is worth to note that a number of studies conducted in California in the 1990s challenge the rationale behind the use of standard choice modelling methods for the elicitation of households' preferences for driving range. Research undertaken by Kurani et al. (1994, 1996) suggests that alternative fuel vehicles with a maximum range of 150 miles have the potential to gain a substantial share in new purchases of light-duty vehicles in California, provided that they are sold at a relatively low price premium above equivalent gasoline vehicles. Based on innovative types of interviews and surveys, they find "hybrid households'" preferences to be highly unstable and sensitive to the provision of elaborate information on the use of AFVs and interactions with other people. Kurani et al. opine that the use of standard SP approaches to explore consumers' preferences for driving range is simplistic and inappropriate, as these methods fail to consider that consumers do not have well-developed preferences for driving range. Driven by their lack of experience with driving range limitations, individuals tend to anchor to the range of their current gasoline-fuelled vehicle and overstate their willingness to pay.

3. Meta-analysis

The term 'meta-analysis' denotes the synthesis of the findings of a well-defined collection of primary empirical studies by means of statistical methods (Glass, 1976). Meta-analysis has been gaining increasing popularity in transportation research during the last two decades, where it has been employed to review, for instance, literature on the value of travel time savings (e.g. Zamparini and Reggiani, 2007; Abrantes and Wardman, 2011; Wardman & Ibáñez, 2011) and the value of statistical life (de Blaeij et al., 2003), the externalities of transport activities (e.g., Button, 1995; Nelson, 2004; Quinet, 2004), the supply and demand of public transport (e.g., Brons et al., 2005; Holmgren, 2007) and the psychological determinants of car use (e.g., Gardner and Abraham, 2008).

Three methodological pitfalls of meta-analysis have been of primary concern to researchers (see for instance, Stanley, 2001, 2005; Florax, 2002; Nelson and Kennedy, 2009). These comprise selection and publication bias, heterogeneity among primary studies and heteroskedasticity, and correlation between the sampled effect sizes. Meta-analysis literature has proposed various ways to identify the existence of the aforementioned pitfalls and address them. Encompassing fugitive literature, namely studies presented in conference papers, working papers, theses, dissertations, as well as reports prepared by government agencies or private consulting firms, in the scope of the literature search is an initial step to mitigate the possibility of selection and publication bias. Once the study sample has been established, funnel graphs and Galbraith plots can be utilised to identify the possible existence of publication bias (Stanley, 2005).

In transportation research, pinpointing the main sources of heterogeneity underlying a specific effect size is often at least as important as the measurement of the effect size itself. This accounts for the popularity that meta-regression models have gained in meta-analyses performed in this context (e.g., de Blaeij et al., 2003; Holmgren, 2007; Abrantes and Wardman, 2011);. Meta-regression models are employed to identify and quantify observed sources of heterogeneity among primary studies, captured primarily by the use of dummy variables. These sources usually concern characteristics or measures of the commodity of interest (e.g., driving range), methodological considerations of the primary studies (e.g., model specification, estimation method), as well as contextual aspects, such as the time and location in which the primary study is carried out (Nelson and Kennedy, 2009).

In the context of meta-regression analysis, heteroskedasticity can be addressed both by the use of a weighting approach taking under consideration the precision with which effect sizes have been estimated in the primary studies and by the use of heteroskedasticity-robust variance-covariance estimators (Florax, 2002). In the context of the first method, the inverse of the variances with which the effect sizes were estimated in the primary studies or, on their absence, the sample sizes employed therein can serve as appropriate weights. Weighting can also moderate the effects of publication bias, as it can substantially lessen the influence of effect-sizes coming from small-sample primary studies.

A less extensively discussed problem in meta-analysis is the correlation existing among the effect sizes arising from the aforementioned sources (Florax, 2002; Nelson and Kennedy, 2009). This caveat is particularly relevant for meta-analyses of welfare measures, where multiple sampling from the same study is dominating. In order to circumvent this problem, literature suggests the use of hierarchical regression methods or panel data procedures. The use of these methods can also provide important insights into the relevance of the distinction between a fixed and a random effect size, which is of paramount importance in the meta-analysis literature. Essentially, the difference between the two concepts lies with the ex ante consideration of a fixed population effect size or of a population effect size being a random draw from a normal distribution (Florax, 2002).[6]

4. Descriptive analysis of the study sample and the WTP for driving range

Stanley (2001) claims that a study sample composed by primary studies of different perceived quality provides the meta-analyst with additional opportunities to gain insights into how different methodologies and modelling choices influence study results, rather than confounding the synthesis of the main findings of the literature. Adopting his argument, we undertook an extensive keyword-based search in order to identify relevant pieces of literature. We looked into numerous paper and electronic sources, such as GoogleScholar, EBSCOHost, JSTOR and ProQuest, several online databases (e.g., TRID and EVRI) and relevant conference websites (e.g., ETC, TRB and Kuhmo-NECTAR), as well as into the websites of a large number of academic publishing companies, academic institutions, public agencies and private consulting firms. Furthermore, a handful of studies were obtained via personal communications with individual researchers.

Our search was completed in July 2011 and resulted in the identification and collection of more than 80 studies examining consumers' preferences for alternative fuel vehicles.[7] For a study to be included in our meta-sample, it should be allowing the computation of the Hicksian surplus for the consumer, or the compensating variation, associated with a change in the driving range of a light-duty vehicle. A considerable number of the collected studies did not fulfil this criterion, either because they were not concerned with light-duty vehicles or because the derivation of the WTP for driving range was not possible, and were excluded from the meta-analysis.[8]

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[6] It should be noted that, in a meta-analysis context, the definition of a "population effect size" may have either a rather limited scope, such as for instance the "WTP for driving range in Californian households", or a wider one, such as the "WTP for driving range".

[7] Three interesting studies could not be accessed as they were not found to be publicly available (Morton et al., 1978; Train and Hudson, 2000; Baumgartner et al., 2007).

[8] Some studies were excluded due to insufficient information about the characteristics of the primary samples (Hensher, 1982; Train, 2008; Hess et al., 2009; Molin and Brinkman, 2009; Paleti et al., 2011) or

Survey data on consumers' preferences for alternative fuel vehicles have been often used for the demonstration of novel modelling and estimation approaches. The first application of an ordered logit model for the analysis of rank ordered data was based on SP data on consumers' rankings of conventional and electric vehicles (Beggs et al., 1981). Brownstone and Train (1999), McFadden & Train (2000) and Dagsvik et al. (2002) used also datasets drawn from SP exercises examining preferences for various fuel technologies to establish the application of the, innovative at that time, random parameter logit models. In the same context, Brownstone et al. (2000) and Hensher and Greene (2001) modelled stated and revealed preference data jointly in a random parameter framework, Train (2008) demonstrated methods for the nonparametric estimation of mixing distributions in discrete choice models and Hess et al. (2009) emphasised the usefulness of cross-nested logit models. As a result, the meta-analysis presented in this paper has to compromise with a relatively limited and strongly heterogeneous pool of primary studies providing insights into the effect size of interest. As in most meta-analyses of welfare measures, multiple sampling of estimates of an effect size from the same study is essential to allow any sensible use of standard statistical methods and the extraction of any meaningful conclusions.

Our meta-analysis draws on 31 primary studies yielding 132 WTP and 128 CV useable estimates.[9] Some of these studies use stated preference data collected in the framework of other sampled studies in order to investigate the performance of different models or sampling procedures. Consequently, our review is based on the results obtained from the primary analyses of 21 different sets of stated preference data. Table 1 provides an overview of the primary studies used in the meta-analysis. It also presents the minimum, mean, and maximum estimate of WTP per mile derived from each study. WTP estimates are standardised into PPP-adjusted 2005US$,[10] to take account of international and intertemporal differences in consumers' purchase power.

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the study design (Segal, 1995). In the first set of studies, changes in prices or driving range were modelled as percentages of reference values, expressing the levels of consumers' current vehicle holdings or of the ones they intend to acquire. However, these reference values were not reported in the study, rendering, thus, the derivation of WTP measures impossible.

[9] The difference of four estimates between the two welfare measures stems from Jensen (2010).

[10] The annual consumer price index (CPI) and 2005 PPP index used for this purpose are provided by OECD.Stat. For the adjustment of the WTP estimates derived by Molin et al. (submitted), we use the CPI index of the second quarter of 2011.

Table 1: Summary of the primary studies included in the sample.

Study	Country	Year of survey	Observations	WTP per mile		
				Mean estimate	Lowest estimate	Highest estimate
Batley and Toner (2003)	Leeds, UK	2002	12	84	19	167
Batley et al. (2004)	Leeds, UK	2001	6	35	31	36
Beggs and Cardell (1980), Beggs et al. (1981)	USA	1978	6	93	64	132
Brownstone and Train (1999), Kavalec (1999), Brownstone et al. (2000), McFadden and Train (2000)	California, USA	1993	11	99	58	202
Bunch et al. (1993)	California, USA	1991	3	101	95	106
Calfee (1985)	California, USA	1980	1	195	195	195
Dagsvik et al. (2002)	Norway	1995	4	25	14	30
Ewing and Sarigöllü (1998, 2000)	Montreal, Canada	1994	12	20	17	22
Golob et al. (1997)	California, USA	1994	8	117	76	202
Hensher and Greene (2001)	Sydney, Australia	1994	4	23	14	31
Hidrue et al. (2011)	USA	2009	6	67	52	81
Jensen (2010)	Denmark	2010	6	30	14	62
Knockaert (2010)	Flanders, Belgium	2004	9	39	31	45
Christensen et al. (2010), Mabit (2010), Mabit and Fosgerau (2011)	Denmark	2007	4	20	18	23
Mau et al. (2008)	Canada	2003	4	6	3	9
Molin et al. (2007)	Amsterdam, Netherlands	2006	1	8	8	8
Molin et al. (submitted)	Netherlands	2011	2	44	43	45
Nixon and Saphores (2011)	USA	2010	2	51	46	55
Ramjerdi et al. (1996)	Norway	1994	16	71	33	231
Tompkins et al. (1998)	USA	1995	6	64	44	102
Train and Weeks (2005), Train and Sonnier (2005), Hess et al. (2006), Daziano (2011)	California, USA	2000	9	100	87	131

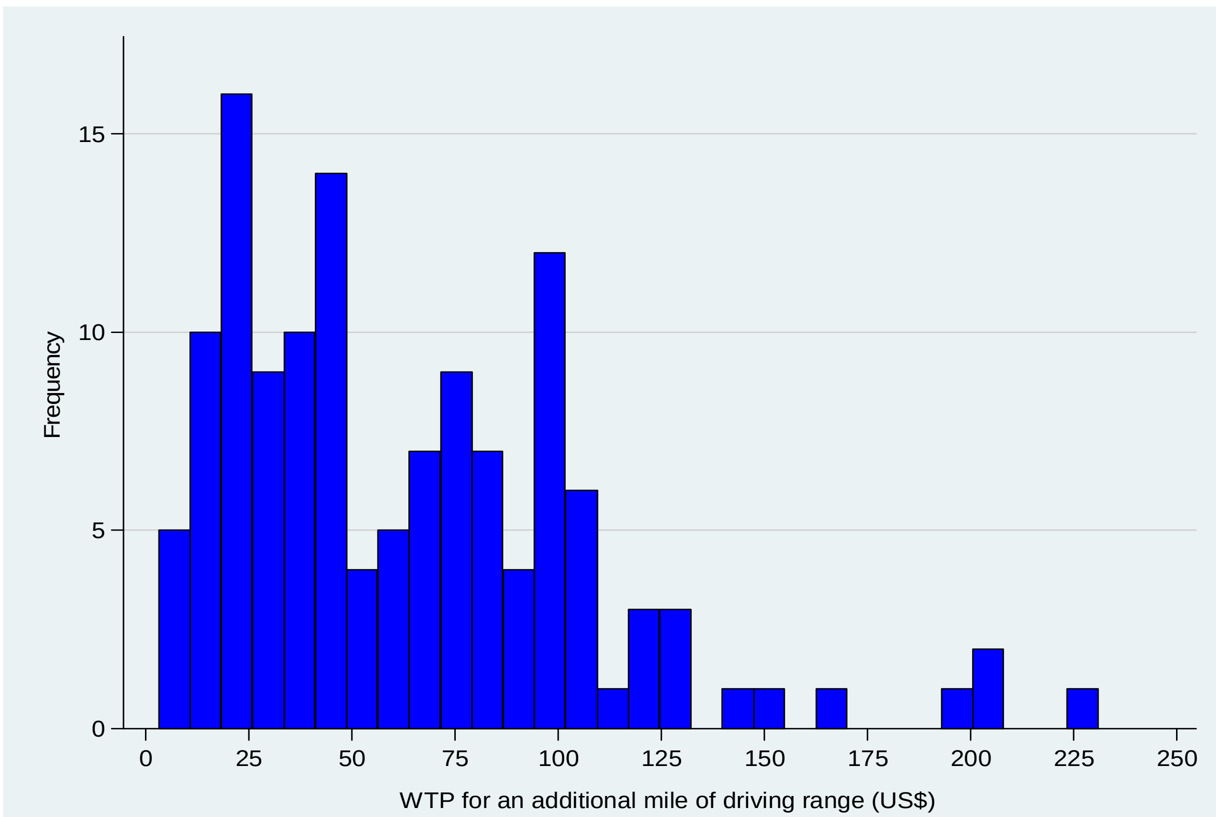
Note: WTP estimates are in PPP-adjusted 2005 US$.

Figure 1 illustrates the distribution of the WTP for a one-mile increase in driving range. It is positively skewed with a mean value of 64 US$ and a median of 53 US$.[11] The distributions of the two compensating variation measures are also skewed to the right. The mean CV for an increase in driving range from 100 to 150 miles is around 3,500 US$ with a median of 3,050

[11] It should be noted that the study sample exhibits a relatively limited geographical variation, strongly oriented towards high income economies of North America, Europe and Australia. In this sense, the findings presented here may not be representative of the average car buyer in lower income economies.

US$, while the value of an increase from 100 to 350 miles escalates to almost 16,200 US$ with a median of 13,200 US$. This implies that consumers would be indifferent between an average conventional car and a 100-mile-range car if the latter was 13,200 US$ – 16,200 US$ cheaper than the first. Ceteris paribus, taking into account that a new car in the USA was costing, on average, around 28,400 US$ in 2005 (National Automobile Dealers Association, 2006), a 100-mile-range car should be offered in prices reduced by 46-57% in order to be considered a competitive alternative by consumers.

Figure 1: Distribution of WTP for an additional mile of driving range.

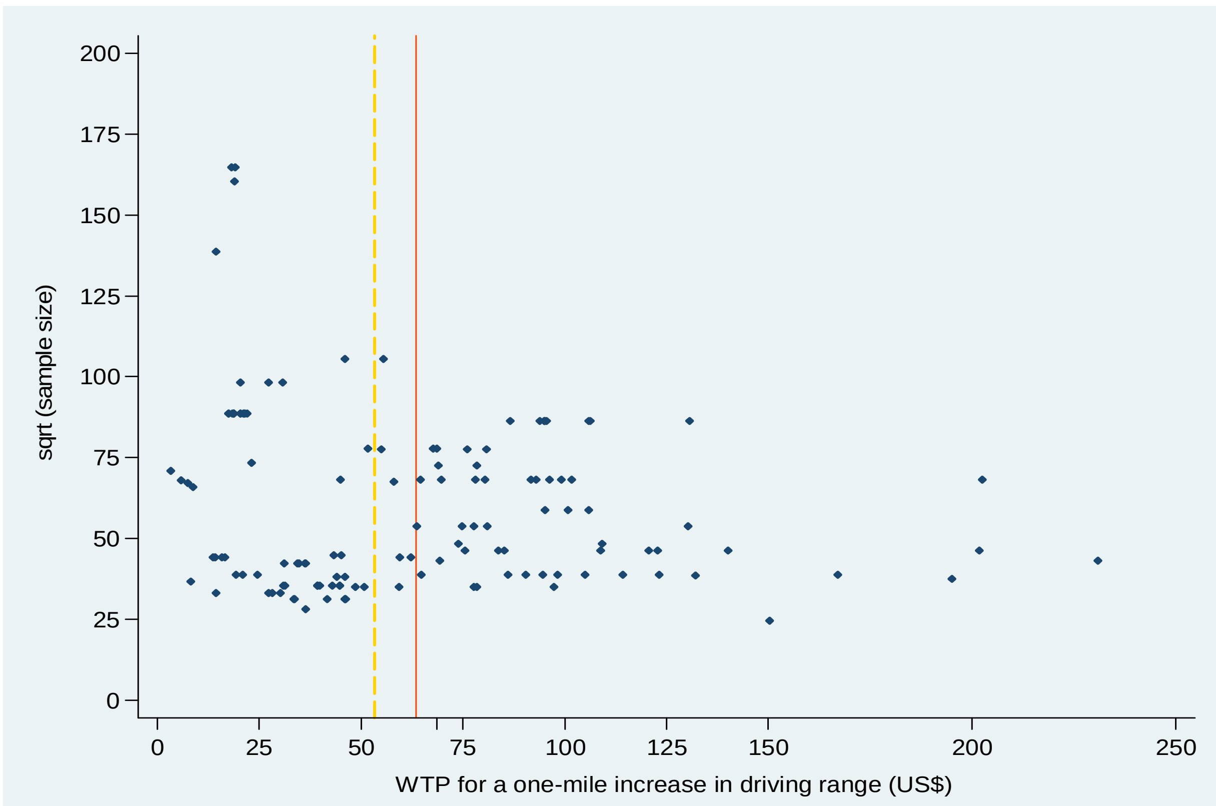


Note: WTP estimates are in PPP-adjusted 2005 US$.

However, the reduction in operating costs offered by the majority of AFVs, due to lower fuel and maintenance costs, is likely to decrease these figures to a certain extent. Daziano (2011) discusses this issue in the context of a comparison among BEVs, gasoline-fuelled and hybrid vehicles, while Delucchi and Lipman (2010) provide an elaborate analysis of the estimated lifetime costs among BEVs, Fuel-Cell and Plug-in Hybrid Vehicles. An intriguing aspect of EVs and other AFVs is that while their cost advantage increases with the annual mileage driven, the annual mileage remains limited as long as their driving range is short.

Although providing an impression of the magnitude of the welfare measures of interest, the computation of these statistics does not take under consideration the strong correlation among the WTP estimates induced by drawing multiple estimates from the same primary study or from studies analysing the same stated preference dataset (Stanley and Jarrell, 1989; Florax, 2002). Furthermore, it does not account for the heterogeneity underlying our study sample. It treats WTP estimates stemming from small, convenience samples as equivalent to estimates arising from much larger samples.

Figure 2: Funnel plot for WTP for driving range.



Note: The solid line illustrates the mean WTP, whereas the dashed one the median WTP.

The funnel plot displayed in Figure 2 serves two purposes. The first is to provide insights into the possible existence of publication bias in our study sample. The second is to illustrate the importance of considering possible differences between the results stemming from small sample and larger sample studies. The plot of the square root of the sample size[12] used in the primary study to the WTP for driving range reveals that smaller sample studies result in somewhat higher WTP estimates than studies employing relatively large samples, inflating, thus, the mean WTP. The mean WTP of the top 5% of sample sizes is only around 29 US$, while the one for the top 15% hardly exceeds 23 US$. The fact that the plot is skewed to the right is an indication of the existence of publication bias in our study. The examination of the distribution of the estimates of the two CV measures and the relevant funnel plots lead to similar results. Nevertheless, the insights provided by funnel plots are confounding when heterogeneity is present in the study sample (Stanley, 2005), as we will show later that it is the case here, so they cannot serve as evidence for the existence of publication bias per se.

The discussion provided above calls for the adoption of a weighting approach, in order to mitigate the effects of correlation, heterogeneity and possible publication bias in the meta-sample. To this end, Table 2 compares unweighted and weighted summary statistics of WTP and of the two CV measures. The results of two weighting schemes are presented. In the first scheme, estimates are weighted by the inverse of the number of estimates drawn per dataset, in order to take account of the applied multiple sampling per SP study. To this end, welfare measure estimates are clustered in 20 datasets.[13] The summary statistics produced under this weighting scheme are slightly lower than the ones derived in the case of no weighting, while the wider confidence intervals observed thereof should be attributed to the extremely high or low welfare measure estimates derived from the studies allowing the extraction of solely one estimate per welfare measure.

The second scheme employs a weighting approach aiming to mitigate the influence of both the correlation[14] and the heterogeneity among primary effects sizes present in our sample.

[12] Sample size is defined as the number of observations used for the estimation of the relevant choice or ranking model and it is equal to the number of choices made or the scenarios ranked by the total number of respondents.

[13] Bunch et al. (1993) and Tompkins et al. (1998) are grouped in the same cluster, due to the use of a choice model pooling the SP data of the two experiments in the latter study. This clustering approach is adopted throughout our analysis.

[14] Although this approach seems to be taking into account the correlation among WTP estimates introduced by multiple sampling from the same dataset, Florax (2002) notes that it only mitigates the influence of heteroskedasticity, while leaving the impact of correlation unaffected.

The applied weights are equal to the product of the sample size employed in the primary study and the inverse of the number of estimates drawn per dataset:[15]

$$w_{ij} = n_i / d_j , \qquad (5)$$

where w_{ij} is the weight applied to welfare measure's estimate i from dataset j, n_i denotes the size of the primary sample used for the estimation of i, and d_j is the number of welfare measure estimates drawn from dataset j. As expected from the insights gained from the funnel plot (Figure 2), the mean and median of the welfare measure estimates calculated on the basis of the second weighting scheme are considerably lower than the unweighted ones. The weighted means of all three measures lie below the unweighted median estimates, confirming that the unweighted approach leads to inflated estimates of the mean values. Still, however, the mean weighted WTP lies within the 95% confidence interval of its unweighted counterpart.[16]

Table 2: Summary statistics of WTP and CV estimates under different weighting schemes.

Treatment of welfare measure estimates	Willingness to Pay			Compensating Variation 100-150 miles			Compensating Variation 100-350 miles		
	Mean	Median	95% c.i.	Mean	Median	95% c.i.	Mean	Median	95% c.i.
Unweighted	63.6	53.3	46.3 - 80.8	3,489	3,053	2,459 - 4,519	16,160	13,185	11,584 - 20,736
Weighted by the inverse of the number of observations per dataset	60.2	45.1	38.6 - 81.8	3,017	2,398	2,150 - 3,884	13,552	11,171	9,583 - 17,520
Weighted by the inverse of the number of observations per dataset and the sample size used in the primary study	47.0	30.8	26.5 - 67.5	2,866	2,773	2,009 - 3,723	12,370	10,186	8,348 - 16,393
Number of welfare measure estimates	132			128			128		

Note: 95% confidence intervals are calculated on the basis of heteroskedasticity-robust standard errors, clustered by dataset. Welfare measure estimates are in PPP-adjusted 2005 US$.

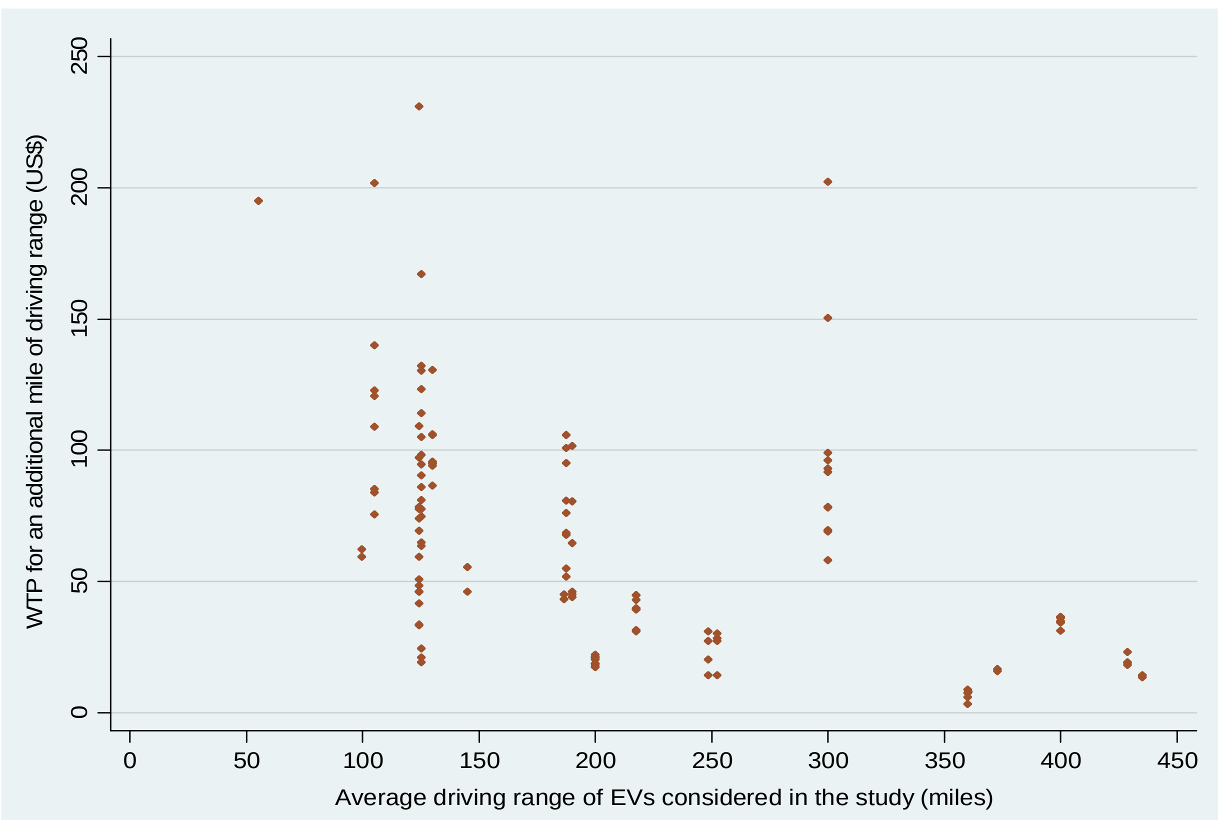
As mentioned in Section 2, the studies considered in our meta-analysis do not reach agreement on the way in which driving range enters consumers' utility function. Intuitively, the WTP for driving range should be a decreasing function of the car's range. It is not reasonable to expect that a marginal increase in the vehicle range from a reference level of 100 miles and from

[15] Meta-analysis literature suggests as ideal weights for this purpose the inverses of the variance with which effect sizes were estimated. However, these were readily available or could be computed on the basis of available information for very few WTP estimates. Following common practice in the field (e.g., de Blaeij et al., 2003; Brons et al., 2008), we use instead the sample sizes employed to estimate the effect sizes in the primary studies. A similar weighting approach in a meta-regression context is adopted by Van Houtven et al. (2007).

[16] Heteroskedasticity-robust, clustered by dataset, estimators have been used for the calculation of the confidence intervals, in order to take under consideration the heteroskedasticity underlying our sample.

one of 500 miles has the same value for the consumer. It is striking, however, that the most commonly used specification presumes that the marginal utility of range is constant across range levels. Exceptions are Brownstone et al. (2000) and Bunch et al. (1993), who consider also a quadratic term for driving range in consumers' utility function, Calfee (1985), Jensen (2010), Kavalec (1999), Mabit (2010) and Mabit and Fosgerau (2011) who employ the logarithmic transformation of driving range in the utility function they specify and Beggs et al. (1981), Ewing and Sarigöllü (1998, 2000) and Hidrue et al. (2011) who use, inter alia, a dummy variable specification for range. Although Molin et al. (2007) and Molin et al. (submitted) test the performance of a utility function using an effects-coded specification for range, they conclude that they fail to reject the hypothesis of a utility function linear in driving range and purchase price.

Figure 3: WTP for driving range against the average EV range considered in the study.



A graphical illustration of the WTP against the mean level of driving range of EVs considered in the study (Figure 3) does not provide support for the adoption of a utility function linear in driving range. On the contrary, it shows that WTP is a decreasing function of the average vehicle range level considered in the primary study, possibly linear in the inverse of the average driving range level. This finding provides some encouragement for the employment of a utility specification linear in the logarithmic transformation of range, while it does not oppose the adoption of a dummy codification scheme. It comes, however, in strong contradiction with the commonly used linear-in-range utility specification.

Table 3 provides descriptive information about the heterogeneity among primary WTP and CV estimates across different groupings of studies. The groupings employed are based on the location in which the study was carried out, the publication status of the study, the stated preference method used to elicit consumers' preferences, the labelling of the alternative options presented to the respondents, the way in which driving range was assumed to enter consumers' utility functions, the number of individuals whose preferences were examined in the study and the time period in which the survey was undertaken.[17] The table presents the differences in means identified among different groups and the results of standard t-tests examining the statistical significance of these differences. Table 3 uses a bivariate perspective; a multivariate analysis where interdependences between the explanatory variables are taken into account is given in Section 5.

Driving range has much higher importance for Americans than Europeans, Australians or Canadians. The average WTP in the USA is almost 80% higher than in Europe, and even fourfold the one in Australia and six times the one in Canada. The results for Canada and Australia should be interpreted with caution as they are based only on two studies and one study respectively. The high importance of driving range in the USA can be explained by factors concerning both the actual range needs of Americans, as well as by their strong association of feelings of freedom and independence with travelling by car. Furthermore, the annual distance travelled by a car in the United States is, on average, higher than the one of a car in Canada, Australia or any of the European countries included in our dataset, with the possible exception of Denmark (IRF, 2003).

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[17] We examined several other groupings of WTP estimates on the basis of characteristics of the design of the SP study (e.g. inclusion of AFV-relevant attributes (refuel time, fuel availability), consideration of specific AFV technologies, the customisation of cost-related attributes on reference values provided by the respondents), as well as on the basis of the models employed to analyse the SP data. These groupings, however, did not reveal any statistically significant differences in the means of the welfare measures of interest.

Table 3: Differences in means of WTP and CV among different groups of studies, in PPP-adjusted 2005US$.

Group	Willingness to Pay		Compensating Variation	100 to 150 miles	100 to 350 miles
	Observations	Mean	Observations	Mean	Mean
Region					
USA	52	93.6***	52	5,149***	23,113***
Canada	16	16.3***	16	815***	4,077***
Australia	4	25.0***	4	1,250***	6,250***
Europe	60	*52.7*	56	*2,872*	*13,863*
Publication type					
Conference paper / Working paper	47	69.5	47	3,572	17,597
Ph.D / Masters' dissertation	15	35.6***	11	2,047***	9,385***
Peer-reviewed journal / book	70	*65.6*	70	*3,660*	*16,259*
Stated preference method					
Contingent Ranking	16	77.3	16	3,866	19,330
Discrete Choice Experiment	116	*61.7*	112	*3,435*	*15,707*
Labelling of alternatives					
Labelled	67	52.1***	63	2,729***	13,069***
Unlabelled	65	*75.4*	65	*4,226*	*19,155*
Treatment of driving range in the utility function					
Logarithmic	11	44.7	7	3,714	11,475**
Quadratic	8	93.4**	8	7,863***	24,944
Effects-coded/dummy-coded	20	38.5***	20	1,924***	9,618***
Linear	93	*68.7*	93	*3,433*	*17,164*
Number of survey respondents					
Respondents ≤ 300	51	53.5**	47	2,699***	13,117**
Respondents > 300	81	*69.9*	81	*3,948*	*17,926*
Year of survey					
1978 - 1989	7	107.8**	7	4,619**	21,909**
1990 - 1999	64	66.9	64	3,807*	17,030
2000 - 2011	61	*55.1*	57	*2,993*	*14,476*

Note: t-tests explore statistical significance in differences between a group's mean value and the mean of the reference group (last category of each grouping: relevant mean values reported in italics). t-tests do not impose the restrictive assumption that the variances between the groups are equal. *** and ** indicate that the difference is statistically significant at the 5% or 10% significance level respectively.

Examining differences in the mean WTP and CV for driving range among different types of publications reveals a small and statistically insignificant difference between studies appearing in peer-reviewed journals and books and ones available as conference papers or technical reports. On the contrary, master's and PhD students' dissertations appear to be leading to significantly lower WTP values, possibly reflecting the relative inexperience of the researchers undertaking these studies. Discrete choice modelling is the prevalent SP method used for the elicitation of consumers preferences in the context of AFVs. An attempt to check whether there are differences in means between studies employing discrete choice experiments and ones using contingent rankings reveals that the latter method results in higher WTP values. However, the difference in the mean WTP derived with the two methods is statistically insignificant.

In the context of stated preference studies of AFVs, differences in the labelling of the alternatives draw on the distinction between experiments where type-of-fuel labels are attached to the alternative vehicle options presented to the respondents (labelled experiments) and ones where vehicle options are labelled with generic labels (e.g., Car 1, Car 2, and so on), leaving the reveal of the fuel type to one of the attributes (unlabelled experiments). The decision on whether a stated preference study will be based on a labelled or an unlabelled experiment is known to have a considerable impact on the design of the experiment (Hensher et al., 2005 (pp. 112-114)). We further find that this decision has important implications for the WTP values derived by a study. Studies using unlabelled experiments result in significantly higher valuations of the WTP for driving range. This difference cannot be attributed to labelled experiments' potential to provide estimates of alternative-specific part-worth utilities, as one might expect. For driving range, such coefficients are only reported by Ramjerdi et al., 1996, and Hensher and Greene, 2001, while for the car's purchase price, they are totally absent from our study sample.[18]

The t-tests concerning differences in means among different utility specifications show that welfare change estimates are strongly influenced by the assumptions imposed on consumers' utility functions. Indeed, the employment of a dummy codification for range results in significantly lower WTP and CV estimates than the ones derived in the case of a linear specification. On the other hand, utility functions being quadratic in driving range lead to higher welfare change estimates than utility functions linear in range. Logarithmic specifications do not seem to lead in welfare estimates significantly different from linear ones, with the exception of the CV from 100 to 350 miles. This last finding, however, is not robust in the multivariate analysis presented in Section 5. It is, thus, important for future SP studies in the field to consider carefully the validity of the assumption that individuals' utility is linear in vehicle's range.

Testing for differences among studies using relatively small, usually convenience, samples to elicit preferences for driving range and ones using larger samples, we find that SP studies drawing on samples with less than 300 respondents lead to lower estimates of consumers'

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[18] The exclusion of the two studies reporting alternative-specific driving range coefficients from the analysis does not mitigate the difference between the two groups of studies, it rather reinforces it.

WTP and CV for driving range.[19] It is, thus, important that researchers place particular emphasis on the size of the sample they use to extract conclusions on consumers welfare measures and its representativeness of the population of interest. Small, non-random samples of respondents can lead to a systematic shift of the WTP and result in misleading conclusions about how consumers value specific attributes.

Last, three main waves of SP studies of AFVs are distinguished, based on the differences in the policy objectives underlying the examination of consumers' preferences for AFVs, elaborated in Section 2. Studies triggered by the 1970s energy crises lead to significantly higher valuations of driving range than studies undertaken in 1990s and 2000s. Two facts should mainly account for this result. First, all studies carried out before 1990 and included in our study sample were undertaken in the USA, where range valuations are higher. Second, the levels of the driving range attribute considered by these early studies are relatively low, inducing, thus, higher valuations of range. In addition, in one of these early studies low range levels are explicitly related to other unappealing characteristics of BEVs, such as long refuel times and high battery replacement costs (Beggs et al., 1981).

5. Meta-regression analysis

Although the bivariate analysis presented above is useful for the identification of possible factors affecting the magnitude of estimates of WTP and CV for driving range, a multivariate approach is required to disentangle the impact of each of these sources of variation on the effect size of interest. To this end, we employ a linear meta-regression model using the logarithmic transformation of the WTP estimates (in hundreds of 2005 US$) as a dependent variable. Two main reasons motivate the use of the logarithmic transformation: our study sample contains only positive WTP estimates and the transformed figures are known to be less sensitive to the problem of heteroskedasticity (Konstantopoulos and Hedges, 2009). The distribution of ln(WTP) is depicted in Figure 4.

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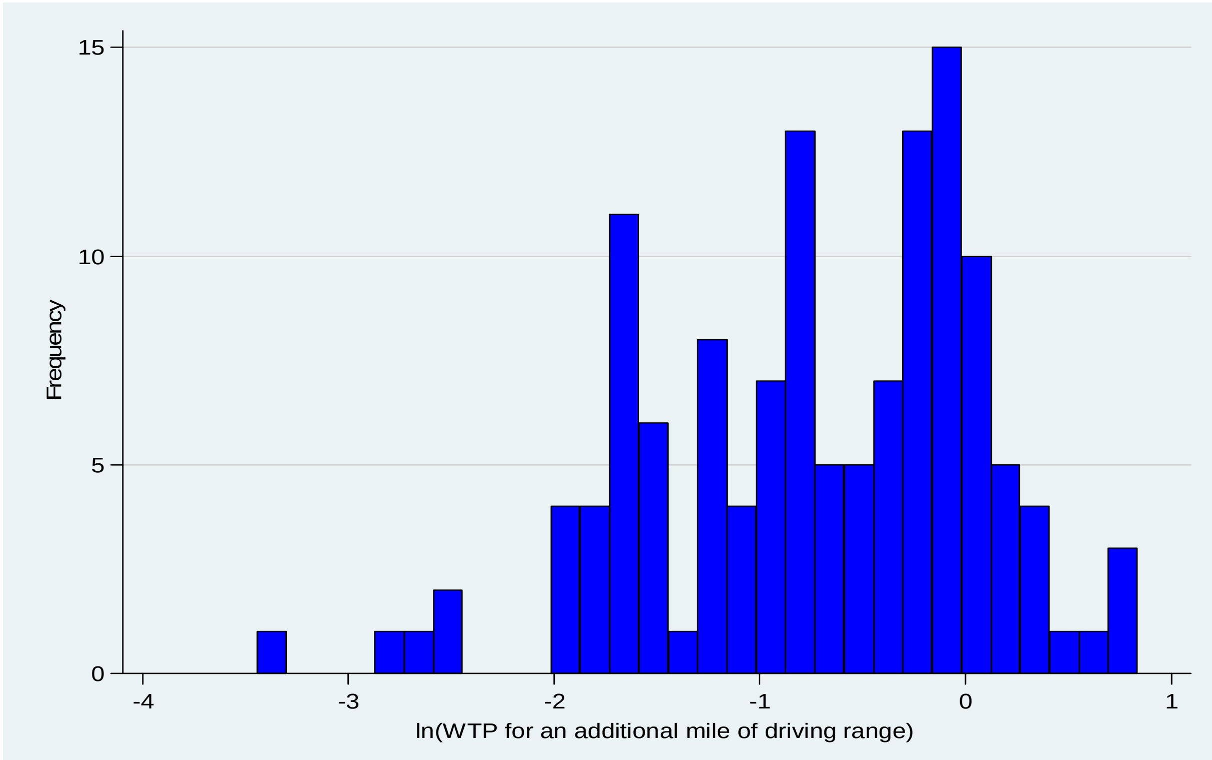
[19] We also tested for differences in mean WTP estimates among more elaborate groupings of the number of respondents employed in the primary study (e.g., between 300 and 500, 500 and 1000, 1000 and 2000 and 2000 and more respondents). These groupings, however, resulted in minor, statistically insignificant, differences in WTP estimates. Therefore, only differences between primary studies drawing on the responses of less than 300 individuals and ones drawing on more than 300 are discussed here.

Figure 4: Distribution of ln(WTP) for an additional mile of driving range.



Note: WTP estimates are in hundreds of PPP-adjusted 2005 US$.

The meta-regression model we employ to explain the variation in the logarithm of WTP estimates *i*, can be described as follows:[20]

$$\ln(WTP_i) = \alpha + \beta_R \ln(Range_i) + \beta_P P_i + \beta_L L_i + \beta_T T_i + \beta_D D_i + \varepsilon_i, \qquad (6)$$

where *ln(Range)* is the natural logarithm of the average level of driving range of EVs or AFVs employed in the primary study,[21] *P* is a dummy variable reflecting whether the primary study is published in a peer-reviewed journal or book, *L* denotes a vector of dummy variables indicating the study site, *T* is a vector of dummy variables revealing the time period in which the survey was carried out, *D* denotes a vector of variables measuring selected aspects of the research design of the primary studies, and ε is an error term with mean zero and variance σ_i^2. α and

[20] The meta-regression models for the CVs from 100 to 150 miles and from 100 to 350 miles are similar; the only differences between them and the WTP meta-regression model are the dependent variable used and the number of estimates utilised. In all cases, we use the logarithmic transformation of the welfare measure of interest.

[21] In case that both EV and AFV options are included in the study, we consider the average driving range level of EVs. The average driving range is measured in hundreds of miles.

vector β are parameters which shall be estimated by ordinary least squares and weighted least squares.

Table 4: Definitions and means of the explanatory variables used in the meta-regression analysis.

Variable	Description	Mean
ln(Range)	Natural logarithm of the average driving range for EVs or AFVs used in the study (measured in hundreds of miles).	0.62
USA	=1 if the study is conducted in the USA and 0 otherwise	0.39
Canada	=1 if the study is conducted in Canada and 0 otherwise	0.12
Other_country	=1 if the study is conducted in Europe or Australia and 0 otherwise *(omitted category)*	0.48
Before_1990s	=1 if the study is conducted before 1990 and 0 otherwise	0.05
1990_1999	=1 if the study is conducted between 1990 and 1999, and 0 otherwise	0.48
2000_2011	=1 if the study is conducted from 2000 onwards and 0 otherwise *(omitted category)*	0.46
Published	=1 if the study is published in a peer-reviewed journal or book and 0 otherwise	0.53
Ranking	=1 if the Contingent Ranking method is used and 0 otherwise	0.12
Labelled	=1 if the alternatives are labelled in the SP exercise and 0 otherwise	0.51
Quadratic	=1 if the utility function is assumed to be quadratic in driving range and 0 otherwise	0.06
Logarithmic	=1 if the logarithmic transformation of vehicle range is used in the assumed utility function and 0 otherwise	0.08
Effects_coded	=1 if a series of dummy variables are used to capture the effect of different driving range levels in consumers' utility and 0 otherwise	0.15
Linear	=1 if the utility function is assumed to be linear in driving range and 0 otherwise *(omitted category)*	0.70
Hybrid	=1 if a hybrid petrol-electric vehicle is among the alternatives considered in the study and 0 otherwise	0.20
Attributes	The maximum number of attributes used per alternative in each choice scenario, (including the label of the alternative, if applicable)	8.79
Small_sample	=1 if the study is based on the responses of less than 300 individuals and 0 otherwise	0.39

Table 4 presents the definitions of the moderator variables used in the meta-regression models, alongside with their mean values. The majority of the variables employed have been already discussed in the context of the bivariate analysis. The number of attributes used per alternative presented to the respondents has been found to have a negative impact on the WTP and CV for range and it was, thus, included in the considered set of moderator variables.

Furthermore, the inclusion of a hybrid petrol-electric vehicle[22] in the pool of AFVs from which respondents are invited to choose their preferred option is also associated with lower WTP and CV values.

Table 5 presents the estimation results of two meta-regression models for each of the effect sizes of interest. The first model presented for each welfare measure is estimated with ordinary least squares (OLS), while the second one with weighted least squares (WLS). The weights used are as defined in Equation (5). The standard errors reported are heteroskedasticity-robust, clustered by dataset. All models explain a relatively high share of the variation in the effect size, as indicated from their adjusted R-squared values.

It has often been discussed in the literature that OLS should be used with caution in the context of meta-regression analysis, due to the violation in the assumptions underlying the validity of OLS, caused by the dependence of observations drawn by the same study and the possible publication bias. WLS has several advantages over OLS in the context of a meta-analysis. It can discount the effect of more poorly designed small-sample studies, mitigate the correlation existing among WTP estimates derived from the same study, lessen the influence of publication bias, while also take account of heteroskedasticity.

In the current context, the two methods do not result in substantially different outcomes, with the exception of the significance of the dummies indicating the time periods in which the SP survey took place and the one reflecting whether the discrete choice or the contingent ranking method was employed in the primary study. For both dummies, the WLS estimation leads to the rejection of the hypothesis that these coefficients are significantly different from zero.

Focussing on the WLS estimates, the average level of range used for EVs or AFVs in the primary study plays an important role in the magnitude of all effect sizes studied. This finding urges for careful consideration and pre-testing of the levels considered in a relevant SP study, as the estimated WTP and CV measures are fairly sensitive to the levels considered. Furthermore, this result provides additional evidence for the erroneousness of the usual assumption that consumers' WTP for marginal changes in the driving range is independent from the range level under consideration. It suggests that the minority of studies going in line with intuition and

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[22] The variable's definition encompasses both full hybrids and plug-in hybrids.

adopting a non-linear in driving range utility specification are likely to be better approximations of the way in which driving range actually enters consumers' utility function.

Table 5: Estimation results for the logarithmic transformations of WTP and CV.

Variable	Willingness to Pay				Compensating Variation 100-150 miles				Compensating Variation 100-350 miles			
	OLS		WLS		OLS		WLS		OLS		WLS	
ln(Range)	*-0.863****	(0.076)	*-0.787****	(0.059)	*-0.619****	(0.123)	*-0.338***	(0.119)	*-0.677****	(0.114)	*-0.515****	(0.125)
USA	*0.654****	(0.144)	*0.637****	(0.052)	*0.516**	(0.246)	*0.539***	(0.212)	*0.510***	(0.206)	*0.416****	(0.143)
Canada	*-0.467****	(0.136)	*-0.513****	(0.081)	*-0.565***	(0.202)	*-0.469***	(0.173)	*-0.517****	(0.169)	*-0.455****	(0.153)
Before_1990s	*-0.684**	(0.333)	*-0.212*	(0.155)	*-0.581*	(0.390)	*-0.211*	(0.422)	*-0.843***	(0.320)	*-0.586*	(0.398)
1990_1999	*0.028*	(0.087)	*0.064*	(0.064)	*-0.072*	(0.126)	*-0.154*	(0.216)	*-0.196**	(0.105)	*-0.298*	(0.178)
Published	*0.173***	(0.063)	*0.055*	(0.038)	*0.155*	(0.126)	*0.027*	(0.069)	*0.180*	(0.108)	*0.103***	(0.047)
Ranking	*0.293*	(0.240)	*-0.060*	(0.106)	*0.312*	(0.255)	*0.034*	(0.210)	*0.446***	(0.199)	*0.191*	(0.176)
Labelled	*-0.638****	(0.059)	*-0.555****	(0.050)	*-0.671****	(0.0816)	*-0.725****	(0.166)	*-0.612****	(0.077)	*-0.735****	(0.147)
Quadratic	*0.111*	(0.101)	*0.027*	(0.150)	*0.539****	(0.116)	*0.409***	(0.181)	*0.181***	(0.072)	*0.067*	(0.082)
Logarithmic	*0.414***	(0.173)	*0.397****	(0.129)	*0.873****	(0.299)	*1.101****	(0.329)	*0.683***	(0.302)	*0.806***	(0.289)
Effects_coded	*-0.255****	(0.066)	*-0.298****	(0.084)	*-0.273****	(0.093)	*-0.281**	(0.160)	*-0.306****	(0.090)	*-0.302***	(0.131)
Hybrid	*-0.749****	(0.096)	*-0.718****	(0.087)	*-0.726****	(0.161)	*-0.725****	(0.170)	*-0.849****	(0.135)	*-0.813****	(0.140)
Attributes	*-0.052****	(0.008)	*-0.056****	(0.004)	*-0.046***	(0.018)	*-0.047***	(0.019)	*-0.035***	(0.017)	*-0.029*	(0.019)
Small_sample	*-0.358***	(0.126)	*-0.454****	(0.073)	*-0.611****	(0.183)	*-0.857****	(0.204)	*-0.578****	(0.148)	*-0.804****	(0.176)
Constant	*0.570****	(0.078)	*0.635****	(0.109)	*2.217****	(0.143)	*2.199****	(0.270)	*1.484****	(0.128)	*1.561****	(0.208)
Observations	132		132		128		128		128		128	
R^2	0.821		0.922		0.790		0.874		0.782		0.870	
R^2*-adjusted*	0.799		0.912		0.764		0.858		0.755		0.854	
RMSE	0.359		0.247		0.389		0.299		0.380		0.285	

Note: Robust standard errors, clustered by dataset, in parentheses. ***,** and * indicate that the parameter is statistically significant at the 1%, 5% or 10% significance level respectively. The weights used for the WLS are the products of the inverse of the number of welfare measure estimates drawn per dataset and of the sample size employed in the primary studies, as described in Equation 5.

The differences found in the valuations of driving range among Americans, Canadians and Europeans in the bivariate analysis presented above hold in the multivariate analysis as well. Unfortunately, the clustering of standard errors according to the dataset on which each study is drawing does not allow the identification of any differences among European and Australian respondents, since the Australian WTP estimates are derived from a single dataset.

The meta-regression results with respect to the time period in which the SP survey took place provide little evidence of a change in consumers' preferences for driving range during the examined period.[23] Differences in welfare measures between time periods, statistically significant only in the OLS model, are mainly manifested in the CV from 100 to 350 miles. As decades pass, consumers report higher implicit values for this 250-mile increase. This might be explained by the simultaneous increase in the driving range of the average petrol-fuelled car in the same period, which has led to an increase in the driving range reference values that consumers use. Indicatively, Beggs et al. (1981) use in their survey an average range of 200 miles for petrol-fuelled vehicles, while Hensher and Greene (2001) assume one of 360 miles.

The estimates obtained for the impact of publication on the effect size of interest provides another indication of the existence of publication bias. Although the effect of publication is statistically significant only in two models, the results seem to suggest that studies published in peer-reviewed journals and books tend to report higher welfare measure estimates than the ones presented as conference papers, technical reports or dissertations.[24]

The difference in WTP estimates between SP studies using labelled and ones using unlabelled experiments, identified through the bivariate analysis, is also robust in the meta-regression analysis. Ceteris paribus, unlabelled choice experiments are associated with higher effect-size estimates. This divergence cannot be explained by the measurement of the impact of alternative-specific range or price attributes on vehicle choice, in the context of labelled experiments, as the common practice is the measurement of generic attributes. It can neither be attributed to the inclusion of alternative specific constants in the SP analysis models, capturing the impact of vehicle's fuel type on consumers' preferences, in the context of labelled experiments. Fuel type variables are actually included in the majority of models analysing SP data coming from unlabelled experiments. Adding in the meta-regression models a variable distinguishing between primary models considering a fuel type variable and ones which do not

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[23] We also employed a single-variable codification to test whether the year in which the survey was carried out affects the WTP for range. The relevant variable was defined as the difference between the year in which the survey was carried out and the year in which the first survey in our sample was implemented, i.e. 1978. This alternative codification, however, did not result in the relevant variable being statistically significant, while the fit of the model was also not improved.

[24] Motivated by the insights provided by the bivariate analysis, we also employed a model distinguishing between students' dissertations and other publications. This specification, however, neither improved the fit of the model nor did it result in a statistically significant coefficient for the publication variable.

does not provide any significant improvement to the fit of the meta-regression models or substantially change the size or significance of the labelling variable.

Hensher et al. (2005, p.113), suggest that the assumption of the Independence of Irrelevant Alternatives (IIA) is less likely to hold in labelled experiments, as survey respondents may perceptually relate the label to other attributes presented to them. A straightforward example, in this context, is the perception that electric cars are limited-range vehicles (Bunch et al., 1993; Chéron and Zins, 1997). Thus, the analysis of SP data stemming from labelled experiments with models assuming the validity of the IIA assumption, such as the multinomial logit or the exploded logit, is likely to lead to erroneous results. In our study sample, 70% of the WTP estimates derived from labelled experiments are bound to this pitfall.[25] However, our empirical results do not suggest any statistically significant difference between WTP values estimated by models requiring the adoption of the IIA assumption and by ones which do not, neither when the scope is limited to labelled experiments nor when we consider all the estimates in our study sample.[26]

The results of the meta-regression models once again suggest that the utility specification adopted with respect to the driving range variable appears to significantly affect the estimated WTP. We find that specifications employing the logarithmic transformation of range lead, ceteris paribus, to significantly higher valuations of vehicle range than the ones adopting a linear in range specification, even after controlling for the average range levels used in the study. Taking into account the insights gained in Figure 3, this might be an indication that the majority of studies tend to underestimate the WTP for driving range at relatively low range levels. On the contrary, studies making use of an effects-coded approach to capture the non-linearity of consumers' utility in driving range result in lower WTP values. Last, studies employing a quadratic specification appear to have a statistically significant positive impact only on the CV from 100 to 150 miles.

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[25] Notably, the relevant share for unlabelled experiments is only 46%.

[26] Furthermore, the estimates stemming from models not requiring the adoption of the IIA assumption deviate more strongly from the mean WTP of unlabelled experiments than the ones adopting it. The inclusion of an additional variable capturing the interaction effect between labelled experiments and the use of models adopting IIA in the meta-regression model was not found to lead to any improvement in the fit of the model; the coefficient of the variable was also statistically insignificant.

The consideration of a hybrid petrol-electric (HEV) alternative in the SP study has a relatively strong negative impact on the WTP and CV for range. Two possible explanations may account for this finding. First, as hybrids constitute the category with the highest driving range among the available vehicle categories, studies considering HEV alternatives are also much more likely to consider higher levels of average driving range.[27] In this case, the aforementioned finding is just a reflection of the highest average driving range values considered by these studies. It is not possible, however, to test this assumption, due to insufficient information provided in the primary studies with respect to the driving ranges considered for conventional fuel technologies. Second, survey respondents may be perceptually attaching a "long-range vehicle" quality to HEVs, which induces them to pay less attention to this attribute while choosing or ranking their preferred alternatives from sets of options including HEV alternatives.

Consumers' valuations for specific attributes are not independent from the total number of attributes they are presented with. It is known that, other things being equal, an increase in the number of attributes used per alternative leads to an increase in the variance of the random component of consumers' utility function (De Shazo and Fermo, 2002; Caussade et al., 2005). In the current context, we further find that as the number of attributes considered in the SP exercise increases, the WTP and CV for driving range diminish. This is in agreement with Hensher (2006), who shows that the value of free-flow and slowed-down travel time savings decreases as the number of attributes is increased. Other things being equal, a larger number of attributes creates more cognitive burden to the respondents.[28] Respondents may react on this by anchoring to specific attributes, giving an erroneous impression of the trade-offs between attributes they actually make and therefore of their WTP and CV for these attributes. Hensher (2006) finds, however, that when the effect of the number of attributes is not examined in isolation from other design dimensions (e.g., number of choice sets, attribute levels, etc.), but in combination with them, it is not statistically significant. Unfortunately, the heterogeneity of our study sample and

[27] The average driving range values we are taking under consideration in the meta-regression model are the ones used for EVs or other AFVs. The average values for the universe of the fuel-type options considered in the study are usually much higher than the one considered for EVs or AFVs.

[28] Sælensminde (2001) notes, however, that an increase in the complexity induced by the inclusion of an additional attribute should be evaluated against the latter's potential contribution to the realism of the choice setting addressed by respondents and the gain generated by evaluating a larger number of attributes.

the unavailability of some relevant pieces of information in the primary studies do not allow us to test whether this holds in our analysis as well.

Last, we find that SP surveys employing non-random samples of less than 300 respondents systematically lead to lower valuations of WTP and CV for driving range. Even though it is possible that it is not sample size per se which induces this difference, but other unobserved study characteristics correlated with relatively small sample sizes, we would recommend that future studies in the field consider the use of larger samples of survey respondents, as representative as possible of the population of interest.

In addition to the analysis delineated above, we also looked into other approaches capable of taking into account the possible correlation among WTP estimates *i*, stemming from the same dataset *j*. A meta-regression model formed thereof would be as follows:

$$\ln(WTP_{ij}) = \alpha + \beta_R \ln(Range_{ij}) + \beta_P P_{ij} + \beta_L L_{ij} + \beta_T T_{ij} + \beta_D D_{ij} + u_j + \varepsilon_{ij}, \qquad (7)$$

where all the terms are defined as in Equations (5) and (6) and u is an error term with zero mean and variance σ'^2.

A panel data procedure commonly used in this context is the random-effects generalised least squares (GLS) method (e.g., Van Houtven et al., 2007).[29] The application of the method to a model with the explanatory variables presented in Table 4 resulted in results almost identical to the ones derived by the application of OLS and WLS. Other specifications we attempted to estimate led to results very similar to the ones presented in Table 4. The applied Breusch-Pagan LM tests largely failed to provide support for the use of the random-effects GLS method. Thus, we do not present these results here.

6. Conclusions

Following an unsuccessful attempt for their large-scale introduction during the 1990s, electric cars have recently reappeared in the production line of car manufacturing plants and the agendas

[29] It should be noted that our dataset does not form a panel, but rather a sample of pooled data (Florax, 2002). We also attempted to employ a fixed-effects panel model. In agreement with existing meta-analysis literature (e.g., Van Houtven et al., 2007; Nelson and Kennedy, 2009), however, we found this option to be particularly problematic when the moderator variables do not vary substantially within studies, the study sample is relatively small and not all studies allow the derivation of multiple effect size estimates.

of policy makers as an environmentally sustainable alternative to petrol-fuelled vehicles. However, literature investigating consumers' preferences for alternative fuel vehicles suggests that technological breakthroughs permitting a substantially higher driving range than the one currently achievable by electric cars is of pivotal importance for their successful market penetration.

In this paper we perform a meta-analysis of 31 discrete choice and contingent ranking studies investigating consumers' preferences for alternative fuel vehicles in order to provide insights into the trade off between driving range and car purchase costs. Based on the analysis of 132 WTP estimates, we find that consumers are willing to pay an amount between 47 and 64 US$, on average, for a one-mile increase in the vehicle's driving range. In line with intuition, but in contrast with common practice, we find evidence that consumers' marginal willingness to pay (WTP) for additional range can be better described as a decreasing function of vehicle range. The analysis of 128 compensating variation (CV) estimates derived from the same studies reveals that a driving range of 100 miles, equal to the one that the majority of currently available BEVs exhibit, is strongly penalised by vehicle purchasers. Our meta-regression analysis reveals that the wide divergence in the WTP and CV estimates among the examined stated preference studies can be mainly attributed to differences in the study design, the location at which the study was conducted and the size of the sample it was addressed to.

Our review suggests a very limited potential market for vehicles with a driving range at the level of most currently commercialized electric vehicles, unless they are offered at prices substantially lower than their conventional counterparts. Hence, it supports the continuation of R&D efforts directed towards the reduction of EV battery costs and the development of advanced battery technologies permitting higher driving ranges. We further recommend that future studies examining consumers' preferences for alternative fuel vehicles reconsider the validity of the usual assumption that decision-makers treat driving range, refuel time and the availability of fuelling facilities as independent when considering a car purchase.

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