Modeling demand for electric vehicles: the effect of car users' attitudes and perceptions

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Abstract

The near arrival of electric vehicles on the car market generates a need for new models in order to understand and predict the impact it has on the current market shares. This research aims at providing contributions regarding several issues related to the evaluation of the demand for electric vehicles, i.e. related to the survey design, demand models and forecasting. In this paper we focus on the first of these three methodological issues. We present the design of a stated preference survey which will enable us to accurately model and predict demand for electric vehicles. Our aim is to propose choice situations involving electric cars and petrol-driven ones and in particular which include the respondents' own cars. An experimental design is set up in order to test the effect of the variation of several characteristics related to electric cars on vehicle preferences. Opinion and perception data are also collected to capture the impact of attitudinal variables on the purchase decision. This document also presents promising preliminary results of the estimation of the logit model with multiple alternatives.

Key words

Electric vehicles, discrete choice modeling, demand prediction, experimental design, transportation, attitudes and perceptions.

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Contents

1 Introduction and motivation

Electric vehicles have been proposed on the car market since many years, but in a rather marginalised way: only a few models with rechargeable batteries were sold. In the current situation where governments and public authorities are putting a huge pressure to reduce the environmental impact of fossil fuels, the demand for such vehicles is likely to increase. Hence, many car manufacturers are preparing to launch electric vehicles on the market in a large scale. This upcoming release might affect the market shares of the different fuels in a significant way.

Electric vehicles have major advantages compared to the petrol-driven ones: they do not emit carbon dioxyde and greenhouse gases and are silent. Nevertheless they also have a certain number of drawbacks: their range is limited, a full charge of the battery lasts up to 8 hours (before fast charges are available) and currently, few charging stations and infrastructures are available. The electric car user is hence compelled to charge the battery of his vehicle at home or at work only. These advantages and disadvantages can hence affect the individuals' purchase choices of cars in a positive or negative way. For instance, the environmentally friendly aspect of an electric vehicle is likely to attract individuals concerned by ecology, whereas its limited range can discourage prospective car buyers.

In order to evaluate up to what extent the arrival of electric vehicles impacts on the car market, new demand models need to be developed. This raises challenges which are related to several topics, namely in the data collection, in the specification of new demand models and in the application of the latter. We plan to address them in this research. Regarding data collection techniques we aim at recreating choice situation contexts as close as possible to reality by customizing them according to the respondents' profiles. On the modeling side, we wish to capture individuals' attitudes and perceptions of various vehicle types and assess their impact on choice. Finally, we want to account for population heterogeneity and current market properties when we forecast market shares of different vehicle types.

So far several stated preference surveys have been conducted to collect data on interest for alternative-fuel or electric vehicles in order to forecast their demand. Train (1980), Brownstone et al. (1996) and Alvarez-Daziano and Bolduc (2009) present choice situation contexts involving vehicles with diversified engine types, including standard, alternative-fuel and/or electric vehicles. In particular, Brownstone et al. (1996) first collect data on the vehicles owned by the respondent's household and then design choice situation contexts based on the information the latter reported.

Discrete choice methodology has been widely used in literature in order to analyze the demand for alternative-fuel or electric vehicles, but in diverse ways. Train (1980) analyzes the behavior of individuals in two situation contexts, namely in a 'most likely case' and an 'optimistic case' involving different types of alternative-fuel or electric vehicles in each case. Brownstone et al. (1996) involves vehicle transaction decisions, that is, adding a vehicle into the respondent's household, replacing or disposing of an existing vehicle. Schiraldi (2010) also proposes a model of vehicle transaction, but which involves a temporal dimension and includes both new and used car markets. Alvarez-Daziano and Bolduc (2009) apply a hybrid choice model (Ben-Akiva et al., 2002) in order to analyze demand for electric vehicles. In particular, they assess the effect of individuals' environmental concern on the vehicle preferences.

Forecasting analysis is fundamental to predict the future market share for electric vehicles. This issue has been addresed by Train (1980) and Brownstone et al. (1996) among others in the case of demand for alternative-fuel and electric vehicles. The particularly interesting feature of Train (1980) is the correction of the predicted market shares by the proportion of cars in each segment of the real market.

In order to tackle the methodological issues raised in the context of the upcoming release of electric vehicles on the market, a stated preference survey is designed. We address the data collection issue of presenting personalized choice situation contexts to the respondent by including a vehicle owned by his household. We then define petrol-driven and electric alternatives to the latter such that they match its segment. Our motivation for this is to recreate a choice situation context as close as possible to reality. The attributes of the alternatives are characteristics such as the purchase price, the costs of usage or the maintenance costs. For the electric car in particular, characteristics related to the battery are also shown. The purpose of introducing these variables is to evaluate the respondents' sensitivity to their variations.

Our assumption regarding modeling is that latent variables capturing attitudes or perceptions of individuals have a non-negligible impact on choice. This effect can be assessed via a hybrid choice model (see Walker (2001), Walker and Ben-Akiva (2002) and Ben-Akiva et al. (2002)). In the stated preference survey we collect two types of indicators of attitudinal variables: ratings of statements regarding several topics such as their perception of an electric vehicle as an ecological solution or attitude towards new technologies, and freely reported adjectives characterizing their perception of different vehicle types.

The estimation results of the discrete choice model enable us to forecast the future market shares of electric vehicles. Obtaining shares which reflect the market in a realistic way is a difficult task. We approach that problem by accounting for the distribution of purchase prices and fuel costs in the current market and by correcting for the bias resulting from the over- or under-representation of some population segments in the sample relatively to the target population.

In this paper we focus on the first of the three objectives raised for this research, i.e. the design of a stated preference survey involving realistic choice contexts which enables us to collect accurate preference data. Some preliminary modeling results are also presented. This survey is conducted in the framework of a collaborative project between Renault Switzerland and EPFL's Transportation Center. The electric vehicles proposed in the stated preference experiments are sub-compact and compact cars of the electric product line which Renault is going to release in a very near future. The document is constructed as follows.

Section 2 describes the data collection procedure, including a survey overview, a description of the respondents that were sampled, an explanation of the sampling protocol and finally a detailled description of the structure of the survey. Section 3 presents the experimental design used to build the survey as well as a brief explanation of the logit model. Section 4 describes the specification of the latter as well as some estimation results. Section 5 presents a conclusion on the main outcomes of the model and section 6 outlines the future steps planned for this research work.

2 Data collection

A survey was set up at the beginning of year 2011 in order to collect data on people's preferences towards different types of vehicles. This section describes the type of survey, called *stated preference survey*, the panel of respondents, as well as the sampling protocol. It finally presents the complete structure of the questionnaire.

2.1 Survey scope

The type of survey allowing for the evaluation of demand in hypothetical choice contexts, as in the case of demand for electric cars, is a stated preference survey. Such survey was typically designed in order to apply discrete choice methodology.

The core idea of that type of survey is to present hypothetical choice situations to the respondents. In our case, the following vehicles are proposed to each respondent:

- A vehicle that the respondent's household currently owns;
- An analogous model from Renault, if the respondent's vehicle is from a different brand;
- A similar model in the electric product line from Renault.

By including each respondent's vehicle in the choice situation, the survey shows realistic choice situations, despite the fact that the context is hypothetical. This involves a data collection in two phases though: the first time to gather information about the cars in the respondents' households and the second time to present choice situations that are adapted to the profile of each participant of the survey.

The corresponding online survey was conducted in collaboration with the market research institute GfK Switzerland.

2.2 Target groups

The sample of the survey consists of the following four types of respondents:

Recent buyers: Individuals who bought a new car in the last three years.

Prospective buyers: Individuals who plan to buy a new car in the next six months.

Current and future Renault customers: Individuals who already own a Renault car or who pre-ordered an electric vehicle in the Renault product line.

EV-fans: Individuals who joined the Renault newsletter on electric vehicles.

The four groups were selected in order to be representative of the population which has faced or is likely to have to face a purchase choice between a conventional vehicle and an electric one.

The two first groups, i.e. the recent and prospective buyers were sampled by GfK Switzerland till they both reached a size of at least 150 respondents. For the third and fourth groups, i.e. the current and future Renault customers, and the EV-fans, the questionnaire was sent to a list of addresses provided by Renault, but the number of responses was not guaranteed as for the two first sample groups. The number of responses after phase I and phase II are reported in Table 1, for each sample group.

	Group name	Sent	Phase I		Phase II		Phase I vs phase II
			Number	Rate	Number	Rate	Rate
1	Recent buyers	3006	150	10.0%	141	9.4%	94.0%
2	Prospective buyers		151		141		93.4%
3	Renault customers	1042	168	16.1%	139	13.3%	82.7%
4	EV-fans	656	197	30.0%	172	26.2%	87.3%
	Total	4704	666	14.2%	593	12.6%	89.0%

Table 1: Number of online questionnaires sent, numbers and rates of responses after phase I and phase II, and between both phases, for each sample group.

Table 1 shows that the response rate after phase I was much higher for respondents of sample group 4. Indeed the latter was about 30.0% for that group. This can be explained by the fact that subscribers to a newsletter on electric vehicles might be more interested in a questionnaire about electric vehicles than recent or prospective buyers of vehicles with classical engines, or Renault customers. After phase II, we obtained the highest response rate for that group as well.

Let us note that the response rate between the two phases is very high for all four target groups. It is indeed ranging from 82.7% to 94.0%.

2.3 Sampling protocol

The respondents to the stated preference survey were sampled in order to be representative of three socio-economic characteristics:

- The language region (German, French or Italian);
- The gender (male or female);
- The age category (18-35 years, 36-55 years or 56-74 years).

Gender and age are classical socio-economic variables for which we wish the survey sample to match the real population proportions. But in this particular survey design, we also targeted sample representativity of the three main language regions. Former studies have indeed shown that inhabitants of different language regions do not show the same mobility habits (see Bierlaire et al. (2006), Hurtubia et al. (2010) and Atasoy et al. (2010)).

The targeted proportions for each socio-economic group, as well as the obtained ones are shown in Table 2. For the language group and the age category, no obvious difference occurs between the targeted proportions and the ones that were obtained at the end of phase I. A difference in the response rates between the two genders is noticeable: more men answered to the survey than women. Between phase I and phase II the proportions did not change much, which could be expected, as the total response rate between the two phases was very high (89.0%).

Variable	Level	Targeted rate	Rate phase I	Rate phase II
Language	German	72.5%	67.3%	67.8%
	French	23.0%	27.2%	26.6%
	Italian	4.5%	5.56%	5.56%
Gender	Male	49.4%	74.0%	74.2%
	Female	50.6%	26.0%	25.8%
Age category	18-35 years	33.6%	23.0%	21.8%
	36-55 years	41.6%	51.8%	52.6%
	56-74 years	24.8%	25.2%	25.6%

Table 2: Targeted and real response rates in each socio-economic group (language, gender and age) after phase I and phase II. The targeted rates are the Swiss proportions of each group.

2.4 Structure of the stated preference survey

As already mentioned in section 2.1, the stated preference survey is structured in two phases due to the complexity of generating personalized choice situations. In this section, the structure of both phases is explained in details.

2.4.1 Phase I

Phase I consisted of three major sections:

Characteristics of the respondent's car(s): The respondent is required to report the characteristics of all cars in his household, that is, their makes, models, types of fuel, motorisations and versions, as far as he knows them. The information reported in this section will enable us to create personalized choice situations that will be shown in phase II questionnaire.

Socio-economic information: The respondent is asked to answer some standard socio-economic questions, such as gender, age, education, etc. This will be used in the discrete choice model in order to uncover the population segments which express different vehicle preferences.

Mobility habits: The last section of the first phase of the stated preference survey consists of questions on the respondent's mobility habits. For example, the respondent has to report the length of his daily trips or the transport mode(s) he uses for some particular types of trips. Our assumption is that different mobility habits, such as the use of public transports, can induce preferences for different vehicles types.

2.4.2 Phase II

Phase II was launched two weeks after phase I and consisted of the three following parts:

Opinions on five topics related to electric vehicles: In order to model more complex underlying attitudes that might affect the decision maker's choice to purchase an electric vehicle, sentences related to five different topics were shown to him. For each of the statements, the respondent was asked to rate his agreement on a five-point *Likert scale*, ranging from 'Total disagreement' to 'Total agreement'. Five sentences were shown per theme. The five topics were the following:

The ecological perception of the electric vehicle: Assuming that individuals concerned by ecology are more likely to be interested in a transport mode with a more environmentally friendly propulsion system, statements related to their general perception of ecology were included in the questionnaire. An example of such sentences is given hereafter:

> *I prefer driving a car with a powerful engine than a car that emits little carbon dioxyde.*

The attitude towards new technologies: An electric car represents the future generation of vehicles: it involves a novel type of engine, which might attract customers that are interested in new technologies. Hence, statements related to the latter topic were shown in the survey. For example, the following statement was presented to the respondents:

> *I never travel without a GPS.*

The reliability, security and use of an electric vehicle: Some population segments might be reluctant to purchase an electric vehicle, fearing that the technology of the latter could not entirely be trusted, due to its novelty. Statements on the reliability, security or general use of an electric vehicle were hence included into the survey. An example of such sentences is reported below:

> *The low autonomy of the battery is a real disadvantage.*

The importance of design: As a new technology of propulsion involves a new car design, statements related to the importance of the car's appearance were included. For example, the following sentence could be shown:

> *The capacity of transporting persons and luggages matters more in the choice of a car than its appearance.*

The perception of leasing: Renault plans to rent the battery of the electric vehicles which are going to be released soon. The persons used to having a leasing contract might be less concerned by this decision than the ones that generally prefer to pay the total amount of a car they purchase. This topic is also covered in the questionnaire by a series of statements. An example of such statement is reported below:

> *Leasing is the optimal solution for me as it enables me to change car frequently.*

We plan to use the ratings collected on these statements as indicators of individuals' attitudes towards the five themes presented above. These attitudes are assumed to have an important impact on the purchase choice and can be modeled using a hybrid choice model.

Perceptions of four categories of vehicles: In the next section of phase II questionnaire, respondents had to report adjectives that described best a certain type of vehicle according to them. For each of these categories, three adjectives were asked. The purpose of this particular part of the survey was to collect data on the respondents' perceptions of the following types of vehicles:

- Vehicles with a classical combustion engine;

- Hybrid vehicles;
- Electric vehicles;
- Renault vehicles.

These data are particular, as they consist of words freely reported by respondents. Their interest is that they are very diverse across respondents and provide a great amount of information about the latter's perceptions of different vehicle types. We are indeed assuming that these perceptions have a non-negligible impact on people's vehicle choices. As for the attitude data collected in the previous section, we plan to capture this effect via a hybrid choice model.

Choice situations: This section builds the core of the entire survey. We wish indeed to be able to explain and predict each individual's preference towards a particular type of vehicle, i.e. a standard petrol- or diesel-driven car versus an electric one. Five choice situations are shown to each respondent. The aim of each choice situation is to show three different cars to the respondent: his own car, the analogous model of the Renault brand (also with combustion engine) and finally a similar model in the Renault product line of electric cars. Such a choice situation experiment enables us to define nests of alternatives, which could be 'petrol-driven' vehicles for the respondent's own vehicle and the analogous petrol-driven vehicle by Renault, or 'Renault alternatives' for the Renault car with combustion engine which is analogous to the respondent's current vehicle and the electric model. It eventually allows for the application of nested and/or cross-nested logit models.

Nevertheless it is not always possible to present this exact three-alternative configuration as the respondent may own a Renault model, not have any car at all or have a too special car for which it is difficult to identify an analogous Renault model with a combustion engine. The three possible types of choice situations are summarized in Table 3.

Type	Alternatives	Case
1	Respondent's car Analogous petrol-/diesel-driven Renault model Similar electric car from Renault brand	The respondent's household owns a rather standard car from a non-Renault brand.
2	Respondent's Renault car Similar electric car from Renault brand	The respondent's household owns a Renault car.
3	Renault car with combustion engine Similar Renault electric car	The respondent's household does not own any car or has only very special ones.

Table 3: Types of possible choice situations in phase II questionnaire. Column 'Alternatives' shows the different types of vehicles which are presented to the respondent and column 'Case' gives the circumstance to which each choice situation applies.

Let us note that contrary to choice situations types 1 and 2 of Table 3, choice situation type 3 is not personalised to the respondent's profile. Nevertheless, it shows classical settings involving a petrol-driven subcompact or compact car versus their respective analogous models in the electric product line.

An example of choice situation type 1, i.e. for a respondent with a standard non-Renault car, is shown in Table 4 below. Each vehicle is characterized by a list of attributes defined in collaboration with Renault. The latter include make, model, type of fuel, purchase price, possible governmental incentive, maintenance costs, fuel/electricity costs and battery lease.

Characteristics	**Your vehicle**	**Renault vehicle with combustion engine**	**Renault electric vehicle**
Make	Audi	Renault	Renault
Model	A4	Laguna	Fluence
Fuel	Petrol	Petrol	Electricity
Purchase price (in CHF)	42′400	37′200	56′880
Incentive (in CHF)	0	0	−1′000
Total purchase price (in CHF)	42′400	37′200	55′880
OR: Monthly leasing price (in CHF)	477	399	693
Maintenance costs (in CHF for 30′000 km)	850	850	425
Cost in fuel/electricity for 100 km (in CHF)	11.70	13.55	3.55
Battery lease (in CHF per month)	0	0	125
	☐	☐	☐

Table 4: An example of choice situation (type 1) presented to respondents with a standard non-Renault car in their household. The respondent had to tick the box below the column corresponding to the vehicle he would choose if he had to change his car at present.

Table 4 is an example of personalized choice situation for an individual owning a particular car model, an Audi A4. The steps that were followed in order to build the table cells are explained in details below:

1. The make, model and fuel type of the respondent's car are obtained from the vehicle description filled in during phase I.
2. The purchase price and the fuel cost of driving 100 km relative to the respondent's car are inferred from a data base containing information on the vehicles currently released on the market.
3. The definitions of the analogous petrol-driven and electric vehicles from the Renault brand are inferred from the information on the respondent's car given in phase I, such that the segments of the respondent's car, the analogous Renault model with a combustion engine and the electric vehicle match at best.

4. The purchase price and the fuel cost of driving 100 km relative to the Renault petrol-driven model are inferred from the same car data base as in 2.
5. The maintenance costs for the three vehicles, i.e. the respondent's vehicle, the analogous petrol-driven Renault model and the similar electric Renault model are fixed to 850 CHF, 850 CHF and 425 CHF, respectively. The average maintenance cost for vehicles with a combustion engine is set to 850 CHF for 30′000 km according to an evaluation performed using information given on the website of Touring Club Suisse (TCS), a swiss repair service for vehicles. For standard petrol-driven vehicles, the maintenance works include the change of the brake fluid, the air filter and the oil. For electric vehicles, we make the working hypothesis that the maintenance cost is half that price. The governmental incentives for all vehicles with combustion engines are set to 0 CHF, as no such help currently exists in Switzerland. The battery lease is fixed to 0 CHF for all petrol-driven vehicles and is displayed against the battery lease of the electric vehicle for comparison purposes.
6. For the electric vehicle, the purchase price, the governmental incentive, the cost of driving 100 km and the battery lease are subject to a fractional factorial design, which will be explained in details in subsection 3.1.
7. For all three vehicles, the total purchase price, that is, the purchase price minus the governmental incentive, and the alternatively suggested monthly leasing price are inferred from the purchase price and leasing conditions given by Renault.

3 Methodology

Here we present both the survey methodology and the modeling framework.

3.1 Experimental design

In order to analyze the respondents' sensitivity to characteristics of electric cars such as the purchase price, a possible incentive from the government, the operating costs or the battery lease when they are facing a choice, an experimental design is considered. For each characteristic, we select realistic ranges of values. The goal is then to vary these characteristics in a systematic way withing these ranges, and measure their impacts on the choice of an electric vehicle.

In this section, the creation of this experimental design is explained, as well as the *sampling procedure*, i.e. the way the different levels of the design variables are selected to create a choice experiment.

3.1.1 Design fractionation

The experimental design is based on the four following variables:

Purchase price: As the price is the first key factor when purchasing a car, it is important to model the responsiveness of individuals to this variable when they face a choice involving electric vehicles, as the latter are not yet on the market. Due to the novelty of the technology, electric cars are likely to be more expensive than the ones with combustion engines. Hence the price of an electric car was defined as the price of the respondent's car plus an amount of 5′000 CHF. Moreover, the resulting price was multiplied by one of the three levels 0.8, 1.0 or 1.2, in order to obtain a large enough range of variability in the data such that elasticities can be computed.

Incentive: A possible reduction of the purchase price of electric vehicles through a governmental incentive could promote their use. It is hence important to know how large this incentive should be.

Cost of 100 km: One advantage of the electric vehicles over the petrol- or diesel-driven ones is a noticeable lower cost of fuel. Charging the battery of an electric car in order to perform a distance of 100 km is much cheaper than refueling the tank of vehicles with standard combustion engines, to perform the same distance. Due to the variability of the energy prices in Switzerland, several levels were elaborated for the cost of use of electric vehicles (measured for 100 km of driving).

Battery lease: As the batteries of the electric vehicles on which the study is based will be leased to customers, this generates an additional monthly cost for their future users. Hence, it is relevant to analyse how large the battery lease should be so that it does not result in a loss of interest for the electric vehicles.

The numerical values of the levels of the variables described above are reported in Table 5.

Level	Purchase price P	Incentive I	Cost C of 100 km	Battery lease L
1	$(P_{\text{own}} + 5'000) \cdot 0.8$	-0 CHF	1.70 CHF	85 CHF
2	$(P_{\text{own}} + 5'000) \cdot 1$	-500 CHF	3.55 CHF	105 CHF
3	$(P_{\text{own}} + 5'000) \cdot 1.2$	$-1'000$ CHF	5.40 CHF	125 CHF
4	-	$-5'000$ CHF	-	-

Table 5: Levels of the variables related to the electric vehicles which are subject to an experimental design, that is, the purchase price P, based on the price P_{own} of the respondent's car, a possible governmental incentive I, the cost C of driving 100 km and the battery lease L.

Knowing the values of the levels of each variable of Table 5, let us compute the size of the experimental design. The purchase price P, the cost C of 100 km and the battery lease L have 3 levels and the incentive I has 4 levels. This generates a *full factorial design* of size

$$S = 3 \times 3 \times 3 \times 4 = 108.$$

This implies that 108 different *sequences of levels* can be drawn when generating each choice situation. Before the complete survey was launched, at least 100 valid questionnaires per respondent group were expected at the end of phase II[1], implying a total of $4 \times 100 = 400$ questionnaires at minimum. Each respondent had to face 5 choice situations, hence giving a total of $400 \times 5 = 2'000$ answers to the choice situations of all questionnaires. For significance purposes, we set the number of answers per sequence of levels to 30. This lead to a design size of

$$2'000/30 \cong 67.$$

In other words, the number of sequences of levels should be reduced from 108 to a value close to 67.

[1] In reality, we obtained a higher response rate than expected (see Table 1).

In order to reduce the full factorial design, we need to take a fraction of it. Factors with different numbers of levels hence must be transformed into two-levels factors (Montgomery, 2001). Precisely, a three-level or four-level variable becomes two two-level variables, therefore giving a full factorial design of size 2^8. The above computation showed that the size of the design should be close to 67. The power of 2 which is the closest to 67 is $2^6 = 64$, implying that a 1/4 fraction of the full factorial design of size 2^8 should be taken.

In the *fractional factorial design* of size 2^6, two out of the four-factor interactions are confounded, hence giving a reduced design of resolution V.

Let us note that the fractional factorial design is orthogonal in the main effects.

3.1.2 Sampling strategy

In section 2.2, the four groups of respondents of the survey were introduced. Due to the differences between these types of individuals, some undesired variability could occur in their answers to the choice situations. For example, members of the newsletter on electric vehicles could have a priori preferences for the electric alternative than individuals who recently bought a car. This source of variability can be avoided by performing *blocking*.

We considered the four following blocks, corresponding to the target groups of section 2.2.

Though blocking allows for reducing variability across respondent groups, it has a noticeable drawback: the effect of some high-order interactions becomes indistinguishable. In this survey, two interactions of order three are considered in order to form the blocks. They consist of two two-level factors and each pair of values from these two variables generates one of the four blocks. More information on the blocking procedure is given in chapter 6 of Montgomery (2001).

Let us now consider the sequences of levels generated by the blocking procedure for one of the respondent groups, e.g. the recent buyers. These are reported in Table 6.

	Incentive	Price	Fuel cost of 100 km	Battery lease
1	0	0.80	1.70	85
2	0	1.00	3.55	125
3	0	1.00	5.40	105
4	0	1.20	3.55	105
5	−500	0.80	1.70	125
6	−500	1.00	3.55	85
7	−500	1.00	5.40	105
8	−500	1.20	3.55	105
9	−1000	0.80	3.55	105
10	−1000	1.00	5.40	105
11	−1000	1.00	3.55	85
12	−1000	1.20	1.70	125
13	−5000	0.80	3.55	105
14	−5000	1.00	5.40	105
15	−5000	1.00	3.55	125
16	−5000	1.20	1.70	85

Table 6: Sequences of four levels sampled for the respondents of group 'recent buyers'.

Table 6 shows the sequences of levels that will be sampled when creating the choice situations for the recent buyers. For each choice situation of a repondent n, the following *sampling strategy* is used:

1. Selection of the sequences of levels relative to respondent n's sample group, i.e. the recent buyers in this example.

2. Sampling with replacement of the sequences of levels of individual n between the respondents.

3. Sampling without replacement of the sequences of levels that will be used in the construction of the choice situations relative to individual n.

In Table 6 the intermediate levels of variables 'Price', 'Fuel cost of 100 km' and 'Battery lease' are sampled twice more often than the two other levels. Therefore, this will generate a bias in the answers to the choice situations if a simple random sampling is used for points 2 and 3. In order to correct for this bias, we defined a new sampling strategy, that aims at selecting each level as often as the others. For example, level 0.80 of variable 'Price' should be sampled with probability 1/3, level 1.00 with probability 1/3 and level 1.20 with probability 1/3, instead of having probabilities 1/4, 1/2 and 1/4 with a random sampling.

To perform this strategy, we need to compute *sampling weights* for each sequence of levels. This calculation is performed by applying the *iterative proportional fitting (IPF)* algorithm. The latter is generally used to correct for oversampled or undersampled observations in a sample with respect to the real socio-demographic structure of the population. We apply it here in a different context, i.e. we aim at finding sampling weights for a stated preference survey.

3.2 Discrete choice model

In this section we present the methodology to model demand for electric vehicles.

The type of model we used in a preliminary modeling phase is a *logit model with multiple alternatives*. Its purpose is to understand the effect of attributes of alternatives on the choice as well as capturing heterogeneity of preferences in the population. In such model, each alternative i is associated with a utility function given as follows, for each respondent n:

$$U_{in} = V_{in} + \varepsilon_{in}, \qquad \text{with } \varepsilon_{in} \sim \text{EV}(0,1) \tag{1}$$

Equation (1) is made of two terms: a deterministic term V_{in} which must be determined by the modeler and a random term ε_{in}, which captures what cannot be observed from the available data.

The deterministic part can be described as a function $V : \mathbb{R}^{2p} \longrightarrow \mathbb{R}$ of explanatory variables X_{in}, which consist of characteristics of the alternatives and socio-economic information of the individuals, and of a p-dimensional vector of parameters β. It can be written as follows:

$$V_{in} = V(X_{in}; \beta). \tag{2}$$

The random part is a random variable ε_{in} with a extreme value distribution of location parameter 0 and scale parameter 1.

For some individuals, part of the alternatives might not always be available. Hence, we need to define a choice set C_n for each person n which contains the alternatives i that are available for n.

For each individual n we are interested in computing the probability that each alternative i is selected. In the case of a logit model, this probability is given by the following formula:

$$P_n(i|C_n) = \frac{e^{V_{in}}}{\sum_{j=1}^{J_{C_n}} e^{V_{jn}}},$$

where J_{C_n} is the number of available alternatives for C_n.

In order to identify which variables have an effect on inviduals choices, we need to estimate the vector β of parameters on the collected data. This is performed by maximum likelihood estimation, where the following likelihood function $\mathcal{L}$ is maximized:

$$\mathcal{L} = \prod_{n=1}^{N} \prod_{i=1}^{J_{C_n}} P_n(i|C_n)^{y_{in}},$$

where y_{in} is an indicator that respondent n chose alternative i. Mathematically, variable y_{in} is defined as follows:

$$y_{in} = \begin{cases} 1 & \text{if } U_{in} = \max_j U_{jn} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

The vector of parameters β is estimated using the extended version of software BIOGEME (Bierlaire, 2003), which is described in Bierlaire and Fetiarison (2009).

4 Model specification and estimation

This section presents a preliminary vehicle choice model that was calibrated on the data described in section 2. The type of model is a logit model with multiple alternatives (see section 3.2 for more details on the methodology).

The choice respondents are facing is a vehicle choice between their own current car, a possible analogous petrol- or diesel-driven car of brand Renault and finally a similar electric car of brand Renault too.

The choice sets vary across respondents. For an individual n owning car from a different brand than Renault, the choice set $C_n^{\text{non-Renault}}$ is defined as n's own car, the analogous petrol-driven model from the Renault brand and a similar electric car:

$$C_n^{\text{non-Renault}} = \{\text{own, Renault, electric}\}.$$

For an individual m owning a Renault car, the choice set C_m^{Renault} is defined as m's own car (of brand Renault) and a similar electric car:

$$C_m^{\text{Renault}} = \{\text{own, electric}\}.$$

The specifications of the deterministic parts V_{own}, V_{Renault} and V_{elec} of the utility functions of these three alternatives are represented by Table 7. For each alternative i, each deterministic utility V_i is given by the inner product between the left-hand column 'Utilities' and the column corresponding to i. For instance, deterministic utility V_{own} is given by the inner product between column 'Utilities' and column 'Own car'.

Utilities	Own car	Renault car	Electric car
ASC_{own}	1	-	-
ASC_{Renault}	-	1	-
$\beta_{\text{price}_{\text{own}}}$	$\text{price}_{\text{own}}$	-	-
$\beta_{\text{price}_{\text{Renault}}}$	-	$\text{price}_{\text{Renault}}$	-
$\beta_{\text{price}_{\text{elec}}}$	-	-	$\text{price}_{\text{elec}}$
$\beta_{\text{UseCostPetrol}}$	$\text{UseCostPetrol}_{\text{own}}$	$\text{UseCostPetrol}_{\text{Renault}}$	-
$\beta_{\text{UseCostElec}}$	-	-	UseCostElec
$\beta_{\text{BatteryHigh}}$	-	-	BatteryHigh
$\beta_{\text{IncentiveHigh}}$	-	-	IncentiveHigh
$\beta_{\text{PT}_{\text{own}}}$	PT	-	-
$\beta_{\text{PT}_{\text{Renault}}}$	-	PT	-
$\beta_{\text{Income}_{\text{own}}}$	Income	-	-
$\beta_{\text{Income}_{\text{Renault}}}$	-	Income	-
$\beta_{\text{NbCars}_{\text{own}}}$	NbCars	-	-
$\beta_{\text{NbCars}_{\text{Renault}}}$	-	NbCars	-
$\beta_{\text{SitFam}_{\text{own}}}$	SitFam	-	-
$\beta_{\text{SitFam}_{\text{Renault}}}$	-	SitFam	-
$\beta_{\text{Age}_{\text{own}}}$	Age	-	-
$\beta_{\text{Age}_{\text{Renault}}}$	-	Age	-

Table 7: Specification table of the utilities

In the case where the respondent owns a Renault car, alternative V_{Renault} is made unavailable and is not included in the computation of the likelihood function.

The assumptions regarding the utility functions are the following:

- All three utility functions contain a constant term, namely ASC_{own}, $\text{ASC}_{\text{Renault}}$ and ASC_{elec}, but the constant for the electric alternative, i.e. ASC_{elec}, is fixed to 0.
- In each function, the purchase price of the vehicle was also included. The purchase price, i.e. $\text{price}_{\text{own}}$, $\text{price}_{\text{Renault}}$ and $\text{price}_{\text{elec}}$, was included in all alternatives with alternative specific parameters. For the petrol-driven alternatives, the refueling costs $\text{UseCostPetrol}_{\text{own}}$ and $\text{UseCostPetrol}_{\text{Renault}}$ were also introduced with a generic coefficient. In particular, variables $\text{UseCostPetrol}_{\text{own}}$ and $\text{UseCostPetrol}_{\text{Renault}}$ were included via the following piecewise-linear functions:

$$\text{UseCostPetrol}_{\text{own}} = \min(\text{Cost100}_{\text{own}}, 15)$$

$$\text{UseCostPetrol}_{\text{Renault}} = \min(\text{Cost100}_{\text{Renault}}, 15),$$

  where $\text{Cost100}_{\text{own}}$ and $\text{Cost100}_{\text{Renault}}$ denote the cost (in CHF) for driving 100 km with the car owned by the respondent and the petrol-driven car from Renault, respectively. Our assumption was that for vehicles with a use cost of more than 15 CHF per 100 km, i.e. with engines with high consumptions, the use cost does not affect any more the utility of petrol-driven cars in a negative way.

- Some other design variables were also included in the utility of the electric car, that is the highest level of cost of usage UseCostElec (equal to 5.40 CHF), the highest level of battery lease BatteryHigh (equal to 125 CHF) and the highest level of governmental incentive IncentiveHigh (equal to 5′000 CHF).

- In the utility functions related to the petrol-driven alternatives, socio-economic variables were also included, in order to capture the heterogeneity within the population regarding the choice of electric vehicles versus standard vehicles. Variables FamSit, PT, Income, Age and NbCars were related to the following socio-economic information: the household composition, the usage of public transportation, the income, the age and the number of cars in the respondent's household.

The parameters related to the variables described hereabove are estimated by maximum likelihood on a sample of 2′965 observations resulting from the answers of 593 individuals. Let us recall that each respondent had to answer to five choice situations. We obtain a value of the final log-likelihood of $-2'822.32$ and of $\bar{\rho}^2$ of 0.2.

The estimates of the parameters are reported in Table 8. All parameters are significant at a 95% level except parameters $\beta_{\text{FamSit}_\text{Renault}}$, $\beta_{\text{Income}_\text{Renault}}$, $\beta_{\text{NbCars}_\text{Renault}}$ and $\beta_{\text{Age}_\text{Renault}}$ relative to part of the socio-economic information in the utility of the petrol-driven vehicle by Renault, and the two constants ASC_own and $\text{ASC}_\text{Renault}$ relative to the alternatives of the vehicle owned by the respondent and of the petrol-driven car from the Renault brand.

Name	Value	t-test
$\mathrm{ASC}_{\mathrm{own}}$	0.44	1.77*
$\mathrm{ASC}_{\mathrm{Renault}}$	-0.90	-2.46*
$\beta_{\mathrm{price}_{\mathrm{own}}}$	-0.03	-1.89
$\beta_{\mathrm{price}_{\mathrm{Renault}}}$	-0.28	-3.78
$\beta_{\mathrm{price}_{\mathrm{elec}}}$	-0.45	-10.47
$\beta_{\mathrm{UseCostPetrol}}$	-0.08	-3.52
$\beta_{\mathrm{UseCostElec}}$	-0.21	-2.45
$\beta_{\mathrm{BatteryHigh}}$	-0.18	-2.05
$\beta_{\mathrm{IncentiveHigh}}$	0.65	7.15
$\beta_{\mathrm{PT}_{\mathrm{own}}}$	-0.50	-5.09
$\beta_{\mathrm{PT}_{\mathrm{Renault}}}$	-0.47	-2.43
$\beta_{\mathrm{FamSit}_{\mathrm{own}}}$	-0.25	-2.91
$\beta_{\mathrm{FamSit}_{\mathrm{Renault}}}$	-0.08	-0.48**
$\beta_{\mathrm{Income}_{\mathrm{own}}}$	-0.30	-3.58
$\beta_{\mathrm{Income}_{\mathrm{Renault}}}$	-0.18	-1.10**
$\beta_{\mathrm{NbCars}_{\mathrm{own}}}$	-0.24	-4.16
$\beta_{\mathrm{NbCars}_{\mathrm{Renault}}}$	-0.06	-0.65**
$\beta_{\mathrm{Age}_{\mathrm{own}}}$	0.20	2.03
$\beta_{\mathrm{Age}_{\mathrm{Renault}}}$	-0.14	-0.67**

Table 8: Estimates of the coefficients of the logit model of demand for the three car types, with values of t-test. (** Statistical significance $< 90\%$, * Statistical significance $< 95\%$)

An analysis of the signs of the estimates of the parameters indicates that the higher the purchase price of any type of vehicle is, the lower its utility is. The price effect is the highest for the electric alternative, the second highest for the Renault car with combustion engine and the lowest for the respondent's own car. The parameter relative to the use cost for the two petrol-driven alternatives has the expected negative sign, implying that for cars with a use cost of less than 15 CHF per 100 km, the more expensive the fuel cost is, the less likely individuals are going to select a petrol-driven alternative.

Regarding the parameters of the design variables, we also notice that a too high battery lease has a negative effect on the choice of an electric vehicle, a high governmental incentive can encourage its purchase and a high cost of usage decreases its interest. More specifically, an analysis of willingness-to-pay shows us that if the battery lease increases from one of the lowest level of 85 CHF or 105 CHF to the highest level of 125 CHF, the purchase price of the electric vehicle can decrease of 4′000 CHF. Similarly, if a governmental incentive of 5′000 CHF is provided when a new electric vehicle is purchased, the latter's cost can be reduced of 14′444 CHF. Finally, if the cost of driving 100 km increases from one of the two lowest levels 1.70 CHF and 3.55 CHF to the highest level 5.40 CHF, the purchase price of the electric vehicle can decrease of $4'667$ CHF.

The estimates of the parameters relative to socio-economic variables characterize the potential customers. They show a meaningful interpretation. A next step in this research is to combine these estimation results with real car market data in order to forecast the potential market share of the electric alternative as well as the induced changes in the market shares of the two other vehicle types.

5 Conclusion

In this paper, we presented the design of a survey which aims at evaluating individuals' demand for electric vehicles in a context where their release on the market is expected in a near future. In order to forecast the future market share of such vehicles, an analysis of the factors driving people's purchase choice is necessary.

The complexity of the survey lies in its two-phase construction, whose purpose is to define choice situations which are adapted to each respondent, and in its sampling procedure, which includes a correction of the probabilities of sampling each series of levels of the variables subject to a fractional factorial design.

Another interest of the survey is the inclusion of statements in order to capture individuals' opinions on topics related to the choice they need to perform, e.g. their concern about ecology, their general interest in new technologies, etc. Questions related to their perception of different types of vehicles, such as electric or hybrid cars, were also included. The particularity of the answers is that they do not consist of numerical values, but of adjectives freely reported by the respondents, which generates new modeling challenges.

We also obtained preliminary modeling results by applying a logit model with multiple alternatives to the data collected from the survey. These results are encouraging and enable us to quantify the impact of design variables as well as socio-economic information on choice. Although preliminary, the model estimates are consistent with the expectations.

6 Future works

The inclusion of socio-economic variables in the model gave some hints for the identification of the target population segments that are likely to be interested in electric vehicles. This could be investigated more in detail by calibrating a discrete choice model with latent classes.

The data collected also involved statements or questions reflecting people's opinions. A next step in this research would be to model the latter's latent attitudes or perceptions such as their ecological concern or their attitude towards new technologies by using these data as measurements. A hybrid choice model could then be applied. Such methodology could also be used in order to assess the effect on choice of the individuals' perceptions of different vehicle types, which were measured via adjectives reported by the respondents.

The model applied so far is rather simple, though the choice set could involve a nested structure. Two alternatives are indeed petrol- or diesel-driven, i.e. the respondent's own car and the analogous Renault model with combustion engine, while the third one is driven by electricity. Moreover, two vehicles are from brand Renault, while the respondent's car is usually from a different brand. This allows for the calibration of nested or cross-nested logit models. The development of such models is a next phase in this research.

As respondents had to perform five choice experiments, a panel term could also be specified in the model, in order to take into account the correlation between answers reported by a same individual.

Further works also include simulations to evaluate the demand elasticity regarding variations of prices of the electric vehicles.

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