Costs, emissions, and preferences for electric vehicles: New evidence from a stated choice experiment with randomized interventions

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Preliminary version

Abstract

The higher purchase prices of electric vehicles and the high CO_2 emissions generated in the production process are major barriers to the acceptance of electric vehicles among consumers. However, electric vehicles tend to be more cost-effective and energy-efficient over time due to lower fuel costs and lower CO_2 emissions in vehicle use. This paper examines whether greater awareness of potential lifetime financial savings and emissions reductions can increase the preferences for electric vehicles. Our empirical analysis is based on data from a stated choice experiment with more than 2,200 citizens in Germany that includes two randomized information interventions addressing the total costs and CO_2 emissions of vehicles over time and emphasizing lower operational costs and emissions. Our econometric analysis with mixed logit models shows a significantly positive effect of the emissions information treatment on the preferences for extended-range and plug-in hybrid electric vehicles (and consequently on a reduction in CO_2 emissions in the passenger transport sector) for frequent drivers in the past and in the future. With respect to the preferences for battery electric vehicles, this information treatment only has a significantly positive effect for individuals with a very high planned mileage. Therefore, we conclude that only corresponding targeted information campaigns for frequent drivers can be a successful component in increasing the purchase of electric vehicles.

Keywords: Vehicle purchase decisions, total costs and emissions, electric vehicles, stated choice experiment, randomized interventions, mixed logit models

JEL: R41, Q54

1. Introduction

As the effects of climate change become more and more devastating, it is critical to take action to reduce the greenhouse gas emissions produced by society. The transportation sector has very strong negative environmental impacts. For example, in the European Union (EU) 25% of all greenhouse gas emissions are caused by the transportation sector (e.g. European Environment Agency, 2024). In Germany, which is the focus of our study, transportation accounted for more than 19% of greenhouse gas emissions in 2021 (e.g. Umweltbundesamt, 2023a). According to the German Federal Climate Protection Act ("Bundes-Klimaschutzgesetz") the greenhouse gas emissions from transportation must almost halve (-48%) by 2030 compared to 2019 emissions. Further Germany must become greenhouse gas neutral by 2045, which presumably means reducing greenhouse gas emissions to zero in the transportation sector (e.g. Umweltbundesamt, 2023b). One main measure for achieving this target is the transition to electric vehicles (EV), particularly (pure) battery electric vehicles (BEV). Consequently, one target of the current government in Germany is to reach a stock of 15 million EV by 2030 and thus become one of the leading markets in this field. But even with an increasing number of newly registered EV in Germany, with a stock of 1.2 million EV at the beginning of 2022 this target seems very ambitious. For such a rapid transition to EV, a broad acceptance of EV among consumers is needed. Therefore, it is crucial to research consumer preferences regarding electric vehicles and understand the main barriers to adoption.

Our study contributes to the existing literature on preferences for electric vehicles compared to conventional vehicles with internal combustion engines (ICE) (e.g. Egbue and Long, 2012, Ziegler, 2012, Hackbarth and Madlener, 2013, 2016, Rezvani et al., 2015, Kanberger and Ziegler, 2024). Previous studies show that, in Germany, there is a strong aversion to electric vehicles, particularly battery electric vehicles (e.g. Ziegler, 2012, Hackbarth and Madlener, 2013, Kanberger and Ziegler, 2024). Therefore, this study focuses on selected barriers for the adoption of EV by consumers. Main barriers identified in the literature, which are not focus of this study, are the limited driving range, the long charging time, and the limited availability of charging stations (e.g. Hidrue et al., 2011, Achtnicht et al., 2012, Egbue and Long, 2012, Hackbarth and Madlener, 2013, Schneidereit et al., 2015, Biresselioglu et al., 2018, Krishna, 2021, Pamidimukkala et al., 2023). Another very important barrier to consumer acceptance of EV, which will be the subject of this study, is the higher initial purchase price of EV compared with conventional vehicles (e.g. Hidrue et al., 2011, Hackbarth and Madlener, 2013, Krishna, 2021). The broad field of literature regarding life-cycle costs (also referred to as the total costs of ownership) assesses the total costs of EV during their lifespan and compares these costs with the corresponding costs of a conventional vehicle (e.g. Bubeck et al., 2016, Moon and Lee, 2019, Costa et al., 2021, Liu et al., 2021). Most of these studies find, that even with higher initial purchase prices EV tend to be more cost-effective over their total lifespan compared to conventional vehicles with internal combustion engines (e.g. Cox et al., 2018, Moon and Lee, 2019). This is especially caused by the significantly lower operating costs of EV (i.e. among others fuel costs per 100 km). These financial benefits of EV depend highly on electricity costs, fuel costs, and individual driving patterns, as the potential financial savings improve for individuals who drive a higher total number of kilometers (e.g. Bubeck et al., 2016, Moon and Lee, 2019, Costa et al., 2021, Liu et al., 2021).

Further previous studies show that CO_2 emissions in the production and in the use have a significantly negative effect on the choice of a vehicle (e.g. Achtnicht, 2012, Kanberger and Ziegler, 2024). Based on this another barrier to the broad acceptance of EV among consumers are the high CO_2 emissions generated during the production of EV[1], leading to doubts about the environmental benefits of electric vehicles (e.g. Krishna, 2021). The literature of life-cycle emissions of EV estimates the emissions of EV that arise during the vehicle's entire lifespan and identifies factors which influence these total emissions (e.g. Ellingsen et al., 2016, Helmers and Weiss, 2017, Li et al., 2017, Moon and Lee, 2019, Liu et al., 2021). Despite the high CO_2 emissions generated in the production of EV, studies indicate that EV tend to be more energy-efficient than conventional vehicles, highly depending on the current electricity mix in the country and individual driving patterns (e.g. Helmers and Weiss, 2017, Del Pero, 2018, Moon and Lee, 2019, Wietschel et al., 2019, Shafique and Luo, 2022).

Despite the potential financial savings and reductions in CO_2 emissions caused by the low fuel costs and emissions per 100 km of EV, studies find that consumers do undervalue these future savings during their purchase decisions (e.g. Greene, 2011, Allcott and Wozny, 2014, Grigolon et al., 2018, Leard, 2018). Consequently, some studies examine various methods to emphasize fuel costs and CO_2 emissions in the use, to increase consumer awareness of these vehicle attributes, in which EV generally perform better (e.g. Avineri and Waygood, 2013, Dumortier et al., 2015, Daziano et al., 2017, Long et al., 2021). Some of these studies examine the effect of different information framings, so different ways to present the information (e.g. Avineri and Waygood, 2013, Daziano et al., 2017, Long et al., 2021). Furthermore, Dumortier et al. (2015)

[1] Within the production of EV particularly the extraction of resources and the production of the battery generate very high CO_2 emissions.

examine the effect of including the fuel costs savings for the next five years, compared to an average vehicle, and the total (monthly) costs of ownership as vehicle attributes on the choice of EV.

Compared to these studies, our empirical analysis specifically focuses on information treatments (see e.g. the overview in Haaland et al., 2023). We contribute to this field of literature in three different ways: Based on data from a stated choice experiment among more than 2,200 German citizens with randomized information treatments, we examine the effect of general information about the total costs and total emissions of vehicles, with highlighting the operating costs and emissions, before the purchase decision, on the choice of EV, as the information treatments emphasizes the benefits of those vehicles. The first treatment information addresses the cost dimension of vehicles. Thus, we further analyze the effects of the first treatment information on the preferences for the purchase price and the fuel costs of a vehicle. As the second treatment gives information about the CO_2 emissions of vehicles, we additionally examine the effect of this information on the preferences regarding CO_2 emissions in the production and in the use of a vehicle. Since the benefits of lower operating costs and emissions increase with the total number of km individuals travel by car, we finally contribute to the literature by analyzing the heterogeneity in treatment effects regarding the total number of kilometers (km) individuals traveled by car in the last twelve months and the total number of km individuals plan to drive with a soon purchased vehicle within one year.

The remainder of this paper is organized as follows: Section 2 describes the data and the variables used in our econometric analysis. Section 3 explains the econometric approach and reports the estimation results succeeding with the conclusion and policy implications in section 4.

2. Data and variables

2.1 Survey design

The data for the empirical analysis were collected by means of large-scale computer-assisted web interviews among citizens in Germany. The survey was carried out by the German market research company Psyma during April and May 2021. The target population comprised adults, who were either solely or partially responsible for household decisions. The sample was stratified according to gender, age, place of residence, and education so that it is widely representative for the target population in Germany in terms of these characteristics. Across all respondents, the median completion time of the survey was about 31 minutes. Respondents, who did not pass some survey quality checks, which were embedded in random batteries of questions,[2] or indicated unrealistic values in the survey, are not considered in the empirical analysis. The questionnaire that was used in the survey contained several parts. After some screening questions and some first socio-demographic variables, the first part comprised questions on economic preferences, environmental attitudes, and planned vehicle purchase decisions in the future.

The main part of the survey referred to the stated choice experiment on the preferences for different vehicles and the corresponding randomized interventions. Each participant of the survey faced twelve different choice sets, each containing the choice among four hypothetical vehicle types, i.e. three electric vehicles and a conventional vehicle. The experiment included several experimental (e.g. information) interventions at the beginning and/or after the sixth choice set. However, not all treatments are considered in this paper due to the focus on the treatment information regarding total costs and total emissions which highlights the operating costs and emissions. Consequently, we consider the first six choice sets for overall 1,128 respondents in the control group without any interventions, 561 respondents in the first treatment group, which refers to total costs, and 554 in the second treatment group, which considers the total emissions of a vehicle, as discussed below.

The questions on environmental attitudes, economic preferences, and planned vehicle purchase decisions in the future were asked prior to the stated choice experiment to prevent the answers of the respondents from being influenced by the stated choices in the experiment. Finally, the last part of the questionnaire comprised some questions about the Corona crisis, which are not considered in this paper, and some additional socio-economic and socio-demographic variables.

2.2 Stated choice experiment

To empirically examine individual preferences for different vehicle types and attributes, we conducted an appropriate stated choice experiment. In each choice set, the participants of the experiment had to choose among four hypothetical vehicles, which were labeled according to their propulsion technology (e.g. Ferguson et al., 2018) to keep the experiment more realistic and enable the consideration of initial vehicle type preferences among the respondents (e.g. Louviere et al., 2000). Specifically, in each choice set, the participants of the experiment were

[2] Specifically, the respondents were asked to select a specific option to make sure that they were reading the instructions attentively.

asked to choose among one conventional (i.e. gasoline or diesel) vehicle with an internal combustion engine, one plug-in hybrid vehicle with a combination of an internal combustion engine and one or more small electric engines, one extended-range electric vehicle with one or more electric engines and a small internal combustion engine as range extender, and finally one (pure) battery electric vehicle with only one or more electric engines.

The alternative vehicles were additionally characterized by the following eight quantitative attributes:

- Purchase price (in Euro)
- Average CO_2 emissions caused in use per 100 km (in kg)
- Total CO_2 emissions caused in the production of the vehicle (in kg)
- Average range with a fully charged battery (in km)
- Average range with a full tank (in km)
- Average time to recharge the battery (in minutes)
- Average time to refuel the tank (in minutes)
- Average fuel costs per 100 km[3] (in Euro)

With the exception of CO_2 emissions in vehicle production, the attributes and their levels are based on previous studies. Furthermore, these attributes are found to be among the most important vehicle features for (stated) vehicle purchase decisions (e.g. Hackbarth and Madlener, 2013, 2016). On this basis, we expect a positive effect of vehicle range and a negative effect of purchase price, time to recharge the battery and refuel the tank, and fuel costs on the choice among the four vehicle types. Kanberger and Ziegler (2024) show that the preferences for a reduction of CO_2 emissions in the production of a vehicle are higher than the preferences for lower CO_2 emissions in vehicle use. Since the study of Kanberger and Ziegler (2024) is based on the same data but only refers to the control group we examine if these preferences change due to the second treatment information. The level ranges of the attributes were aligned to realistically fit the respective vehicle type. Table 1 gives an over-view of all attributes and the corresponding attribute levels across the different vehicle types in the stated choice experiment.

To keep the hypothetical vehicle alternatives as realistic as possible, some attributes were customized or grounded to reality according to certain indications by the respondents (e.g. Hensher, 2010, Hensher et al., 2015). The purchase price levels were customized according to the average

[3] It should be noted that in our experiment, fuel costs refer not only to gasoline and diesel but also include electricity costs for electric vehicles.

indicated Euro value the participants of the experiment were willing to pay in future purchase decisions, while the CO_2 emissions and operating costs levels were based on individual reference values of the preferred vehicle class. The purchase price levels as well as the levels of CO_2 emissions and operating costs thus differed across the respondents. To allow the respondents to compare the hypothetical vehicles in each choice set, the purchase prices and fuel costs were presented in Euro and the CO_2 emissions were given in kg. The reference values for the emission levels in different vehicles were based on Wietschel et al. (2019). CO_2 emissions caused in vehicle production, have not been considered in previous studies so far. Therefore, the range of the levels according to the reference values were defined along the line of CO_2 emissions in vehicle use.

Methodologically, a fractional factorial design was employed for the attribute combinations, whereby the statistical software Sawtooth was used to efficiently generate choice sets for all participants of the experiment. The order of the four vehicle types was randomized in each choice set, whereby the respondents always had to choose one of them. The complete survey including the stated choice experiment was pre-tested to ensure comprehensibility among the respondents. Table 2 shows a translated exemplary choice set, while Figure 1 presents the corresponding original (German) screenshot of it. To avoid or at least reduce the hypothetical bias of the stated choice experiment, a cheap talk script, alerting the respondents to strongly consider their financial situation when making a decision, was implemented at the beginning of the experiment (e.g. Mariel et al., 2021).

In the next section, we will describe the treatment information implemented in the stated choice experiment, on which our econometric results are based. Following that, we will provide a description of the variables used in the empirical analysis.

2.3 Randomized information interventions on costs and emissions

The stated choice experiment, which is the base for our analysis, was combined with two different randomized information interventions addressing the total costs and total emissions of a vehicle. Each of the respective treatment information was presented to the respondents after the introduction of the choice experiment. The first treatment information which refers to the total costs of a vehicle with presenting the purchase price as well as the costs in use of a vehicle was the following:

When making your decision, please note that the total costs of the cars over their entire service life depends on the ***operating costs*** *and thus on the average fuel costs for gasoline, diesel, or electricity per 100 km driven, as well as on the* ***purchase price.***

The total costs of two example cars over their entire service life are shown below:

	Example car 1	*Example car 2*
Costs in use	*10 Euro per 100 km*	*5 Euro per 100 km*
Purchase price	*20.000 Euro*	*24.000 Euro*

The purchase price for example car 1 is lower than for example car 2. The operating costs, on the other hand, are lower for example car 2 than for example car 1.

With an average total distance of 20,000 km driven per year, the total costs of example car 2 with the higher purchase price are thus already lower than example car 1 after four years of use.

With an average total distance driven of 10,000 km per year, the total costs of example car 2 with the higher purchase price are only lower than example car 1 after eight years of use.

This treatment information aims to raise individuals' awareness of potential future financial savings resulting from reduced operating costs. EV not only have the potential of financial savings but provide the opportunity to significantly reduce the emissions in the passenger transportation sector. Thus, the second treatment information refers to the total emissions of a vehicle with highlighting the emissions in the use. The information shown to the participants before the first choice set in the second treatment group was the following:

When making your decision, please also bear in mind that the total CO_2 emissions of cars over their entire service life depend on the ***CO_2 emissions caused during use*** *and thus on the average CO_2 emissions caused per 100 km driven, as well as on the* ***CO_2 emissions caused during car production****.*

The total CO_2 emissions of two example cars over their entire service life are shown below:

	Example car 1	*Example car 2*
CO_2 emissions in use	*20 kg per 100 km*	*10 kg per 100 km*
CO_2 emissions in car production	*5.000 kg*	*13.000 kg*

CO_2 emissions caused during car production are lower for example car 1 than for example car 2. CO_2 emissions caused during use, on the other hand, are lower for example car 2 than for example car 1.

With an average total distance of 20,000 km driven per year, the total CO_2 emissions of example car 2 with the higher CO_2 emissions caused during car production are thus already lower than example car 1 after four years of use.

With an average total distance of 10,000 km driven per year, the total CO_2 emissions of example car 2 with the higher CO_2 emissions caused during car production are only lower than example car 1 after eight years of use.

With these two information interventions we expect to increase the stated choices of EV and further affect the preferences regarding the 'purchase price', the 'fuel costs per 100 km', and the preferences regarding the two emission-related attributes. We further anticipate heterogeneity in treatment effects since the potential financial savings and reductions in CO_2 emissions depend on driving patterns such as the total number of individual driven kilometers. Table 3 present some first descriptive statistics for the choice among the different vehicle types and reveal that in all three groups, with around 38-42.5%, the highest share of stated choices refers to conventional vehicles compared to stated choices for each of the respective EV. Furthermore, Table 3 shows that the frequency of stated choices for conventional vehicles in the control group is the highest at around 42.5%, compared to 39.75% in the first treatment group and 38.39% in the second treatment group. In addition, it is noteworthy that the frequency of stated choices for extended-range electric vehicles and (pure) battery electric vehicles is higher in both treatment groups than in the control group. In the first treatment group, 13.76% and in the second treatment group, 13.51% of all respondents chose extended-range electric vehicles, compared to 12.16% of all respondents in the control group. Table 3 shows that the stated choices for battery electric vehicles in the treatment groups are about 2.5-3% higher than in the control group, suggesting possible treatment effects. However, these descriptive results should be interpreted with caution as they do not control for the included attributes or correlations over the different choices of one respondent.

Therefore, we consider the estimation results in multinomial discrete choice models in section 3.2. In the next section we will describe the variables included in the analysis following by an explanation of the econometric approach.

2.4 Variables in the econometric analysis

Experiment-related variables

Our dependent variable refers to the stated choice among the four vehicle types, i.e. conventional vehicles, plug-in hybrid electric vehicles, extended-range electric vehicles, and battery electric vehicles. Technically, alternative-specific constants for the three types of electric vehicles are included in the econometric analysis with mixed logit models as discussed below, considering conventional vehicles as base category. The experiment-related explanatory variables are based on the eight attributes as discussed above. While the first financial attribute is termed 'purchase price (in 1000 Euro)', the two emission-specific attributes are termed 'CO_2 emissions in use per 100 km (in kg)' and 'CO_2 emissions in the production (in tons)'. We now consider the latter variable in tons to avoid very high parameter estimates in the econometric analysis. As the preferences for the range attributes are not the focus of this study, we summarized the two attributes for driving range in the variable 'range with a fully charged battery and/or a full tank (in 100 km)'[4]. The two time-specific attributes are termed 'time to recharge the battery (in hours)' and 'time to refuel the tank (in minutes)', whereby the former variable is now measured in hours to avoid very high parameter estimates in the econometric analysis. Finally, the second financial attribute is termed 'fuel costs per 100 km (in Euro)'.

Since we examine the effect of the treatment information on the preferences for EV, we additionally include interaction terms between the respective treatment dummy variables and the alternative-specific constants in our econometric analysis. As the first treatment information addresses the total costs of a vehicle with emphasizing the operational costs, we further include interaction terms with the first treatment dummy variable and respectively the 'purchase price' and the 'fuel costs per 100 km'. With the second treatment information we address the total

[4] The preferences for the range in vehicles and their influence on the choice between vehicles, including different interventions, were examined in a complementary paper (Staar and Ziegler, 2024).

emissions of a vehicle with highlighting the 'CO_2 emissions in the use per 100 km'. This is why we additionally include interaction terms between the second treatment dummy variable and the 'CO_2 emissions in use per 100 km' and the 'CO_2 emissions in the production' as we expect to affect the preferences regarding these attributes.

Individual characteristics

For analyzing heterogeneity in treatment effects, we consider split samples regarding two individual specific characteristics which reflects the driving patterns. The first variable we use for the heterogeneity analysis is the individual number of total km traveled by car within the last twelve months. The respondents, who used a car in the last twelve months as means of transport, were therefore asked how many kilometers they drove within the last year. As described before we further asked the respondents if they plan to purchase a car in the future. For participants who did indicate that they will purchase a car in the future, the survey included further questions about the features of a potential vehicle. The answers regarding these questions are used for customization of some attributes, as explained above, and for the analysis of heterogeneous treatment effects. The second variable, used to create split samples for the analysis of heterogeneity in treatment effects, is the 'planned mileage'. Therefore, the respondents were asked what the approximated total distance is, which must be covered by the purchased vehicle within one year.

In the next section we describe the econometric approach used in this study and report the estimation results.

3. Empirical analysis

3.1 Econometric approach

In our econometric analysis we use mixed logit models (e.g. McFadden and Train, 2000, Hensher and Greene, 2003, Greene, 2012), i.e. random parameters logit models. In contrast to common multinomial logit models the random parameters logit models are much less restrictive and more flexible by including random parameters of the explanatory variables. This model maintains the assumption that error terms ε_{ijm} are independently and follow a standard (type 1) extreme value distribution, but it allows the inclusion of random coefficients. Consequently, it eases the "independence of irrelevant alternatives" (IIA) assumption seen in multinomial models (e.g. Hensher et al., 2005, Cameron and Trivedi, 2010). Mixed logit models are particularly able to capture unobserved taste heterogeneity and correlations due to the panel nature of the data since each respondent was faced with several choice sets. Incorrectly neglecting taste heterogeneity and/or correlations in multinomial logit models, assuming fixed parameters of the explanatory variables, can therefore lead to distorted estimation results due to the underlying model misspecification (e.g. Greene, 2012).

As described above, in the stated choice experiment which forms the basis for our discrete choice analysis the respondents choose between four different alternative vehicles. The (hypothetical) utility of individual i $(i = 1,...,N)$ for alternative j (j = 1, …, 4) in choice set m (m = 1,…,6) is given by the following equation (e.g. Greene, 2012, Gutsche and Ziegler, 2019):

$$U_{ijm} = \beta_i' x_{ijm} + \varepsilon_{ijm}$$

The utility thus depends on the vectors of explanatory variables $x_{ijm} = (x_{ijm1},\ldots,x_{ijmK})'$ that are based on (not exclusively) the attributes and the corresponding unknown parameter vectors $\beta_i = (\beta_{i1},\ldots,\beta_{iK})'$ where K = 20. As outlined in the theory of random utility maximization (e.g. McFadden, 1974), when faced with a choice set m, individual i chooses alternative j if the utility derived from alternative j is higher than the utility of all other options. Whereas the utility U_{ijm} of each alternative is not observable, it is possible to observe the decision of the respondents. The choice y_{ijm} of respondent i in the choice set m is represented as dummy variable, which takes the value one if the respondent chooses the alternative j and zero otherwise (e.g. Greene, 2012). This observed variable y_{ijm} can thus inform about which alternative provides the greatest utility for the individual (e.g. Greene, 2012). The choice probability that individual i chooses alternative j in choice set m can thus be written as following (e.g. Gutsche and Ziegler, 2019):

$$P_{ijm} = P\left(U_{ijm} > U_{ij'm};\ \forall j \neq j'\right) = P(\beta_i' x_{ijm} + \varepsilon_{ijm} > \beta_i' x_{ij'm} + \varepsilon_{ij'm}; \forall j \neq j')$$

For our SML estimation of mixed logit models we assume normally distributed parameters of all attributes (except for the purchase price, which will serve as basis for the estimations of WTP). It is important to note that the treatment effects on the choice of electric vehicles are estimated by including interaction terms in the mixed logit models. Specifically, the respective treatment dummy variables are interacted with the alternative-specific constants (ASC), considering conventional vehicles as base category, as discussed above. Because we expect our treatment interventions to (additionally) affect preferences for the ‘purchase price’, ‘fuel costs per 100 km’, and ‘CO_2 emissions in the production’ and in the use of a vehicle, we also included interaction terms between the first treatment dummy variable and respectively the ‘purchase price’ and the ‘fuel costs per 100 km’. For the second information treatment we included further interactions between the second treatment dummy variable and first the ‘CO_2 emissions in the production’ and second the ‘CO_2 emissions in use per 100 km’. The parameters of these interaction terms are typically assumed to be non-random.

In random parameters logit models, it is assumed that the parameters β_{ik} $(i = 1, \ldots, N)$ of those explanatory variables which are assumed to be random are continuously distributed across i (e.g. Greene, 2012, Gutsche and Ziegler, 2019):

$$\beta_{ik} = \beta_k + \sigma_k u_{ik}$$

The u_{ik} reflect the individual specific heterogeneity and are independently normally distributed with mean zero and standard deviation one. Furthermore, σ_k captures the standard deviation of the distribution of β_{ik} around the mean β_k. In contrast, the parameters for the purchase price and all interaction terms are specified as fixed since it is common practice if the estimated parameter is used for willingness to pay (WTP) estimations (e.g. Hensher et al., 2005). Conditional on knowing the unknown vector β_i the probability that respondent i chooses alternative j in choice set m is the standard logit (e.g. Revelt and Train, 1998; Hole, 2007):

$$L_{ijm}(\beta_i) = \frac{e^{\beta_i' x_{ijm}}}{\sum_{j=1}^{4} e^{\beta_i' x_{ij'm}}}$$

However, the maximum likelihood estimation requires, in this case, the joint conditional probability $S_i(\beta_i)$ of the sequence of observed choices across all M =6 choice sets (e.g. Revelt and Train, 1998, Gutsche and Ziegler, 2019), which is the product of the standard logits (e.g. Revelt and Train, 1998, Train, 2009):

$$S_i(\beta_i) = \prod_{m=1}^{6} L_{ij(i,m)m}(\beta_i)$$

Where $j(i,m)$ represents the alternative that respondent i chooses in choice set m. Integrating the conditional probability over the distribution of β_i gives, thus, the unconditional probability of the sequence of observed choices (e.g. Revelt and Train, 1998):

$$P_i(\theta) = \int \prod_{m=1}^{6} L_{ij(i,m)m}(\beta_i)\ f(\beta_i|\theta)\ d\beta_i$$

In line with, for example, Revelt and Train (1998), the log-likelihood function can be written as $LL(\theta) = \sum_{i=1}^{N} \ln P_i(\theta)$, which is the sum of the natural logarithms of the probabilities across all respondents (e.g. Gutsche and Ziegler, 2019). However, the probabilities $P_i(\theta)$ cannot be solved analytically because they are characterized by multiple integrals (e.g. Gutsche and Ziegler, 2019; Schwirplies et al., 2019). Consequently, exact maximum likelihood estimations are not possible, but can instead be approximated through simulation methods (e.g. Train, 2009). According to, for example, Revelt and Train (1998), $P_i(\theta)$ is approximated through the aggregation over randomly chosen values of β_i. First, a value of β_i is drawn from $f(\beta_i|\theta)$ for any given value of θ. Second, the product of the standard logits (i.e. $S_i(\beta_i)$) is calculated using the drawn value of β_i. Finally, the latter two steps are repeated several times, and the results are averaged. Hence, the simulated probability of the sequence of choices of a respondent *i* is (e.g. Revelt and Train, 1998; Train, 2009):

$$SP_i(\theta) = \left(\frac{1}{R}\right) \sum_{r=1}^{R} S_i(\beta_i^{r|\theta})$$

Where $\beta_i^{r|\theta}$ represents the simulated r^{th} draw from $f(\beta_i|\theta)$ and R is the number of Halton draws. $SP_i(\theta)$ is, by design, an unbiased estimator of $P_i(\theta)$ whose variance decreases as the number of Halton draws R increases (e.g. Revelt and Train, 1998; Train, 2009). Accordingly, the simulated log-likelihood function can be written as (e.g. Revelt and Train, 1998; Hole, 2007):

$$SLL(\theta) = \sum_{i=1}^{N} \ln \left[\frac{1}{R} \sum_{r=1}^{R} S_i(\beta_i^{r|\theta}) \right]$$

Recall that mixed logit models account for unobserved taste heterogeneity by assuming a continuous distribution for the parameters, which must be defined by the analyst (e.g. Kanberger and Ziegler, 2023). As explained above, we assume the parameters of the purchase price attribute and the interaction terms to be fixed and the parameters of the rest of the attributes to be normally distributed. We use the Stata command “mixlogit”, which was written by Hole (2007). Furthermore, we use 1,000 Halton draws in all SML estimations[5].

[5] Note that all other estimations and statistical analyses considered in this paper were also conducted using Stata.

Based on the estimated parameters, it is subsequently possible to additionally estimate the mean WTP for the attributes of the vehicles. Mean WTP can be obtained by setting the total derivative of the utility function with respect to the attributes and the purchase price equal to zero while assuming that all other attributes are held constant (e.g. Gutsche and Ziegler, 2019). Mean WTP refers to the change in the purchase price that holds the utility constant for a marginal change in the explanatory variable of interest (e.g. change in CO_2 emissions) (e.g. Gutsche and Ziegler, 2019). In the case of the common multinomial logit models (which assume fixed parameters), the value of the mean WTP can be obtained mathematically through dividing the negative value of the estimated parameter of the explanatory variable of interest by the estimated parameter of the monthly household costs (e.g. Kanberger and Ziegler, 2024). However, in our case with mixed logit models with assumed random parameters, the mean WTP for the attributes of the future transport systems is calculated through dividing the negative values of the estimated means of the random parameters by the estimated fixed parameter of the purchase price (e.g. Revelt and Train, 1998; Gutsche and Ziegler, 2019).

Recall, however, that we also consider interaction terms in our model. Typically, the parameters of such interaction terms are assumed to be non-random. Therefore, their corresponding mean WTP is estimated through dividing the negative value of the estimated parameter of the interaction term by the estimated parameter of the purchase price (e.g. Kanberger and Ziegler, 2024). Let $\widehat{\beta_k}$ denote the estimated mean of the (random) parameter k and $\widehat{\beta_{cost}}$ the estimated fixed parameter of the purchase price. Then, mathematically, the estimated mean $\widehat{WTP}_k$ can be expressed as follows (e.g. Scarpa and Rose, 2008; Daziano and Achtnicht, 2014):

$$Mean\,\widehat{WTP}_k = -\frac{\widehat{\beta_k}}{\widehat{\beta_{cost}}}$$

In the next section we describe the estimation results regarding the main treatment effects following by an analysis of heterogeneity in treatment effects.

3.2 Preliminary estimation results

Treatment effects

Table 4 reports the SML estimation results in a mixed logit model that includes the variables based on the vehicle attributes, as explained above, the alternative-specific constants for the three different electric vehicle types considering conventional vehicles as base category, the interaction terms between the first treatment variable and respectively the ‘purchase price’ and the ‘fuel costs per 100 km’. Additionally, the interaction terms between the second treatment variable and the ‘CO_2 emissions in the production’ and ‘CO_2 emissions in the use’ of a vehicle are included. The parameter estimates and the corresponding (cluster) robust z-statistics in the first column refer to the mean of the random parameters whereas the second column refers to the estimated standard deviations of the random parameters and the corresponding robust z-statistics, whereby no standard deviations are estimated for the parameters, which are assumed to be fixed. The second column of Table 4 shows that all estimated standard deviations of the parameters are significantly different from zero, which indicates strong unobserved heterogeneity in the estimated preferences and thus confirms the superiority of the application of mixed logit models compared to multinomial logit models that implicitly assume standard deviations of zero due to the underlying fixed parameters. The third column of Table 4 reports the results of the willingness to pay estimations based on the purchase price.

According to the first column of Table 4 the ‘range with a fully charged battery and/or a full tank’ has the expected significantly positive effect, whereas the ‘time to recharge the battery’, ‘time to refuel the tank’, as well as the ‘fuel costs per 100 km’ have the expected significantly negative effect on the choice of a vehicle. This is in line with findings in previous studies (e.g. Hidrue et al., 2011, Noel et al., 2019). Furthermore, the first column reveals that the ‘purchase price’ has the expected significantly negative effect on the choice of a vehicle. Since the estimated parameter for the ‘purchase price’ is significantly different from zero we can consider the mean WTP estimates for the other variables considered in the analysis if the respective parameters are significantly different from zero. The estimated mean of the parameters for the ‘CO_2 emission in the production’ and in the use of a vehicle indicate a significantly negative effect on the choice of a vehicle which indicates preferences for lower ‘CO_2 emissions in the production’ as well as in the use of a vehicle. These findings are in line with the literature (e.g. Hidrue et al., 2011, Achtnicht, 2012, Kanberger and Ziegler, 2024). Further, in line with previous studies (e.g. Achtnicht, 2012), the estimation results for the alternative-specific constants in Table 4 reveal strong initial preference for conventional vehicles since conventional vehicles are considered as base category and the estimated means of the parameters for all three electric vehicle types are strongly significantly negative. The estimated stated preference is especially low for extended-range and battery electric vehicles.

However, the estimation results for the ‘purchase price’, the ‘fuel costs’, both emission-related variables, and the alternative-specific constants only refer to the control group, since we included interaction terms between the respective treatment variable and all these variables. We expect our information treatments to have a significantly positive effect on the preferences for EV which would result in significant positive estimated parameters for the interaction terms between the ASC and the treatment variables. The first column of Table 4 shows contrary to our expectation no significant effect for any of the information treatments when considering the whole sample. With the first treatment information, which addresses the total costs, we further expect to affect the preferences for the 'purchase price' and the 'fuel costs per 100 km'. The estimation results for the interaction terms between the first treatment variable and these variables show no significant effect on the preferences for none of the financial variables. Since the second treatment information addresses total CO_2 emissions of vehicles, we also expect to affect the preferences for the 'CO_2 emissions in production' and the 'CO_2 emissions in the use' of a vehicle. Based on the estimation results presented in Table 4 we do not find any significant treatment effect for these interaction terms.

The third column of Table 4 comprises the mean willingness to pay (WTP) estimates in terms of the purchase price, measured in Euro. These estimates are calculated by the ratio between the negative values of the estimated (means of the) parameters and the estimated fixed parameter of the purchase price and multiplied by 1,000 as the purchase price is measured in 1,000 Euro. The mean WTP estimates for the alternative-specific constants for the three different electric vehicle types reveal strong initial preferences for conventional vehicles since all of them are strongly significantly negative. According to the mean WTP estimates the aversion is especially high for extended-range and battery electric vehicles. The estimated mean WTP for extended-range electric vehicles is about -17,200 Euro. For battery electric vehicles the third column of reveals an estimated mean WTP of about -16,700 Euro and about -10,200 Euro for plug-in hybrid electric vehicles compared to conventional vehicles. This indicates that the purchase price for extended-range electric vehicle must be almost 17,200 Euro lower than the purchase price for conventional vehicles that individuals are on average indifferent between two otherwise identical vehicles which only differ in their propulsion technology.

Regarding the attributes the mean WTP estimates indicate that on average individuals are willing to pay 2,060 Euro for an increase in the 'range with a fully charged battery/ full tank' by 100 km, almost 2,500 Euro per hour decrease in recharging time, and more than 1,700 Euro for a decrease of fuel costs of one Euro per 100 km. According to the mean WTP estimates in the third column individuals are on average willing to pay 273.47 Euro for a reduction in 'CO_2 emissions in use per 100 km' by one kg, what means an estimated mean WTP of 27.35 Euro for a reduction by one gram per km. It is difficult to compare the estimated mean WTP estimates for the emissions-related attributes. In line with Kanberger and Ziegler (2024) and following the approach in Achtnicht (2012) and Hulshof and Mulder (2020) the mean WTP estimates for CO_2 emissions in the use of a vehicle can be transformed into an estimated mean WTP for a reduction by one ton over the lifetime of a vehicle by considering an average lifetime mileage of 145,830 km[6]. This leads to an estimated mean WTP of 187,53 Euro for a reduction of one ton in the use over the total lifespan of a vehicle which lies within the range of the mean WTP estimates in Achtnicht (2012) and Hulshof and Mulder (2020). Compared to this, citizens are on average willing to pay 371.99 Euro for a reduction by one ton of 'CO_2 emissions in the production'. These results imply that individuals are on average willing to pay more for a reduction by one ton generated in the production compared to a reduction by one ton in the use over the total lifespan. This confirms consumers' aversion to the high CO_2 emissions generated in the production of electric vehicles, as found in the literature (e.g. Krishna, 2021). It is important to note that the estimated mean of the random parameters regarding the emissions-related variables in Table 4 does not exclusively refer to electric vehicles. Based on our estimation results for the interaction terms we cannot find any significantly change for the estimated mean WTP for the alternative-specific constants for the three different electric vehicle types and the attributes 'purchase price', 'fuel costs per 100 km', 'CO_2 emissions in the use', and 'CO_2 emissions in the production' of a vehicle for the treatment group.

In summary, Table 4 indicates that there is no significant treatment effect on the choice of EV or on the preferences for the two financial attributes and the two emission-related attributes. The potential financial savings and reductions in the total CO_2 emissions caused by operational costs and emissions highly depend on the total number of km individuals drive (e.g. Helmers and Weiss, 2017, Moon and Lee, 2019, Wietschel et al., 2019, Shafique and Luo, 2022), we therefore anticipate that the impact will vary depending on the individual total number of kilometers driven. In the following chapter, we therefore analyze possible heterogeneity in treatment effects by examining split samples based on the total number of kilometers traveled by car in the last twelve months and the total 'planned mileage' within one year for a vehicle that will soon be purchased.

[6] For calculation we multiply the estimated mean WTP of 27.35 Euro with 1,000,000 and divide this result by 145,830 km.

Heterogeneity in treatment effects

Table 5 presents the SML estimation results using the same specifications as in Table 4, but considering split samples based on the total distance driven by individuals in the last twelve months. In the survey only individuals who stated that they used the car within the last twelve months as means of transport saw this question. We assigned a value of zero kilometers to those who stated that they did not use the car as means of transport since they in fact traveled zero kilometers by car. We used different thresholds to separate the split samples. The first two columns of Table 5 show the estimated (mean) parameters and the corresponding (robust) z-statistics for respondents who drove less than or equal to 8,000 km, which is the median value for this variable in our sample (when only considering those who stated a number of kilometers). The third column refers to the mean WTP estimates based on the estimation results in the first two columns. Compared to this, the columns four to six report the estimation results for participants who drove more than 8,000 km. The columns seven to nine refer to the estimation results for individuals who drove more than 10,000 km whereas the last three columns refer to the results for participants who drove more than 12,000 km in the last twelve months. According to the results in Table 5 the initial aversion for the three different electric vehicle types increases with the total number of kilometers driven in the last twelve months. For extended-range electric vehicles, for example, the estimated mean WTP ranges from almost - 13,300 Euro for individuals who drove less than 8,000 km in the last year to more than – 30,800 Euro for those who drove more than 12,000 km in the last twelve months. Similar to this, the estimated mean WTP for a decrease in 'fuel costs per 100 km' by one Euro also increase with the number of kilometers driven in the last twelve months.

Regarding the first treatment information, which addresses the total costs of vehicles, Table 5 reveals a positive treatment effect on the choice of extended-range electric vehicles which is significantly different from zero for individuals who drove more than 8,000 km and for those who drove more than 10,000 km. The sixth column thus reveal an increase in the estimated mean WTP for extended-range electric vehicle for individuals in the first treatment group who drove more than 8,000 km by about 7,430 Euro. The increase in the mean WTP estimate for individuals who drove more than 10,000 km through the information about the total costs, with highlighting the operational costs, is even higher with 10,204 Euro. In contrast, the estimation results in the first column do not reveal any significant treatment effect for the sample with individuals who travelled less than 8,000 km by car. This result confirms our expectation that treatment information has a stronger effect on individuals who use their car more intensively.

Regarding the split sample for individuals who drove more than 12,000 km within the last year the estimation results in the last two columns indicate again no significant treatment effect for the first treatment information. In this regard we must mention that if splitting the sample at a threshold of 12,000 km the sample size for the group of individuals who drove more than 12,000 km is way smaller which leads to a decrease in statistical power. Furthermore, the not existent treatment effect may be explained by other existing barriers such as experienced range anxiety which increases for individuals with a higher number of driven kilometers. Regarding the second treatment information which refers to the total emissions of a vehicle with highlighting the emissions in the use, the estimation results in Table 5 reveal a significantly positive effect on the choice of plug-in hybrid electric vehicles for individuals who drove more than 8,000 km, more than 10,000 km, and more than 12,000 km. The increase in the estimated mean WTP in the second treatment group compared to the control group is again higher for those individuals who drove a higher total number of kilometers in the last year and varies from 6,050 Euro for individuals who drove more than 8,000 km to more than 12,500 Euro for those who stated that they drove more than 12,000 km. This significant effect again cannot be found for individuals who drove less than 8,000 km in the last twelve months. Additionally for the groups who drove more than 10,000 km and more than 12,000 km the results in the seventh and tenth column reveal a weakly significantly positive effect of the treatment information on the choice of extended-range electric vehicles.

Table 6 reports the estimation results for the SML estimations with split samples regarding the total 'planned mileage' of individuals for one year. A few (unplausible) values which were identified in an outlier analysis (e.g. 1 km or 1,000,000 km) were excluded (in the literature referred to as 'trimming', e.g. Lusk et al., 2011) in the econometric analysis. Therefore, we excluded the lowest and highest 0.5 percentile of the values for the 'planned mileage' variable[7]. Since this question was only presented to individuals who did state that they intent to buy a car in the future the observations in the model with split samples regarding this variable are lower than in the other models. The first two columns report the estimated mean parameters and the corresponding (robust) z-statistics for individuals who stated that they plan to drive less or equal to 10,000 km within one year with the soon to be purchased vehicle. We choose the first threshold of 10,000 km as this is the median value in our sample for this variable. The third column

[7] As second approach regarding these values we used winsorizing (e.g. Lusk et al., 2011) and reassigned those values to the first values which are not identified as outliers anymore and again estimated the model with specifications as in in Table 6. These estimation results do not differ qualitatively from the results reported in Table 6. Due to brevity the estimation results are not reported here but are available upon request.

reports the mean WTP estimates which are based on the estimation results in the first two columns. The columns four to six refer to the estimation results for the group which stated to plan to drive more than 10,000 km per year. The last three columns show the estimation results for individuals who stated a planned mileage of more than 15,000 km. For individuals who stated a planned mileage of less than or equal to 10,000 km the estimation results only indicate weakly significantly negative treatment effects on the choice of plug-in hybrid electric vehicles for both treatment information. This may be since both information treatments draw attention to the fact that financial savings and reductions in CO_2 emissions may be less present for individuals who (plan to) drive lower numbers of kilometers. For individuals who stated a planned mileage of more than 10,000 km the second treatment information referring to the total emissions of vehicles with highlighting the operating emissions has a significantly positive effect on the preferences for extended-range and plug-in hybrid electric vehicles. As a result, column six shows that the estimated mean WTP for those individuals in the second treatment group increases by more than 12,500 Euro for extended-range, and by almost 11,300 Euro for plug-in hybrid electric vehicles.

Regarding the first treatment the estimation results in the last two columns reveal a significantly negative effect on the preferences for the purchase price. For this group we can see that the aversion against the purchase price was not as strong as for individuals who have a lower stated 'planned mileage' and by highlighting the costs of vehicles in general this may have increased the awareness regarding the purchase price. Additionally, in the split sample of individuals who stated a planned mileage of more than 15,000 km the second treatment information has a weakly significant positive effect on the preferences for extended-range electric vehicles. Furthermore, for those individuals we find significantly positive treatment effect on the preferences for plug-in hybrid and battery electric vehicles of the second treatment information. The last column reveals that these effects results in a very high increase in WTP for all types of electric vehicles for this group of individuals, i.e. an increase in the estimated mean WTP for extended-range electric vehicles by around 18,600 Euro, for plug-in hybrid EV by 23,600 Euro, and for battery electric vehicles by 24,300 Euro in the second treatment group.

Our findings indicate that especially people who would benefit more from lower operational costs of EV and would highly reduce their CO_2 emissions because lower operational emissions can be influenced by informing about the potential of these lower operational costs and emissions before the purchase decision. In summary both treatment information almost exclusively influences the choice of plug-in and extended-range electric vehicles. This may be because other factors like range anxiety are especially high for battery electric vehicles as this only have one or more electric engines and this the shortest range of the different EV types we included in our study. Only for individuals who plan to drive more than 15,000 km within one year can be positively influenced by the information about the total emissions of a vehicle. Furthermore, based on our estimation results we find a higher potential for the second treatment information.

4. Conclusion and policy implications

This study empirically examines the effect of general information about costs and emissions over the life cycle of a vehicle, by highlighting the operational costs and emissions before the purchase decision on the stated choices of electric vehicles. We further analyze the effect of these two information treatments on the preferences for the purchase price, the fuel costs, the CO_2 emissions in the production and in the use of a vehicle. Considering the whole sample, we cannot find any significant treatment effect. Since the potential financial benefits and reductions in emissions caused by lower operational costs and emissions highly depends on the intensity of vehicle use, we considered split samples regarding the total driven kilometers in the last year and the planned mileage within twelve months for a soon to be purchased vehicle. Our results imply the potential effectiveness of targeted information campaigns for individuals with a higher extent of car use. Providing information about costs and emissions over the life cycle can increase the awareness for potential financial savings and reductions in emissions and thus increase the number of individuals who buy electric vehicles. The results of our SML estimations imply that the information about total CO_2 emissions of a vehicle would have more potential in increasing the preferences and the willingness to pay for electric vehicles. Nevertheless, the information mainly led to an increase in preferences for plug-in hybrid and extended-range electric vehicles. Regarding the preferences for battery electric vehicles, this information treatment only has a significantly positive effect for individuals with a very high planned mileage. Since the target is to reach climate neutrality in the transportation sector (and overall) we conclude that only corresponding targeted information campaigns for frequent drivers can be a successful component in increasing the purchase of electric vehicles and that the information campaign to highlight the energy efficiency could be combined with measures to address other barriers as the fear which is related to the limited driving range of electric vehicles (i.e. range anxiety) and the limited charging availabilities.

As further steps we will conduct further robustness checks and we will consider additional individual characteristics for analyzing the heterogeneity in treatment effects such as the environmental awareness measured by the "New ecological paradigm", the income, and other variables of the survey.

References

Achtnicht, M., G. Bühler, and C. Hermeling (2012), The impact of fuel availability on demand for alternative-fuel vehicles, *Transportation Research Part D* 17, 262-269.

Allcott, H. and M. Greenstone (2012), Is there an energy efficiency gap?, *Journal of Economic perspectives*, 26(1), 3-28.

Allcott, H. and N. Wozny (2014), Gasoline prices, fuel economy, and the energy paradox. *Review of Economics and Statistics*, 96(5), 779-795.

Avineri, E. and E. O. D. Waygood (2013), Applying valence framing to enhance the effect of information on transport-related carbon dioxide emissions, *Transportation research part A: policy and practice*, 48, 31-38.

Biresselioglu, M. E., M. D. Kaplan, and B. K. Yilmaz (2018), Electric mobility in Europe: A comprehensive review of motivators and barriers in decision making processes, *Transportation Research Part A: Policy and Practice*, 109, 1-13.

Brazil, W., S. Kallbekken, H. Sælen, and J. Carroll (2019), The role of fuel cost information in new car sales. *Transportation Research Part D: Transport and Environment* 74, 93–103.

Bubeck, S., J. Tomaschek, and U. Fahl (2016), Perspectives of electric mobility: Total cost of ownership of electric vehicles in Germany, *Transport Policy*, 50, 63-77.

Cameron, A. C. and P. K. Trivedi (2010), *Microeconometrics using stata*. Rev. ed. College Station, Tex.: Stata Press (A Stata Press publication).

Costa, C. M., J. C. Barbosa, H. Castro, R. Gonçalves, and S. Lanceros-Méndez (2021), Electric vehicles: To what extent are environmentally friendly and cost effective? Comparative study by european countries, *Renewable and Sustainable Energy Reviews*, 151, 111548.

Cox, B., C. L. Mutel, C. Bauer, A. Mendoza Beltran, and D. P. van Vuuren (2018), Uncertain environmental footprint of current and future battery electric vehicles, *Environmental science & technology*, *52*(8), 4989-4995.

Daziano, R.A. and M. Achtnicht (2014), Accounting for uncertainty in willingness to pay for environmental benefits, *Energy Economics* 44, 166-177.

Del Pero, F., M. Delogu, and M. Pierini (2018), Life Cycle Assessment in the automotive sector: A comparative case study of Internal Combustion Engine (ICE) and electric car. *Procedia Structural Integrity*, 12, 521-537.

Dumortier, J., S. Siddiki, S. Carley, J. Cisney, R. M. Krause, B. W. Lane, and J. D. Graham (2015), Effects of providing total cost of ownership information on consumers' intent to purchase a hybrid or plug-in electric vehicle, *Transportation Research Part A: Policy and Practice*, *72*, 71-86.

Egbue, O. and S. Long (2012), Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions, *Energy Policy* 48, 717-729.

Ellingsen, L. A. W., B. Singh, and A: H. Strømman, (2016), The size and range effect: lifecycle greenhouse gas emissions of electric vehicles, *Environmental Research Letters*, 11(5), 054010

European Environment Agency (2024), *Transport and mobility*, available at: https://www.eea.europa.eu/en/topics/in-depth/transport-and-mobility (published: January 18th, 2024, modified on January 19th).

Ferguson, M., M. Mohamed, C.D. Higgins, E. Abotalebi, and P. Kanaroglou (2018), How open are Canadian households to electric vehicles? A national latent class choice analysis with willingness-to-pay and metropolitan characterization, *Transportation Research Part D: Transport and Environment* 58, 208-224.

Greene, D. L. (2011), Uncertainty, loss aversion, and markets for energy efficiency, *Energy Economics*, *33*(4), 608-616.

Greene, W.H. (2012), *Econometric Analysis*, 7th ed., Pearson Education, Edinburgh Gate, Harlow.

Grigolon, L., M. Reynaert, and F. Verboven (2018), Consumer valuation of fuel costs and tax policy: Evidence from the European car market, *American Economic Journal: Economic Policy*, 10(3), 193-225.

Gutsche, G., and A. Ziegler (2019), Which private investors are willing to pay for sustainable investments? Empirical evidence from stated choice experiments. *Journal of Banking & Finance*, 102, 193-214.

Haaland, I., C. Roth, and J. Wohlfart (2023), Designing information provision experiments, *Journal of economic literature*, *61*(1), 3-40.

Hackbarth, A. and R. Madlener (2013), Consumer preferences for alternative fuel vehicles: A discrete choice analysis, *Transportation Research Part D: Transport and Environment* 25, 5-17.

Hackbarth, A. and R. Madlener (2016), Willingness-to-pay for alternative fuel vehicle characteristics: A stated choice study for Germany, *Transportation Research Part A: Policy and Practice* 85, 89-111.

Helmers, E. and Weiss, M. (2017), Advances and critical aspects in the life-cycle assessment of battery electric cars, *Energy and Emission Control Technologies*, 1-18.

Hensher, D.A. and W.H. Greene (2003), The mixed logit model: The state of praxis, T*ransportation* 30, 133-176.

Hensher, D.A., N. Shore, and K.E. Train (2005), Households' willingness to pay for water service attributes, *Environmental and Resource Economics* 32, 509-531.

Hensher, D.A. (2010), Hypothetical bias, choice experiments and willingness to pay, *Transportation Research Part B: Methodological* 44, 735-752.

Hensher, D.A., J.M. Rose, and W.H. Greene (2015), *Applied choice analysis*, 2nd ed., Cambridge: Cambridge University Press.

Hidrue, M.K., G.R. Parsons, W. Kempton, and M.P. Gardner (2011), Willingness to pay for electric vehicles and their attributes, *Resource and Energy Economics* 33, 686-705.

Kanberger, E.D. and A. Ziegler (2023), On the preferences for an environmentally friendly and fair energy transition: A stated choice experiment for Germany, *Energy Policy* 182, 113730.

Kanberger, E. D., and A. Ziegler. (2024), On the relevance of life-cycle CO_2 emissions for vehicle purchase decisions, *Transportation Research Part D: Transport and Environment* 126, 104031.

Krishna, G. (2021), Understanding and identifying barriers to electric vehicle adoption through thematic analysis, *Transportation Research Interdisciplinary Perspectives*, *10*, 100364.

McFadden, D. and K. Train (2000), Mixed MNL models for discrete response, *Journal of Applied Economics* 15, 447-470.

Leard, B. (2018), Consumer inattention and the demand for vehicle fuel cost savings, *Journal of choice modelling*, *29*, 1-16.

Li, W., R. Long, H. Chen, and J. Geng (2017), A review of factors influencing consumer intentions to adopt battery electric vehicles, *Renewable and Sustainable Energy Reviews*, 78, 318-328.

Liu, Z., J. Song, J. Kubal, N. Susarla, K. W. Knehr, E. Islam, and S. Ahmed, (2021), Comparing total cost of ownership of battery electric vehicles and internal combustion engine vehicles, *Energy Policy,* 158, 112564.

Long, Z., C. Kormos, R. Sussman, and J. Axsen (2021), MPG, fuel costs, or savings? Exploring the role of information framing in consumer valuation of fuel economy using a choice experiment, *Transportation Research Part A: Policy and Practice*, 146, 109-127.

Louviere, J.J., D.A. Hensher, and J.D. Swait (2000), *Stated choice methods: Analysis and applications*, 1st ed., United Kingdom: Cambridge University Press.

Lusk, E. J., M. Halperin, and F. Heilig (2011), A note on power differentials in data preparation between trimming and winsorizing. *Business Management Dynamics*, *1*(2), 23.

McFadden, D. and K. Train (2000), Mixed MNL models for discrete response, *Journal of Applied Economics* 15, 447-470.

Moon, S. and D. J. Lee (2019), An optimal electric vehicle investment model for consumers using total cost of ownership: A real option approach. *Applied Energy*, *253*, 113494.

Noel, L., A. Papu Carrone, A. Fjendbu Jensen, G. Zarazua de Rubens, J. Kester, and B.K. Sovacool (2019), Willingness to pay for electric vehicles and vehicle-to-grid applications: A Nordic choice experiment, *Energy Economics* 78, 525-534.

Pamidimukkala, A., S. Kermanshachi, J. M. Rosenberger, and G. Hladik (2023), Evaluation of barriers to electric vehicle adoption: A study of technological, environmental, financial, and infrastructure factors, *Transportation Research Interdisciplinary Perspectives*, *22*, 100962.

Rezvani, Z., J. Jansson, and J. Bodin (2015), Advances in consumer electric vehicle adoption research: A review and research agenda, *Transportation Research Part D: Transport and Environment* 34, 122-136.

Scarpa, R. and J.M. Rose (2008), Design efficiency for non-market valuation with choice modelling: How to measure it, what to report and why, *Australian Journal of Agricultural and Resource Economics* 52 (3), 253-282.

Shafique, M., and X. Luo (2022), Environmental life cycle assessment of battery electric vehicles from the current and future energy mix perspective, *Journal of Environmental Management*, 303, 114050

Staar, M. and A. Ziegler (2024), *Range anxiety and preferences for electric vehicles: New evidence from a stated choice experiment with randomized interventions*, unpublished manuscript.

Umweltbundesamt (2023a), Emissionen des Verkehrs, available from: https://www.umweltbundesamt.de/daten/verkehr/emissionen-des-verkehrs#verkehr-belastetluft-und-klima-minderungsziele-der-bundesregierung (published: April 28, 2023).

Umweltbundesamt (2023b), Klimaschutz im Verkehr, available from: https://www.umweltbundesamt.de/themen/verkehr-laerm/klimaschutz-im-verkehr#rolle (published: March 23, 2023).

Wietschel, M., M. Kühnbach, and D. Rüdiger (2019), *Die aktuelle Treibhausgasemissionsbilanz von Elektrofahrzeugen in Deutschland*, Fraunhofer ISI, Working Paper Sustainability and Innovation, No. S02/2019, 50.

Ziegler, A. (2012), Individual characteristics and stated preferences for alternative energy sources and propulsion technologies in vehicles: A discrete choice analysis for Germany, *Transportation Research Part A: Policy and Practice* 46, 1372-1385.

Tables

Table 1: Attributes and attribute levels across different vehicle types in the stated choice experiment

Attributes	Attribute levels	Vehicle types
Purchase price	70%, 80%, 90%, 100%, 110%, 120%, 130% of stated reference value (in Euro)	Conventional vehicle, plug-in hybrid electric vehicle, extended-range electric vehicle, pure electric vehicle
CO_2 emissions in use per 100 km	60%, 80%, 100%, 120%, 140% of reference value according to stated vehicle class (in kg)	Conventional vehicle, plug-in hybrid electric vehicle, extended-range electric vehicle
	0%, 30%, 60%, 80%, 100%, 120%, 140% of reference value according to stated vehicle class (in kg)	Pure electric vehicle
CO_2 emissions in production	60%, 80%, 100%, 120%, 140% of reference value according to stated vehicle class (in kg)	Conventional vehicle, plug-in hybrid electric vehicle, extended-range electric vehicle, battery electric vehicle
Range with fully charged battery	--	Conventional vehicle
	50 km, 75 km, 100 km, 150 km, 200 km	Plug-in hybrid electric vehicle
	100 km, 200 km, 250 km, 300 km, 400 km	Extended-range electric vehicle
	150 km, 200 km, 300 km, 450 km, 600 km	Battery electric vehicle
Range with full tank	450 km, 600 km, 750 km, 900 km, 1050 km	Conventional vehicle
	300 km, 400 km, 500 km, 600 km, 700 km	Plug-in hybrid electric vehicle
	50 km, 100 km, 150 km, 200 km, 250 km	Extended-range electric vehicle
	--	Battery electric vehicle
Time to recharge battery	--	Conventional vehicle
	15 minutes, 30 minutes, 60 minutes, 120 minutes	Plug-in hybrid electric vehicle
	30 minutes, 60 minutes, 120 minutes, 140 minutes	Extended-range electric vehicle
	45 minutes, 90 minutes, 180 minutes, 360 minutes	Battery electric vehicle
Time to refuel tank	3 minutes, 5 minutes, 6 minutes	Conventional vehicle
	2 minutes, 3 minutes, 5 minutes	Plug-in hybrid electric vehicle
	1 minute, 2 minutes, 3 minutes	Extended-range electric vehicle
	--	Battery electric vehicle
Fuel costs per 100 km	60%, 80%, 100%, 120%, 140% of reference value according to stated vehicle class (in Euro)	Conventional vehicle, plug-in hybrid electric vehicle, extended-range electric vehicle, battery electric vehicle

Table 2: Exemplary choice set in the stated choice experiment

<table>
<tr><td colspan="5">Let us start with the first set of choices. Which of the following four cars would you most likely choose?</td></tr>
<tr><td></td><td>Vehicle 1:
Battery electric vehicle [Mouse click: Car powered exclusively by one or more electric motors]</td><td>Vehicle 2:
Electric vehicle with range extender
[Mouse click: Car powered by a combination of one or more electric motors plus a small gasoline or diesel engine for range extension]</td><td>Vehicle 3:
Gasoline or diesel vehicle
[Mouse click: Car powered exclusively by a gasoline or diesel engine]</td><td>Vehicle 4:
Plug-in
hybrid vehicle
[Mouse click: Car powered by a combination of one or more small electric motors and a gasoline or diesel engine]</td></tr>
<tr><td>CO_2 emissions in use per 100 km</td><td>10.1 kg</td><td>11.2 kg</td><td>22.9 kg</td><td>21.2 kg</td></tr>
<tr><td>CO_2 emissions in production</td><td>5,000 kg</td><td>5,800 kg</td><td>6,000 kg</td><td>8,600 kg</td></tr>
<tr><td>Range with fully charged battery</td><td>300 km</td><td>400 km</td><td>-</td><td>150 km</td></tr>
<tr><td>Range with full tank</td><td>-</td><td>50 km</td><td>900 km</td><td>400 km</td></tr>
<tr><td>Time to recharge battery</td><td>180 minutes</td><td>60 minutes</td><td>-</td><td>120 minutes</td></tr>
<tr><td>Time to refuel tank</td><td>-</td><td>2 minutes</td><td>3 minutes</td><td>5 minutes</td></tr>
<tr><td>Fuel costs per 100 km</td><td>3.50 Euro</td><td>7.20 Euro</td><td>5.50 Euro</td><td>7.50 Euro</td></tr>
<tr><td>Purchase price</td><td>8,400 Euro</td><td>15,600 Euro</td><td>14,400 Euro</td><td>12,000 Euro</td></tr>
<tr><td>My choice</td><td>□</td><td>□</td><td>□</td><td>□</td></tr>
<tr><td colspan="5"></td></tr>
<tr><td colspan="5">Would you rather not choose any of the cars shown above and prefer another car instead?
□ Yes
□ No</td></tr>
</table>

Table 3: Frequencies for the stated choice of vehicle types

Conventional vehicle	Plug-in hybrid electric vehicle	Extended-range electric vehicle	Battery electric vehicle
Control group, 1128 respondents, six choice sets, 6768 observations (choices)			
2875 (42.48%)	1631 (24.10%)	823 (12.16%)	1439 (21.26%)
Frequencies for the first treatment group (total costs)			
First treatment group, 561 respondents, six choice sets, 3366 observations (choices)			
1338 (39.75%)	748 (22.22%)	463 (13.76%)	817 (24.27%)
Frequencies for the second treatment group (total emissions)			
Second treatment group, 554 respondents, six choice sets, 3324 observations (choices)			
1276 (38.39%)	808 (24.31%)	449 (13.51%)	791 (23.80%)

Table 4: SML estimation results in a mixed logit model for the choice among four vehicle types, 1,000 Halton draws, 2,243 respondents (1,128 in control group, 561 in treatment group 1, and 554 in treatment group 2), first six choice sets, 13,458 observations (choices)

Explanatory variables	Estimates (robust z-statistics)		Mean WTP estimates in Euro (based on purchase price)
	Mean of the parameter	Standard deviation of the parameter	
Purchase price (in 1000 Euro)	-0.078*** (-12.31)	--	--
Extended-range electric vehicle	-1.343*** (-11.06)	1.121*** (14.84)	-17,185.22
Plug-in hybrid electric vehicle	-0.795*** (-8.38)	1.781*** (25.79)	-10,169.10
Battery electric vehicle	-1.306*** (-8.47)	1.071*** (7.52)	-16,714.35
CO_2 emissions in use per 100 km (in kg)	-0.021*** (-5.37)	0.082*** (12.75)	-273.47
CO_2 emissions in production (in tons)	-0.029*** (-3.83)	0.080*** (5.09)	-371.99
Range with fully charged battery / full tank (in 100 km)	0.161*** (16.19)	0.213*** (14.39)	2,060.52
Time to recharge battery (in hours)	-0.193*** (-8.26)	0.364*** (9.94)	-2,469.06
Time to refuel tank (in minutes)	-0.036** (-2.42)	0.396*** (17.39)	-462.76
Fuel costs per 100 km (in Euro)	-0.136*** (-14.23)	0.239*** (19.60)	-1,740.74
Extended-range electric vehicle × Treatment 1	0.204 (1.19)	--	--
Plug-in hybrid electric vehicle × Treatment 1	-0.044 (-0.28)	--	--
Battery electric vehicle × Treatment 1	0.273 (1.29)	--	--
Purchase price × Treatment 1	-0.002 (-0.15)	--	--
Fuel costs per 100 km × Treatment 1	-0.005 (-0.25)	--	--
Extended-range electric vehicle × Treatment 2	0.193 (1.06)	--	--
Plug-in hybrid electric vehicle × Treatment 2	0.164 (1.02)	--	--
Battery electric vehicle × Treatment 2	0.316 (1.41)	--	--
CO_2 emissions in use per 100 km × Treatment 2	-0.005 (-0.61)	--	--
CO_2 emissions in production × Treatment 2	-0.003 (-0.18)	--	--

Note: * (**, ***) means that the appropriate estimated parameter is different from zero at the 10% (5%, 1%) significance level, respectively, explanatory variables: alternative-specific constants (base category: conventional vehicle), vehicle attributes, interaction terms between alternative-specific constants and the respective treatment dummy variables, interaction terms between the dummy variable for the first treatment and purchase price and fuel costs, interaction terms between the dummy variable for the second treatment and CO_2 emissions in use and CO_2 emissions in production

Table 5: SML estimation results in mixed logit models for the choice among four vehicle types considering split samples regarding the total number of kilometers traveled by car in the last twelve months, 1,000 Halton draws, 13,458 observations (choices)

Explanatory variables	**Less than or equal to 8,000 km**			**More than 8,000 km**			**More than 10,000 km**			**More than 12,000 km**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Mean of the parameter	Standard deviation of the parameter	Mean WTP estimates in Euro (based on purchase price)	Mean of the parameter	Standard deviation of the parameter	Mean WTP estimates in Euro (based on purchase price)	Mean of the parameter	Standard deviation of the parameter	Mean WTP estimates in Euro (based on purchase price)	Mean of the parameter	Standard deviation of the parameter	Mean WTP estimates in Euro (based on purchase price)
Purchase price (in 1000 Euro)	-0.081*** (-9.03)	--	--	-0.073*** (-8.21)		--	-0.072*** (-6.71)	--	--	-0.059*** (-5.25)	--	--
Extended-range electric vehicle	-1.075*** (-6.89)	1.168*** (12.06)	-13,273.53	-1.764*** (-9.29)	1.181*** (10.54)	-24,025.53	-1.800*** (-7.39)	1.141*** (7.94)	-25,048.36	-1.817*** (-6.56)	1.174*** (7.32)	-30,819.90
Plug-in hybrid electric vehicle	-0.648*** (-5.15)	1.844*** (19.61)	-8,009.62	-0.993*** (-6.94)	1.749*** (16.12)	-13,517.29	-0.989*** (-5.75)	1.742*** (13.50)	-13,764.25	-1.043*** (-5.33)	1.650*** (11.40)	-17,684.35
Battery electric vehicle	-1.014*** (-5.13)	-1.210*** (-5.98)	-12,531.39	-1.594*** (-7.03)	-0.628** (-2.43)	-21,705.90	-1.503*** (-5.44)	-0.172 (-0.18)	-20,921.44	-1.507*** (-5.08)	-0.159 (-0.54)	-25,567.19
CO_2 emissions in use per 100 km (in kg)	-0.019*** (-3.65)	0.088*** (10.85)	-237.57	-0.024*** (-3.98)	0.078*** (9.61)	-331.02	-0.028*** (-3.86)	0.076*** (8.19)	-394.29	-0.027*** (-3.29)	0.075*** (8.20)	-461.69
CO_2 emissions in production (in tons)	-0.032*** (-3.28)	0.067** (2.23)	-400.37	-0.023* (-1.89)	0.064 (1.29)	-312.03	-0.024 (-1.64)	0.098*** (3.44)	--	-0.025 (-1.61)	0.098*** (3.36)	--
Range with fully charged battery / full tank (in 100 km)	0.127*** (10.12)	0.201*** (9.77)	1,563.77	0.217*** (13.05)	0.223*** (10.41)	2,948.58	0.236*** (12.07)	0.223*** (9.17)	3,291.07	0.245*** (10.87)	0.222*** (7.52)	4,160.07
Time to recharge battery (in hours)	-0.177*** (-6.39)	0.365*** (9.04)	-2,190.60	-0.239*** (-5.43)	0.372*** (5.97)	-3,261.37	-0.250*** (-4.84)	0.367*** (5.17)	-3,474.26	-0.205*** (-3.09)	0.263** (2.46)	-3,483.03
Time to refuel tank (in minutes)	-0.036* (-1.80)	0.391*** (13.04)	-441.54	-0.019 (-0.83)	0.394*** (12.62)	--	-0.017 (-0.63)	0.410*** (10.94)	--	-0.041 (-1.29)	0.413*** (10.39)	--
Fuel costs per 100 km (in Euro)	-0.135*** (-10.64)	0.240*** (14.49)	-1,672.77	-0.138*** (-9.42)	0.233*** (12.45)	-1,878.26	-0.149*** (-8.46)	0.233*** (10.31)	-2,077.74	-0.140*** (-7.40)	0.216*** (8.83)	-2,371.92
Extended-range electric vehicle × Treatment 1	0.010 (0.05)	--	--	0.546** (1.97)	--	7,430.79	0.733** (2.33)	--	10,204.01	0.593 (1.59)	--	--
Plug-in hybrid electric vehicle × Treatment 1	-0.296 (-1.45)	--	--	0.263 (1.10)	--	--	0.408 (1.41)	--	--	0.363 (1.13)	--	--
Battery electric vehicle × Treatment 1	0.244 (0.92)	--	--	0.141 (0.44)	--	--	0.344 (0.89)	--	--	0.088 (0.20)	--	--
Purchase price × Treatment 1	-0.017 (-0.88)	--	--	0.007 (0.44)	--	--	0.009 (0.47)	--	--	0.004 (0.20)	--	--
Fuel costs per 100 km × Treatment 1	-0.009 (-0.34)	--	--	0.006 (0.22)	--	--	0.020 (0.60)	--	--	0.022 (0.59)	--	--

Table 5 (continued)

Extended-range electric vehicle × Treatment 2	0.022 (0.10)	--	--	0.433 (1.47)	--	--	0.695* (1.95)	--	9,672.30	0.652* (1.67)	--	11,058.38
Plug-in hybrid electric vehicle × Treatment 2	-0.056 (-0.25)	--	--	0.444* (1.87)	--	6,050.40	0.589** (2.09)	--	8,200.34	0.739** (2.40)	--	12,541.04
Battery electric vehicle × Treatment 2	0.126 (0.44)	--	--	0.418 (1.22)	--	--	0.538 (1.36)	--	--	0.600 (1.42)	--	--
CO_2 emissions in use per 100 km × Treatment 2	-0.012 (-1.16)	--	--	0.004 (0.33)	--	--	0.004 (0.27)	--	--	0.012 (0.73)	--	--
CO_2 emissions in production × Treatment 2	-0.001 (-0.06)	--	--	-0.006 (-0.24)	--	--	-0.013 (-0.43)	--	--	-0.012 (-0.39)	--	--
Number of observations	8,238	8,238	8,238	5,220	5,220	5,220	3,630	3,630	3,630	2,802	2,802	2,802

Note: * (**, ***) means that the appropriate estimated parameter is different from zero at the 10% (5%, 1%) significance level, respectively, explanatory variables: alternative-specific constants (base category: conventional vehicle), vehicle attributes, interaction terms between alternative-specific constants and the respective treatment dummy variables, interaction terms between the dummy variable for the first treatment and purchase price and fuel costs, interaction terms between the dummy variable for the second treatment and CO_2 emissions in use and CO_2 emissions in production.

Table 6: SML estimation results in mixed logit models for the choice among four vehicle types considering split samples regarding the 'planned mileage', 1,000 Halton draws, 9,258 observations (choices)

Explanatory variables	**Less than or equal to 10,000 km**			**More than 10,000 km**			**More than 15,000 km**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Mean of the parameter	Standard deviation of the parameter	Mean WTP estimates in Euro (based on purchase price)	Mean of the parameter	Standard deviation of the parameter	Mean WTP estimates in Euro (based on purchase price)	Mean of the parameter	Standard deviation of the parameter	Mean WTP estimates in Euro (based on purchase price)
Purchase price (in 1000 Euro)	-0.093*** (-9.09)	--	--	-0.061*** (-6.13)	--	--	-0.044*** (-3.25)		--
Extended-range electric vehicle	-1.212*** (-6.00)	1.158*** (10.05)	-13,002.40	-1.746*** (-7.57)	1.241*** (9.24)	-28,190.84	-2.128*** (-6.01)	-1.477*** (-6.50)	-48,818.65
Plug-in hybrid electric vehicle	-0.427*** (-2.70)	1.893*** (16.34)	-4,584.58	-1.000*** (-5.60)	1.872*** (14.01)	-16,195.50	-1.318*** (-4.60)	2.009*** (10.21)	-30,236.47
Battery electric vehicle	-1.119*** (-4.27)	1.308*** (6.69)	-12,011.60	-1.446*** (-5.35)	-0.660** (-2.04)	-23,243.45	-1.893*** (-4.65)	-0.679 (-1.60)	-43,420.72
CO_2 emissions in use per 100 km (in kg)	-0.020*** (-3.04)	0.089*** (8.48)	-209.95	-0.024*** (-3.18)	0.083*** (8.87)	-370.61	-0.029** (-2.49)	0.079*** (7.19)	-666.51
CO_2 emissions in production (in tons)	-0.027** (-2.23)	0.058* (1.70)	-290.65	-0.016 (-1.20)	-0.078*** (-2.81)	-260.58	-0.038* (-1.93)	0.074* (1.75)	-863.19
Range with fully charged battery / full tank (in 100 km)	0.169*** (10.41)	0.228*** (10.55)	1,815.41	0.238*** (12.09)	0.234*** (9.34)	3,902.03	0.268*** (8.55)	0.302*** (8.30)	6,151.58
Time to recharge battery (in hours)	-0.230*** (-5.49)	0.394*** (5.72)	-2,467.84	-0.247*** (-5.24)	0.411*** (6.96)	-4,104.43	-0.228*** (-2.94)	-0.410*** (-3.77)	-5,230.25
Time to refuel tank (in minutes)	-0.034 (-1.34)	0.406*** (10.93)	--	-0.030 (-1.09)	0.383*** (11.09)	--	-0.059 (-1.47)	0.357*** (5.87)	--
Fuel costs per 100 km (in Euro)	-0.146*** (-9.16)	0.247*** (13.22)	-1,568.67	-0.144*** (-8.07)	0.256*** (11.49)	-2,344.82	-0.156*** (-6.22)	0.262*** (8.06)	-3,571.95
Extended-range electric vehicle × Treatment 1	0.273 (1.04)	--	--	0.498 (1.54)	--	--	0.310 (0.68)	--	--
Plug-in hybrid electric vehicle × Treatment 1	-0.485* (-1.92)	--	-5,205.35	0.261 (0.92)	--	--	0.248 (0.53)	--	--
Battery electric vehicle × Treatment 1	0.334 (1.01)	--	--	-0.003 (-0.01)	--	--	-0.471 (-0.91)	--	--
Purchase price × Treatment 1	0.007 (0.30)	--	--	-0.021 (-1.29)	--	--	-0.068*** (-2.76)	--	-1,570.21
Fuel costs per 100 km × Treatment 1	-0.023 (-0.75)	--	--	0.014 (0.41)	--	--	-0.011 (-0.22)	--	--

Table 6 (continued)

Extended-range electric vehicle × Treatment 2	0.004 (0.01)	--	--	0.784** (2.37)	--	12,570.47	0.812* (1.72)	--	18,613.10
Plug-in hybrid electric vehicle × Treatment 2	-0.502* (-1.91)	--	-5,388.15	0.704** (2.49)	--	11,295.13	1.029** (2.37)	--	23,608.11
Battery electric vehicle × Treatment 2	-0.034 (-0.09)	--	--	0.588 (1.52)	--	--	1.060** (1.99)	--	24,314,00
CO_2 emissions in use per 100 km × Treatment 2	-0.012 (-0.91)	--	--	-0.008 (-0.60)	--	--	0.008 (0.44)	--	--
CO_2 emissions in production × Treatment 2	-0.001 (-0.03)	--	--	0.005 (0.19)	--	--	0.029 (0.76)	--	--
Number of observations	5,256	5,256	5,256	4,002	4,002	4,002	1,980	1,980	1,980

Note: * (**, ***) means that the appropriate estimated parameter is different from zero at the 10% (5%, 1%) significance level, respectively, explanatory variables: alternative-specific constants (base category: conventional vehicle), vehicle attributes, interaction terms between alternative-specific constants and the respective treatment dummy variables, interaction terms between the dummy variable for the first treatment and purchase price and fuel costs, interaction terms between the dummy variable for the second treatment and CO_2 emissions in use and CO_2 emissions in production.

Figures

Figure 1: Original screenshot of an exemplary choice set in the stated choice experiment