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Potential Demand for Alternative Fuel Vehicles

by

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Abstract

This paper analyzes the potential demand for alternative fuel vehicles. The alternative fuel vehicles we consider are liquid propane gas and electric powered vehicles in addition to a dual-fuel vehicle. The data were obtained from a stated preference survey in which each respondent, in a randomly selected sample, was exposed to 15 experiments. In each experiment the respondents were asked to rank three hypothetical vehicles characterized by specific attributes, according to the respondents' preferences. Several versions of a random utility model are formulated and estimated. They include a model for rank ordered data, and models that allow for different types of correlation in preferences across experiments. Apart from one case the model specifications are estimated from the data on first choices. The most general model turns out to predict aggregate second and third choices rather well. The model is applied to assess the willingness to pay for alternative fuel vehicles.

Keywords: Stated preference, random utility, alternative fuel vehicles, models for ranking, serially dependent preferences.

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1. Introduction

In recent years the major automobile manufacturers have spent an increasing share of their R&D expenditures to develop competitive alternatives to gasoline/diesel vehicles. These include different types of electric, hybrid, natural gas and multiple fuel vehicles. One important reason for this effort stems from governments regulation and the acknowledgement that the world's resources of oil is limited. Furthermore, there is increasing public awareness about the problems caused by pollution from automobiles in many densely populated areas, and the fact that carbon dioxide emission from automobiles affects the world's ozone layers. A well known example of this is found in southern California where air quality is an important concern. Here, the 1990 amendments to the Federal Clean Air Act and the 1990 Regulations by the California Air Resources Board require substantial reduction in vehicle emissions.

So far, alternative fuel vehicles have not been sufficiently developed to appear competitive. One reason for this is that current infrastructure on maintenance and fuel supply is exclusively oriented towards conventional fuel vehicles, i.e. gasoline and diesel vehicles. For example, the current battery technology of electric vehicles necessitates frequent recharging and costly replacement. Thus, the shortcoming of current battery technology prevents electric vehicles from being attractive in the market other than possibly for short/medium range transportation purposes.[1]

In this paper we analyze the potential household demand for alternative-fuel vehicles based on data from a stated preference type of survey conducted by Statistics Norway. Recall that in stated preference surveys respondents are asked to express preferences for hypothetical products characterized by specific attributes. To this end we formulate and estimate several alternative structural demand models based on probabilistic theories of individual choice behavior. The first model we discuss is known as the Luce model for ranking. This model originates from the work of Luce (1959) and Block and Marschak (1960), and has been applied to analyze potential demand for electric vehicles by Beggs et al. (1981). In this model it is assumed that the decision-maker ranks the alternatives presented according to a random utility index where the random components of the utilities are extreme value distributed and independent across alternatives and across experiments (for a given individual). The second model we discuss is an extension of the first one in that we allow the utility index for a given alternative to be dependent across experiments. Specifically, the structure of this model derives from an intertemporal extension of the Luce choice axiom: Independence from Irrelevant Alternatives (see Dagsvik, 2000). The motivation for introducing serially correlated utilities is that there may be memory or taste persistence effects implying that the decision-maker's preference evaluations in successive experiments will be correlated. A version of this model was originally proposed by Dagsvik (1983).

The third model is an extension of the second one that allows individual specific taste persistence effect (fixed effect). The fourth model extends the second one by allowing preference parameters associated with alternative fuel technologies be random.

In the context of studying the potential demand for alternative fuel vehicles, analyses based on stated preference surveys have been carried out by Beggs et al. (1981), Hensher (1982) and Calfee (1985), (these are electric vehicles), Bunch et al. (1991) and Golob et al. (1991). See also Mannering and Train (1985), Train (1980), Brownstone et al. (1996), and Brownstone and Train (1999). In these studies alternative fuel vehicle encompass electric, natural gas, liquid propane gas, hybrid and other multiple fuel vehicles.

The data were obtained from a survey in which each respondent, in a randomly selected sample, was exposed to 15 experiments. In each experiment the respondents were asked to rank three hypothetical vehicles (of which two were alternative fuel ones) characterized by specific attributes. These attributes vary across experiments.

Except for the Luce model for ranking, which is estimated by using all the observations, the remaining models are estimated by using solely data on first choices. This enables us to evaluate the models by doing "out-of-sample" predictions in the sense of prediction (aggregate) of second and third choices. It turns that the most general model specification performs rather well in these prediction exercises.

The organization of the paper is as follows: In the next section we review random utility models for ranking. In Section 3 we discuss random utility models with serially dependent utilities. Section 4 discusses the survey method and provides a descriptive analysis of the data. In Section 5 the empirical specifications are presented and the estimation results are displayed and discussed. Section 6 reports selected price elasticities and the distribution of compensating variation for alternative fuel technologies.

2. Random utility models for ranking

The systematic development of stochastic models for ranking started with Luce (1959), Block and Marschak (1960), and Luce and Suppes (1965). Specifically, they provide a powerful theoretical rationale for the structure of stochastic models for ranking which we shall describe below. An early application of this type of models is Beggs et al. (1981).

Let S denote the choice universe (i.e., the set of all alternatives) and let $C \subset S$ be the choice set of feasible alternatives. Let $\rho_C = (\rho_1, \rho_2, \ldots, \rho_m)$ be the rank ordering of the alternatives in C, where m is the number of alternatives in C. This means that $\rho_i = \rho_i(C)$, denotes the element in C that has the i'th rank.

Let $U(j) = V_j + \varepsilon_j$ be the agent's utility of alternative j, where $\varepsilon_j, j \in S$ are i.i.d. random variables and V_j is the systematic term. Yellott (1977) has proved that for IIA to hold the random variables $\{\varepsilon_j\}$ must be type III extreme value distributed, i.e.,

$$\text{(2.1)} \qquad P(\varepsilon_j \le x) = \exp(-e^{-x}).$$

The implied model has the structure[2]

$$\text{(2.2)}\ P(\rho_C) \equiv P\left(U_{\rho_1} > U_{\rho_2} > \ldots > U_{\rho_m}\right) = \frac{\exp(V_{\rho_1})}{\sum_{k\in C} \exp(V_k)} \cdot \frac{\exp(V_{\rho_2})}{\sum_{k\in C\setminus\{\rho_1\}} \exp(V_k)} \cdots \frac{\exp(V_{\rho_{m-1}})}{\exp(V_{\rho_m}) + \exp(V_{\rho_{m-1}})}$$

for $C \subset S$. As an example, consider the case when $C = \{1,2,3\}$ and $\rho_C = (2,3,1)$. Then (2.2) reduces to

$$\text{(2.3)} \qquad P(2,3,1) = \frac{e^{V_2}}{e^{V_1} + e^{V_2} + e^{V_3}} \cdot \frac{e^{V_3}}{e^{V_1} + e^{V_3}}.$$

In this paper (2.2) is the point of departure for the specification of the first type of empirical model we estimate below.

3. Random utility models with serially dependent utilities

When a sample of individuals is presented with a series of experiments (such as the experiment series analyzed below) the problem of memory effect, and/or taste persistence arises. By this it is meant that the utilities of an alternative may be correlated across experiments even if the corresponding (observable) attributes differ. A psychological reason for this may be that an individual's state of mind and his perception capacities vary more or less slowly over time, i.e. across experiments, and consequently, preference evaluations in the last and current experiments may tend to be more strongly correlated than preference evaluations in experiments that are more remote in “time”. To account for serial correlation in the data one could apply a multinomial probit model with serially correlated disturbances, or a multinomial logit model with random coefficients, cf. Morikawa (1994). A drawback with this kind of approach is that the theoretical foundation for the choice of distribution of the random coefficients (or latent attributes) usually is missing.[3]

In this section we shall describe a different approach to serially dependence, based on a behavioral assumption. This type of models was introduced by Dagsvik (1983, 1988) and further developed in Dagsvik (1995, 2000). Let $U_j(t)$ denote the agent's utility of alternative j at time t (experiment t) which means that $\{U_j(t), t = 1,2,\ldots\}, j \in S,$ become stochastic processes in discrete time. Dagsvik (2000) proposes an extension of IIA (IIIA) to the case where choices take place over time. This assumption can be described as follows: Let J(t,C) denote the choice from C at time t, i.e.,

$$J(t, C) = j \Leftrightarrow U_j(t) = \max_{k \in C} U_k(t). \tag{3.1}$$

The extended version of IIA states that if C_1 and C_2 are two choice sets with $C_2 \setminus C_1 \neq \emptyset$, $j \in C_2 \setminus C_1$, then

$$P\left(J(t, C_2) = j \,\middle|\, J(s, C_1), \forall s < t\right) = P\left(J(t, C_2) = j\right). \tag{3.2}$$

The interpretation is as follows: Consider the particular case in which the past choice sets are constant but where the choice set in the current period is expanded to include new alternatives that were never feasible before. Then the intertemporal version of IIA states that the probability of choosing an alternative among the new alternatives that enter the choice set, given the choice history, is independent of the choice history. The intuition is that even if previous choices provide information about the preferences over the alternatives in the "old" choice set, these choices provide no information about the utility of the "new" alternatives. (Provided the preferences are not affected by previous choice experience, previous choices do not represent information that is relevant for the current choice of a "new" alternative.) In Dagsvik (1995, 2000) the intertemporal version of IIA is proposed as a characterization of rational behavior under the absence of structural state dependence effects, such as learning for example.

When the utility processes are independent Dagsvik (2000) demonstrates (under mild regularity conditions) that the utilities are extremal processes with extreme value distributed marginals. Extremal processes are similar to Wiener processes (or Brownian motion) in the sense that if "plus" is replaced by "max" in the recursive expression for the Wiener process we obtain the extremal process. Thus in this case we can express the utility process $\{U_j(t)\}$, as

$$U_j(t) = \max\left(U_j(t-1) - \theta, V_j(t) + \varepsilon_j(t)\right) \tag{3.3}$$

where $U_j(0) = -\infty, \theta > 0$ is a parameter (possibly time dependent) that measures the degree of serial dependence, $V_j(t)$ is a parametric function of current (time t) attributes associated with alternative j and $\varepsilon_j(t), j \in S, t = 1, 2, \ldots$, are i.i.d. random variables with c.d.f. given by (2.1). From (3.3) it follows recursively that $U_j(t)$ can be expressed as a maximum of extreme value distributed random variables from which one can easily deduce that

$$\exp\left(EU_j(t)\right) = \sum_{r=1}^{t} \exp\left(V_j(r) - (t-r)\theta\right) \tag{3.4}$$

for $t \geq 1$. Eq. (3.4) shows that θ is analogous to a rate of preference parameter. Specifically, the contribution from the period r-specific systematic utility component to the current utility is evaluated by multiplying $\exp(V_j(r))$ by the "depreciation" factor, $\exp(-(t-r)\theta)$. This depreciation factor accounts for the loss of memory and/or decrease in taste persistence as the time lag increases. As demonstrated by Resnick and Roy (1990), we have that

$$\text{(3.5)} \qquad \operatorname{corr}\left(\exp\left(-U_j(s)\right), \exp\left(-U_j(t)\right)\right) = \frac{\exp\left(EU_j(s)\right)}{\exp\left(EU_j(t)\right)} \cdot \exp\left(-(t-s)\theta\right)$$

for $s \le t$. Since by (3.4), $EU_j(t)$ is nondecreasing as a function of t it follows that the right hand side of (3.5) is always less than or equal to $\exp\left(-(t-s)\theta\right)$. For the sake of interpretation suppose for a moment that $\{V_j(r), r = 1,2,\ldots\}$ does not vary over time. Then (3.4) implies that (3.5) reduces to $\exp\left(-(t-s)\theta\right)$ when s and t are large. Thus when θ is small this means that strong taste persistence is present while when θ is large taste persistence is weak. When θ is large (say greater than 5), then the serial correlation is negligible. The implication from the hypothesis of taste persistence is of course that choices at different moments become dependent. As demonstrated by Dagsvik (1988), it follows from (3.3) that the choice process $\{J(t,C)\}$ defined by (3.1) becomes a (first order) Markov chain. Furthermore, the state and transition probabilities, $P_j(t)$ and $Q_{ij}(t-1,t)$, are given by (cf. Dagsvik, 2000)

$$\text{(3.6)} \qquad P_j(t) \equiv P\left(J(t,C) = j\right) = \frac{\sum_{r=1}^{t} \exp\left(V_j(r) - (t-r)\theta\right)}{\sum_{k\in C} \sum_{r=1}^{t} \exp\left(V_k(r) - (t-r)\theta\right)}$$

for $t \ge 1,\ j \in C$,

$$\text{(3.7)} \qquad Q_{ij}(t-1,t) \equiv P\left(J(t,C) = j \mid J(t-1,C) = i\right) = \frac{\exp\left(V_j(t)\right)}{\sum_{k\in C} \sum_{r=1}^{t} \exp\left(V_k(r) - (t-r)\theta\right)}$$

for $j \ne i,\ t \ge 2,\ i, j \in C$, and

$$\text{(3.8)} \qquad Q_{ii}(t-1,t) \equiv P\left(J(t,C) = i \mid J(t-1,C) = i\right) = 1 - \sum_{k\in C\setminus\{i\}} Q_{ik}(t-1,t)$$

for $t \ge 2$. From (3.6) and (3.7) we realize that $P_j(t)$ and $Q_{ij}(t-1,t)$ reduce to the standard multinomial logit model when $\theta \to \infty$. Moreover, the conditional transition probabilities given that a transition occurs equal

(3.9) $$\pi_{ij}(t-1,t) \equiv P\left(J(t,C)=j \,\middle|\, J(t,C)\neq i, J(t-1,C)=i\right) = \frac{\exp\left(V_j(t)\right)}{\sum_{k\in C\setminus\{i\}} \exp\left(V_k(t)\right)}$$

for $j \neq i, t \geq 2, i, j \in C$. The last equation shows that it is possible to identify and estimate the structural parts, $\left\{V_j(t)\right\}$, of the utility function without relying on assumptions about the structure of the taste persistence parameter θ.[4]

The formulas displayed above enables us to analyze data on choice behavior where only the most preferred alternative is recorded. If data with complete rank orderings is available (such as in the present case) then it is desirable to calculate choice probabilities for sequences of rankings, based on (3.3). Unfortunately, this is so far an unsolved problem.

For the sake of clarifying the interpretation of the modeling framework we include a discussion below of the special case where the systematic utility components $\left\{V_j(t)\right\}$ are constant over time. In this case (3.6) and (3.7) reduce to

(3.10) $$P_j(t) = P_j = \frac{\exp\left(V_j\right)}{\sum_{k\in C} \exp\left(V_k\right)},$$

(3.11) $$Q_{ij}(t-1,t) = Q_{ij} = \frac{\left(1-e^{-\theta}\right)P_j}{1-e^{-\theta t}}$$

for $i \neq j$, and

(3.12) $$Q_{ii}(t-1,t) = \frac{e^{-\theta}-e^{-\theta t}}{1-e^{-\theta t}} + \frac{\left(1-e^{-\theta}\right)P_i}{1-e^{-\theta t}}.$$

When the observed attributes are constant across experiments and one assumes that the agents interpret the unspecified technology features as being constant over experiments, one would expect the utilities of a perfectly rational agent to be perfectly correlated over "time". In other words, we realize from (3.11) and (3.12) that the case when $\theta \cong 0$ and t is very large, corresponds to a perfectly rational agent in the sense that he makes consistent choices over "time".

From (3.11) and (3.12) we realize that when $\theta \to 0$ then we obtain in the limit that

(3.13) $$Q_{ij}\left(t-1,t\right) = \frac{P_j}{t}$$

for $i \neq j$, and

(3.14) $$Q_{ii}\left(t-1,t\right)=1-\frac{1}{t}+\frac{P_i}{t}$$

for $t \geq 2$. Thus, when t is not very large the probability of a transition is positive even if $\theta = 0$. The interpretation is that when t is small, the choice history is short and past choices will therefore only provide limited information about the current preferences. As a result, transitions are possible at early stages in the choice process, even if preferences are perfectly correlated over time.

It is also possible to express the autocovariance and autocorrelation function of the *observed* choice process, suitably defined. To this end let $Y_i(t) = 1$ if the agent chooses alternative i in period t, and zero otherwise. It follows readily from (3.7) and (3.8) that one can write

(3.15) $$Q_{ii}(s,t)=P_i(t)-P_i(s)\varsigma(s,t)+\varsigma(s,t)$$

where $Q_{ii}(s,t)$ is the probability of being in state i at time t given that state i was occupied at time s, and

(3.16) $$\varsigma(s,t)=\frac{\sum_k \exp\left(EU_k(s)\right)}{\sum_k \exp\left(EU_k(t)\right)}\cdot\exp\left(-\left(t-s\right)\theta\right).$$

Formulae (3.15) also hold in the case where the utilities are correlated across alternatives with a slightly different expression for $\varsigma(s,t)$, (see Dagsvik, 1988, p. 35). Now from (3.15) we obtain that

(3.17) $$\operatorname{Cov}\left(Y_i(s),Y_i(t)\right)=Q_{ii}(s,t)P_i(s)-P_i(s)P_i(t)=\varsigma(s,t)P_i(s)\left(1-P_i(s)\right).$$

Consequently,

(3.18) $$\frac{\operatorname{Cov}\left(Y_i(s),Y_i(t)\right)}{\operatorname{Var}Y_i(s)}=\varsigma(s,t)$$

which means that $\varsigma(s,t)$ is approximately equal to the autocorrelation function of $\left\{Y_i(t), t>0\right\}$. When the observed attributes vary little over time,

$$\varsigma(s,t)\approx\exp\left(-\left(t-s\right)\theta\right)$$

which means that $\varsigma(s,t)$, approximately, decreases exponentially when $t-s$ increases. In contrast, when choices are generated by a mixed multinomial logit model the autocorrelation function will, approximately, be independent of $t-s$. Thus, by computing the empirical counterpart of (3.18) one may be able to rule out the mixed multinomial logit model a priori. Specifically, if the left hand side of (3.18) is far from exponentially decreasing this can be interpreted as evidence against IIIA. This argument continues to hold in the case where θ is random and when $\varsigma(s,t)$ is represented by (3.16). In this case we have that

(3.19) $$\varsigma(s,t) \approx E\exp\left(-\left(t-s\right)\theta\right)$$

which is a decreasing function of $t-s$.

In several contexts it may be of interest to allow for structural state dependence effects. For example, brand loyalty is one type of state dependence that is found in analyses of vehicle ownership. Dagsvik (2000) discusses how the framework outlined above can be extended to allow for state dependence. In fact, state dependence can be introduced by letting the structural terms $\left\{V_j(t)\right\}$ depend on previous choices. It turns out that the formulae (3.7), (3.8) and (3.9) still hold (but not (3.6), cf. Dagsvik, 2000). This is not immediately evident because when $V_j(t)$ is allowed to depend on previous choices a potential simultaneous equation bias problem arises.

It is well known that in general one cannot separate the effect of taste persistence from the effect of state dependence without imposing theoretical restrictions on the model. If one believes that IIIA represents a reasonable behavioral assumption this enables the researcher to obtain nonparametric identification of state dependence effects. To realize this note that by (3.9)

(3.20) $$V_j(t) - V_1(t) = \log\left(\frac{\pi_{ij}\left(t-1,t\right)}{\pi_{i1}\left(t-1,t\right)}\right)$$

for $i \neq 1, j$. Since (3.20) is independent of the taste persistence parameter θ, and the right hand side is observable, it is clear that one can separate taste persistence from state dependence. In other type of choice models such as the multiperiod probit model the separation of taste persistence and state dependence is more delicate since the probit framework does not have a clear theoretical justification other than being a random utility model.

4. Data and survey method

Since alternative fuel vehicles are almost non-existing in the automobile market we cannot obtain data by observing individuals' demand for these types of vehicles. A possible way to obtain information about agents preferences is to employ the stated preference approach which consists in asking individuals to express their preferences for hypothetical future vehicles.

There are many ways in which one may ask questions to reveal preferences. For our purpose, which is to model consumer preferences, it is of major importance to ask questions in such a way that responses are unambiguous and related to a precisely specified ranking problem. One way to achieve this is to ask each individual to state which alternative in a specified choice set is preferred. Alternatively, as is done in the present study, individuals can be asked to make a complete ranking of a set of hypothetical vehicles, characterized by given attributes. Although the latter strategy yields more information than the former one it may not necessarily be the preferred strategy because it presents more difficulties to the respondent.

In the present study, a survey was conducted in which each individual was exposed to 15 experiments. In each experiment the individual was asked to rank three hypothetical vehicles characterized by specified attributes. The following question was used: “If you were to purchase a new vehicle today and the only vehicle available to you were the three alternative vehicles specified on this card, which one would you purchase?”. This question reveals the respondents' most preferred alternative. To obtain a complete ranking of the three vehicles, we proceeded by asking “If the vehicle you chose in response to the previous question were unavailable to you, which of the remaining two vehicles would you purchase?”. This question reveals respondents' second and third choices and accordingly their complete rank ordering within each of the choice sets presented. By repeating this specific sequence of questions for all fifteen choice sets a data set with rankings of the vehicles with specified attributes for all respondents was obtained.

The survey data was based on interviews of 922 randomly drawn Norwegian residents between 18-70 years of age. One half (A) received choice sets with the alternatives “electric powered”, “liquid propane gas-” (lpg) and “gasoline-fueled” vehicles whilst the other half (B) received “hybrid” (in this study “hybrid” means a combination of electric and gasoline technology), “lpg” and “gasoline” vehicles. Due to a non-response rate of 0.28, thus reducing the sample from 922 to 662 individuals, and to incomplete answers and/or errors in the registration of 40 respondents, estimation of the models is based on data for 319 respondents in group A and 323 respondents in group B.

4.1. Experimental design

We shall now, in detail, consider the construction of the choice sets (experiment design) presented to the survey participants. It is important that the experiment design, to a reasonable degree, is representative for the central part of the attribute space. From the analyst's point of view, it is particularly important that respondents are aware of the importance of making their choices conditional on the assumptions imposed by the analyst in the experimental design. In the present study we have introduced electric powered, lpg- and hybrid (electricity and gasoline) vehicles which all are hypothetical vehicles in the sense that they at present hardly appear as competitive alternatives to conventional gasoline and diesel vehicles[5]. The consensus is that these vehicles more or less are considered as experimental prototypes and the majority of the population has very limited knowledge about these vehicles. Thus, we can not rule out the possibility that respondents, due to their perceptions, do not view these vehicles as realistic and attractive alternatives. Consequently, the revealed preferences may not correspond to the demand in a real market in which all these vehicles exist as competitive alternatives. The discussion above leads to the more general question of external validity for these types of laboratory experiments. Levin et al. (1983) and Pearmain et al. (1991) give a summary of the work on external validity and they conclude that in some cases there seems to be considerable evidence of external validity.

Based on the literature on stated preference methodology (cf. Pearmain et al. (1991)) and on experience from four panel discussions with potential survey participants (focus groups) as well as a pre-survey, “purchase price”, “driving range between refueling/recharging”, “top speed” and “fuel consumption” appeared to be the most important attributes and were used to describe the hypothetical vehicles of the survey. Attributes such as refueling/recharging time and availability, emission level and size of the vehicle were omitted as attributes in the choice sets. Thus, the survey is rather simple as regards to the description of the hypothetical vehicles. Some researchers, for example Pearmain et al. op. cit. claim that it appears difficult for individuals to relate to more than four attribute components. Other studies (see for example Beggs et al., 1981) have applied more complex designs with more than four attributes. In addition to each choice set a description of the choice context was provided. The purpose of this description was to provide explicit conditions about the choice environment and to ensure that the different fuel technologies appear as competitive alternatives to the respondents[6]. Evidently, the difference in levels of education and knowledge about the topic across respondents may yield different anticipations about the development of alternative fuel vehicles, but by introducing these sets of assumptions we expected to reduce some of this heterogeneity.

Worth noting is that we have used fuel consumption, in liter gasoline per 10 km, in contrast to e.g. Beggs et al. (1981) that use fuel cost. The motivation for using fuel consumption is that people generally are found to think in these terms when considering the fuel economy of a gasoline powered vehicle. Hence, for electric, hybrid and lpg vehicles we transformed the fuel costs into liter gasoline per 10 km equivalents.

When selecting appropriate distributions of attributes across experiments and across individuals several conflicting concerns occurred. Ideally, one would like to have as much variation in the attribute values as possible. However, there are two problems with this. One is that the respondents may have difficulties with evaluating the utilities of hypothetical vehicles characterized by “unrealistic” attributes. Second, and perhaps more importantly, we are concerned with obtaining a reasonably good specification and approximation of the systematic part of the utility function. With the limited empirical evidence at hand, the best we can hope for is to obtain a reasonable good *local* approximation of the utility function. To this end we have chosen to limit the variation in the composition of the attribute components to what we perceive as “realistic” descriptions. As mentioned above, the set of experiments for group A and B are different. However, within each group the individuals are exposed to the same experiments. Although this strategy implies a possible loss in efficiency it has, at least in principle, the advantage of permitting us to assess more precisely the extent of heterogeneity in preferences.

Whereas Bunch et al. (1991) randomly generated the order in which the attributes appeared on the choice set card, we followed a different strategy, as mentioned above, by exposing half the sample to 15 different choice sets with the fuel technologies, “electric”, “lpg” and “gasoline”, and the other half to 15 different choice sets with the fuel technologies, “hybrid”, “lpg” and “gasoline”.

5. Empirical specifications and estimation results

In this section we shall discuss empirical specification of the different model versions. To the readers' convenience we display the different models estimated in the next table.

Table 5.1. Outline of the different models estimated

Model 1	Luce model for ranking
Model 2	Luce model for first choices
Model 3	Model 2 with serial correlation
Model 4	Model 3 with fixed effect taste persistence
Model 5	Model 3 with random technology parameters

5.1. Specification with serially uncorrelated preferences (Model 1)

The objective of this section is to elaborate on the theoretical model developed in Section 2 to obtain an empirical model when preferences are independent across experiments (for each individual). Recall that each individual in the sample participates in 15 ranking experiments. In each experiment a participant is asked to carry out a complete ranking of three alternative vehicles, characterized by given attributes (see above). Let $\mathbf{Z}_j(t)=\left(Z_{1j}(t), Z_{2j}(t),\ldots, Z_{nj}(t)\right)$ denote the vector of attributes of alternative j in experiment t. In our case the dimension of $\mathbf{Z}_j(t)$, n equals 4. We assume that the utility function of individual h has the structure

$$U_j^h(t) = V_j(t) + \varepsilon_{jh}(t) = \mathbf{Z}_j(t)\boldsymbol{\beta} + \mu_j + \varepsilon_{jh}(t) \tag{5.1}$$

where $\left\{\varepsilon_{jh}(t)\right\}$ are i.i. extreme value distributed random variables, $\left\{\mu_j\right\}$ are technology-specific parameters and $\boldsymbol{\beta}$ is a vector of unknown parameters. The parameter μ_j is supposed to capture a pure technology preference effect, i.e., it represents the mean taste for technology j when the observable attribute vectors are equal for all alternatives. To ensure identification the μ_j-value that corresponds to the gasoline technology is normalized to be zero. The random terms $\left\{\varepsilon_{jh}(t)\right\}$ may capture aspects of the evaluation process that are random to the consumer himself. In addition, these random terms may also capture the effects of variables that are perfectly known to the consumer but unobserved by the analyst. The linear specification of the systematic part of the utility function (5.1) was chosen after a series of preliminary rounds in which different candidates of functional forms were experimented with. These include power- and logarithmic transforms of the original attribute components. In terms of goodness of fit the linear specification seemed to perform at least as well as the other selected functional forms. It is worth mentioning that according to a strict interpretation of the neoclassical theory of consumer behavior the utility function in (5.1) should be interpreted as a conditional indirect utility function given alternative (vehicle) j. It is indirect in the sense that optimal consumption of other goods is implicit. This conditional indirect utility function should depend on the expenditure of owning vehicle j through income net of (annual) user-cost associated with vehicle j. However, if utility is linear in income net of user-cost without interaction effects, the income variable cancels when utility levels are compared, because it does not depend on the respective alternatives. Only the user-cost remains and this variable may be assumed to be approximately proportional to the purchase price. Since $V_j(t)$ is linear the proportional factor is absorbed into the coefficient associated with purchase price. Hence, only the purchase price remains in addition to technology dummies, top speed, driving range, and fuel consumption.

The likelihood function is given by

$$L(\beta,\mu)=\prod_{h}\prod_{t=1}^{15}\prod_{j\in C_h}\prod_{j\in C_h\setminus\{i\}}\left(P_{ijt}(\beta,\mu)\right)^{Y_{ij}^h(t)}, \tag{5.2}$$

where C_h is the choice set, $\mu=(0,\mu_2,\mu_3,\mu_4)$ and $P_{ijt}(\beta,\mu)$ is the probability of ranking alternative i on top and j second best in experiment t, and $Y_{ij}^h(t)=1$, if individual h ranks alternative i on top, and j second best in experiment t, and $Y_{ij}^h(t)=0$, otherwise. From (2.2) and (5.1) it follows that

$$P_{ijt}(\beta,\mu)=\frac{\exp\left(\mathbf{Z}_i(t)\boldsymbol{\beta}+\mu_i\right)}{\sum_{r\in C_h}\exp\left(\mathbf{Z}_r(t)\boldsymbol{\beta}+\mu_r\right)}\cdot\frac{\exp\left(\mathbf{Z}_j(t)\boldsymbol{\beta}+\mu_j\right)}{\sum_{r\in C_h\setminus\{i\}}\exp\left(\mathbf{Z}_r(t)\boldsymbol{\beta}+\mu_r\right)}. \tag{5.3}$$

Recall that for group A the choice set equals; $C_h=\{\text{Gasoline, Lpg, Electric vehicle}\}$, while in group B, $C_h=\{\text{Gasoline, Lpg, Hybrid vehicle}\}$. Note that since (5.3) is the product of two logit models, we may interpret the data for each individual from each experiment as independent realizations from two sub-experiments with three feasible alternatives in the first one and two feasible alternatives in the second one. Since we have 15 experiments, our data is therefore equivalent to 30 independent observations per individual.

Table 5.2. Parameter estimates*) of the age/gender specific utility function

Attributes	Age/gender					
	18-29		30-49		50-	
	Females	Males	Females	Males	Females	Males
Purchase price (in 100 000 NOK)	-2.530	-2.176	-1.549	-2.159	-1.550	-1.394
	(-17.7)	(-15.2)	(-15.0)	(-20.6)	(-11.9)	(-11.8)
Top speed (100 km/h)	-0.274	0.488	-0.820	-0.571	-0.320	-0.339
	(-0.9)	(1.5)	(-3.3)	(-2.4)	(-1.1)	(-1.2)
Driving range (1 000 km)	1.861	2.130	1.018	1.465	0.140	1.000
	(3.1)	(3.3)	(2.0)	(3.2)	(0.2)	(1.8)
Fuel consumption	-0.902	-1.629	-0.624	-1.509	-0.446	-1.030

(liter per 10 km)	(-3.0)	(-5.1)	(-2.5)	(6.7)	(-1.5)	(-3.7)
Dummy, electric	0.890	-0.448	0.627	-0.180	0.765	-0.195
	(4.2)	(-2.0)	(3.6)	(-1.1)	(3.6)	(-1.0)
Dummy, hybrid	1.185	0.461	1.380	0.649	1.216	0.666
	(7.6)	(2.8)	(10.6)	(5.6)	(7.7)	(4.6)
Dummy, lpg	1.010	0.236	0.945	0.778	0.698	0.676
	(8.2)	(1.9)	(9.2)	(8.5)	(5.7)	(5.6)
# of observations	2760	2220	4140	4670	2580	2910
# of respondents	92	74	138	155	86	97
Log-likelihood	-2015.1	-1747.8	-3140.8	-3460.8	-2040.9	-2333.8

*) t-values in parentheses.

Table 5.2 displays the estimates when the model parameters differ by gender and age. We notice that the price parameter is very sharply determined and it is slightly declining by age. The parameter associated with driving range appears to decline by age while the parameter associated with fuel consumption increases by age. However, when we take the standard error into account these tendencies seem rather weak. Further, the utility function does not differ much by gender, apart from the parameters associated with fuel consumption and the dummies for alternative fuel cars. Specifically, males seem to be more skeptic towards alternative-fuel vehicles than females.

To check how well the model performs, we have applied the model to predict the individuals' choice behavior. The predictions are carried out by computing individual probabilities and aggregating. The results are displayed in Tables 5.6 and 5.7.

5.2. Allowing for serially correlated preferences (Models 3 and 4)

In this section we shall consider the empirical specification and estimation of the model version discussed in Section 3, where the utility functions are correlated across experiments. Recall that in this case we are only able to apply data on first choices. The motivation for a specification that allows for serially correlated utilities is that unobserved taste variables may be temporally persistent (taste persistence). In general, when analyzing choice behavior over time it may also be desirable to allow for state dependence. State dependence may occur as a result of experience with previously chosen alternatives (brand loyalty, for example). In the present case we only have data from a stated preference experiment, which means that the agents do not have “real” experience based on their choices. Accordingly, it seems reasonable to rule out state dependence.

According to (3.3) the utility function is assumed to have the structure

$$U_j^h(t) = \max\left(U_j^h(t-1) - \theta, \mathbf{Z}_j(t)\beta + \mu_j + \varepsilon_j^h(t)\right). \tag{5.4}$$

Let $W_{ij}^h(t)$ be equal to one if individual h ranks alternative i on top in experiment $t-1$ and j on top in experiment t. Then the likelihood function can be written as

$$L(\beta,\mu,\theta)=\prod_{h}\prod_{t=2}^{15}\prod_{i\in C_h}\prod_{j\in C_h} Q_{ij}^{h}(t-1,t)^{W_{ij}^{h}(t)}\prod_{j\in C_h} P_{j}^{h}(1)^{W_{.j}^{h}(1)} \tag{5.5}$$

where $W_{.j}^{h}(1)$ is equal to one if individual h ranks alternative j on top in the first experiment and zero otherwise.

Recall that the likelihood function (5.5) corresponds to the observations on individuals' first choices. As mentioned in Section 3, the structure of the corresponding choice probabilities for complete rank orderings are not known and we are therefore unable to utilize the full set of observations when estimating the model. However, the remaining set of observations on individuals' second choices can be applied to test the model since these observations enable us to perform out-of-sample predictions. It is a well acknowledged principle that out-of-sample observations are necessary to put a model to serious test. In particular, it enables us to check the IIA property which is fundamental in all the model versions discussed in this paper.

We have estimated two versions of this model. In the first version the taste persistence parameter θ is assumed to be the same for all individuals within the respective age/gender groups. In the second version θ is assumed to be an individual specific fixed effect.

Table 5.3. Parameter estimates*) of the age/gender specific utility functions, with taste persistence (Model 3)

Attributes	Age/gender 18-29 Females	18-29 Males	30-49 Females	30-49 Males	50- Females	50- Males
Purchase price (in 100 000 NOK)	-3.256	-3.234	-2.496	-2.932	-2.590	-2.618
	(-15.5)	(-14.4)	(-15.3)	(-18.6)	(-12.3)	(-12.5)
Top speed (100 km/h)	-0.085	1.607	-0.239	0.224	0.525	1.031
	(-0.2)	(3.4)	(-0.6)	(0.6)	(1.1)	(2.1)
Driving range (1 000 km)	3.957	3.938	3.438	3.459	1.552	4.293
	(4.3)	(4.0)	(4.3)	(4.8)	(1.5)	(4.3)
Fuel consumption (liter per 10 km)	-1.583	-2.263	-1.679	-2.828	-1.420	-3.945
	(-3.1)	(-4.1)	(-3.6)	(-6.9)	(-2.4)	(-6.8)
Dummy, electric	1.038	0.276	0.792	0.085	1.081	-0.306
	(3.1)	(0.7)	(2.6)	(0.3)	(2.7)	(-0.8)
Dummy, hybrid	1.330	0.792	1.319	0.660	1.383	0.117
	(5.4)	(2.9)	(5.9)	(3.5)	(4.8)	(0.4)
Dummy, lpg	1.031	0.347	0.700	0.596	0.606	0.148
	(5.5)	(1.7)	(4.0)	(4.1)	(2.7)	(0.7)
Taste persistence, θ	2.748	1.607	1.383	1.971	1.140	0.971
	(13.6)	(14.8)	(19.8)	(20.2)	(15.8)	(17.0)
# of observations	1380	1110	2070	2325	1290	1455
# of respondents	92	74	138	155	86	97
Log-likelihood	-1156.7	-979.1	-1710.7	-1978.5	-1046.0	-1183.9

*) Asymptotic t-values in parentheses.

The results displayed in Table 5.3 show that when utilities are allowed to be serially correlated, then the estimates of the coefficients associated with purchase price, driving range and fuel consumption increase in absolute value compared to the case with independent utilities. Moreover, the parameter associated with driving range becomes more important in this case relative to the parameter associated with purchase price. For males the estimate of the coefficient associated with top speed is now (essentially) only significantly different from zero for young males and it is positive. For all age/gender combinations we find evidence of serially correlated utilities (taste persistence). As expected, taste persistence-effects increase by age but decrease rapidly over “time” (experiments). It follows readily from (3.4) that the correlation between utilities that are two or more experiments apart is rather weak. Thus, in light of the discussion in Section 3 this seems to indicate that the mixed multinomial logit model is not appropriate. Note that the log-likelihood value reported in Table 5.3 should not be compared with the corresponding values in Table 5.2, since only observations on first choices are applied here.

Table 5.4. Parameter estimates*) of the age/gender specific utility functions, with fixed effect taste persistence parameter (Model 4)

Attributes	Age/gender					
	18-29		30-49		50-	
	Females	Males	Females	Males	Females	Males
Purchase price (in 100 000 NOK)	-3.722	-3.844	-3.033	-3.490	-3.627	-3.084
	(-16.0)	(-14.6)	(-16.1)	(-19.4)	(-13.6)	(-13.0)
Top speed (100 km/h)	0.050	1.712	-0.693	-0.069	0.516	0.700
	(0.1)	(3.2)	(-1.6)	(-0.1)	(0.9)	(1.3)
Driving range (1000 km)	4.982	5.318	5.080	4.167	3.780	5.035
	(4.9)	(4.7)	(5.6)	(5.1)	(3.2)	(4.6)
Fuel consumption (liter per 10 km)	-2.178	-3.245	-2.017	-3.347	-1.900	-4.542
	(-3.8)	(-5.3)	(-3.9)	(-7.4)	(-2.9)	(-7.1)
Dummy, electric	0.814	0.077	0.571	-0.178	1.447	-0.491
	(2.3)	(0.2)	(1.7)	(-0.6)	(3.3)	(-1.2)
Dummy, hybrid	1.228	0.675	1.206	0.760	1.551	0.148
	(4.6)	(2.3)	(4.9)	(3.7)	(3.4)	(0.5)
Dummy, lpg	0.984	0.334	0.757	0.648	0.829	0.138
	(4.8)	(1.5)	(4.0)	(4.1)	(3.4)	(0.6)
# of observations	1380	1110	3070	2325	1290	1455
# of respondents	92	74	138	155	86	97
Log-likelihood	-1014.4	-802.4	-1349.2	-1612.4	-754.7	-936.7

*) Asymptotic t-values in parentheses.

In Table 5.4 we report the parameter estimates when the taste persistence parameter θ is assumed to be an individual specific fixed effect. We notice that apart from the technology parameters, absolute value of the remaining parameters seem to increase compared to the estimates of Table 5.4.

5.3. Serially correlated preferences and random technology parameters (Model 5)

In this section we assume that the utility function has the same structure as in (5.4) apart from $\{\mu_j\}$ which are now assumed to be individual specific random effects. Specifically, μ_j^h, $j = 1, 2, 3, 4$, are assumed to be independent and normally distributed; $\mu_j^h \sim N(\bar{\mu}_j, \sigma_j)$, with the mean that corresponds to the gasoline alternative set equal to zero. The motivation for this specification is similar to the motivation for serially correlated preferences. In contrast to the model specification in subsection 5.2 the present specification implies that the structure of the serial dependence is much less restrictive than the one that follows from (5.4). A more general formulation would be to allow a full random coefficient specification, i.e., that all the parameters of the utility function are random. Since the coefficients associated with purchase price, fuel consumption and driving range must be negative and positive, respectively, they cannot be normally distributed. Thus, for simplicity, we have only allowed for random technology parameters. One possible justification for random individual specific technology parameters is that preferences over attributes such as prices and fuel consumption may vary much less across individuals than preferences over technologies. This is so because most people are more familiar with evaluating the effect of prices and costs than the value of technologies.

Let $\boldsymbol{\mu}^h = \left(\mu_1^h, \mu_2^h, \mu_3^h, \mu_4^h\right)$ and

$$L_h\left(\beta,\theta,\boldsymbol{\mu}^h\right) = \prod_{t=2}^{15} \prod_{i \in C_h} \prod_{j \in C_h} Q_{ij}^h\left(t-1,t\right)^{W_{ij}^h(1)} \prod_{j \in C_h} P_j^h(1)^{W_{\cdot j}^h(1)} \tag{5.6}$$

where $Q_{ij}^h\left(t-1,t\right)$ and $P_j^h(1)$ depend on h through $\boldsymbol{\mu}^h$.

The total likelihood, $L\left(\beta,\bar{\mu},\sigma,\theta\right)$, is therefore given by

$$L\left(\beta,\bar{\boldsymbol{\mu}},\boldsymbol{\sigma},\theta\right) = \prod_h E\, L_h\left(\beta,\theta,\boldsymbol{\mu}_h\right) \tag{5.7}$$

where the expectation is taken with respect to $\boldsymbol{\mu}^h$, and $\bar{\boldsymbol{\mu}} = \left(0,\bar{\mu}_2,\bar{\mu}_3,\bar{\mu}_4\right)$, $\boldsymbol{\sigma} = \left(\sigma_1,\sigma_2,\sigma_3,\sigma_4\right)$. The likelihood function (5.7) is approximated by $\tilde{L}\left(\beta,\bar{\boldsymbol{\mu}},\boldsymbol{\sigma},\theta\right)$, given by

$$\tilde{L}\left(\beta,\bar{\boldsymbol{\mu}},\boldsymbol{\sigma},\theta\right) = \prod_h \left[\frac{1}{M}\sum_{r=1}^{M} L_h\left(\beta,\theta,\bar{\boldsymbol{\mu}} + \boldsymbol{\sigma\eta}_h\right)\right] \tag{5.8}$$

where

$$\boldsymbol{\sigma\eta}_h = \left(\sigma_1\eta_{1h},\sigma_2\eta_{2h},\sigma_3\eta_{3h},\sigma_4\eta_{4h}\right),$$

and $\left\{\eta_{jh}\right\}$ are i.i.d. draws from the standard normal distribution. In the actual estimation we have, after some experimentation, chosen $M = 1000$ which turned out to give a very good approximation to the theoretical counterpart given in (5.7).[7]

Table 5.5. Parameter estimates*) of the age/gender specific utility functions with serial correlation and random technology parameters (Model 5)

Attributes	Age/gender					
	18-29		30-49		50-	
	Females	Males	Females	Males	Females	Males
Purchase price (in 100 000 NOK)	-4.376	-4.575	-3.834	-4.575	-4.743	-4.125
	(-14.9)	(-14.2)	(-15.0)	(-14.2)	(-12.8)	(-12.4)
Top speed (100 km/h)	-0.159	2.089	-0.893	-0.121	0.383	0.472
	(-0.3)	(3.5)	(-1.7)	(-0.3)	(0.5)	(0.7)
Driving range (1 000 km)	4.807	5.558	3.310	3.615	2.367	4.710
	(4.3)	(4.5)	(3.3)	(4.0)	(1.7)	(3.5)
Fuel consumption	-1.978	-2.715	-1.590	-3.715	-2.119	-4.676
(liter per 10 km)	(-3.5)	(-4.5)	(-3.0)	(-7.9)	(-2.9)	(-6.6)
Dummy, electric	1.965	0.297	2.582	0.395	3.102	0.075
	(3.5)	(0.4)	(3.6)	(0.8)	(3.4)	(0.1)
Standard error, electric	2.115	2.896	3.614	3.377	3.272	3.604
	(6.1)	(5.4)	(7.7)	(8.0)	(5.0)	(5.7)
Dummy, hybrid	2.061	1.275	3.036	1.239	3.288	1.350
	(4.9)	(2.3)	(6.5)	(3.2)	(4.4)	(2.1)
Standard error, hybrid	1.425	2.286	1.929	2.186	2.587	2.633
	(5.9)	(5.4)	(5.6)	(8.6)	(5.2)	(6.0)
Dummy, lpg	1.715	0.639	1.994	1.347	1.919	1.361
	(5.5)	(1.9)	(4.8)	(5.0)	(3.3)	(2.9)
Standard error, lpg	0.354	0.470	1.397	0.377	1.230	0.979
	(0.8)	(0.7)	(3.2)	(1.2)	(3.4)	(1.7)
Standard error, gasoline	1.803	1.879	2.850	2.359	4.022	3.613
	(8.3)	(6.5)	(6.8)	(10.4)	(6.4)	(5.7)
Taste persistence, θ	6.212	6.857	8.154	24.749	5.832	4.473
	(5.3)	(1.8)	(0.9)	(0.0)	(7.6)	(8.3)
# of observations	1380	1110	2070	2325	1290	1455
# of respondents	92	74	138	155	86	97
Log-likelihood	-965.5	-778.8	-1244.1	-1479.1	-706.0	-850.2

*) Asymptotic t-values in parentheses.

Table 5.6. Prediction performance of the model for group A. Per cent

Gender	First choice			Second choice			Third choice		
	Electric	Lpg	Gaso-line	Electric	Lpg	Gaso-line	Electric	Lpg	Gaso-line
Females:									
Observed	52.1	26.1	21.9	22.3	46.5	31.2	25.6	27.4	46.9
(St.deviation)	(2.8)	(2.5)	(2.3)	(2.3)	(2.8)	(2.6)	(2.5)	(2.5)	(2.8)
Predicted									
Model 1	45.6	36.3	18.1	32.8	38.5	28.8	21.6	25.3	53.2
Model 3	53.4	30.2	16.4	30.4	41.5	28.1	16.2	28.4	55.4
Model 4	51.7	31.2	17.1	29.3	41.0	29.6	19.0	27.7	53.3
Model 5	54.8	31.1	14.1	22.8	47.4	29.8	22.5	21.4	56.1
Males:									
Observed	40.0	34.5	25.5	20.3	43.5	36.2	39.7	22.0	38.3
(St.deviation)	(2.7)	(2.7)	(2.5)	(2.2)	(2.8)	(2.7)	(2.7)	(2.3)	(2.7)
Predicted									
Model 1	32.6	44.2	23.3	32.1	35.5	32.4	35.3	20.3	44.3
Model 3	41.3	38.5	20.2	32.5	39.0	28.4	26.2	22.4	51.4
Model 4	41.7	38.7	19.6	31.3	39.6	29.1	27.0	21.8	51.2
Model 5	40.1	38.6	21.3	22.6	45.8	31.6	37.3	15.6	47.1

In Table 5.5 we report the parameter estimates for the model with taste persistence and random technology parameters. Compared to the results of Table 5.4 the parameter estimates associated with the four observed attributes seem to increase in absolute value in many cases. A striking result is that when one allow the technology parameters to be random then taste persistence almost vanishes. The highest level of taste persistence is found for older men $\left(\hat{\theta} = 4.473\right)$ which implies that the autocorrelation of the utility function from one "period" to the next equals about one per cent. Moreover, we see that for individuals between 18-29 years of age there seem to be very little variation across individuals of the technology parameter associated with the lpg alternative.

Table 5.7. Prediction performance of the model for group B with serially dependent utilities. Per cent

Gender	First choice			Second choice			Third choice		
	Hybrid	Lpg	Gaso-line	Hybrid	Lpg	Gaso-line	Hybrid	Lpg	Gaso-line
Females:									
Observed	45.0	42.0	13.0	33.0	44.9	22.1	22.0	13.1	64.9
(St.deviation)	(2.8)	(2.8)	(1.9)	(2.6)	(2.8)	(2.3)	(2.3)	(1.9)	(2.7)
Predicted									
Model 1	43.0	40.3	16.7	36.9	37.8	25.3	20.1	21.9	58.0
Model 3	45.5	38.8	15.7	36.4	39.9	23.7	18.1	21.3	60.6
Model 4	43.9	41.2	14.9	37.2	39.6	23.3	19.0	19.2	61.8
Model 5	42.8	39.5	17.8	32.7	43.2	24.1	24.5	17.4	58.1
Males:									
Observed	38.1	46.2	15.7	32.9	41.0	26.2	29.0	12.8	58.1
(St.deviation)	(2.7)	(2.8)	(2.0)	(2.6)	(2.7)	(2.5)	(2.5)	(1.9)	(2.8)
Predicted									
Model 1	35.3	45.2	19.5	37.4	35.0	27.6	27.3	19.8	52.9
Model 3	38.4	44.4	17.2	38.2	37.6	24.2	23.4	18.0	58.5
Model 4	40.2	44.6	15.2	38.6	38.4	23.1	21.3	17.0	61.7
Model 5	35.5	44.6	19.9	31.0	41.2	27.8	33.5	14.1	52.3

In Tables 5.6 and 5.7 we report how the models perform with respect to prediction. Recall that since we only apply data from individuals' first choices in the estimation of Models 3, 4 and 5 we are able to report both in-sample as well as out-of-sample predictions. Thus, out-of-sample predictions are given for second and third choices of Models 3, 4 and 5. The predictions are performed through simulations and are carried out as follows: First independent random variables are generated from the extreme value distribution. These random terms are fed into the expression for the utility function which enables us to simulate (predict) rank orderings of the alternatives conditional on the attributes of the experiments and the parameter estimates. Second, to take into account that the utilities are serially correlated we apply the recursive expression given in (5.1) to update the utilities to the next period (experiment). The simulations are replicated a large number of times to eliminate simulation error. In the model with random technology parameters these are drawn for each individual and kept fixed throughout the 15 experiments.

In Table 5.8 we report some summary measures of Goodness of fit. For the sake of comparison we have re-estimated the model with serially uncorrelated preferences, applying solely data on individuals first choices. Accordingly, we obtain estimates for the model with serially uncorrelated preferences (Model 2) and the model with serially correlated preferences (Model 3) that are based on the same data. Thus, Model 2 is a special case of Model 3 obtained by letting $\theta = \infty$. Model 3 is a special case of Model 5 and is also a special case of Model 4. We have employed two different measures of Goodness of fit; one is the log-likelihood value while the other is McFadden's ρ^2

(cf. Ben-Akiva and Lerman, 1985). McFadden's ρ^2 is somewhat analogous to the familiar R^2 used in conventional regression analysis. From Table 5.8 we realize that when allowing for serially correlation in preferences (which entails one additional parameter) the fit is improved substantially. This is particularly the case for individuals above 49 years of age. The fit improved $\left(\rho^2\right)$ dramatically when we allow taste persistence to be individual specific. Although Model 5 fits the data better than Model 4 the difference in terms of goodness of fit is not very large.

Table 5.8. Measures of Goodness of fit

	Age					
	18-29		30-49		50-	
	Females	Males	Females	Males	Females	Males
Log-likelihood, model 1	-2015.1	-1747.8	-3140.8	-3460.8	-2040.9	-2333.8
Log-likelihood, model 2	-1178.1	-1053.1	-1880.8	-1996.4	-1207.0	-1408.6
Log-likelihood, model 3	-1156.7	-979.1	-1710.7	-1978.5	-1046.0	-1183.9
Log-likelihood, model 4	-1014.4	-802.4	-1349.2	-1612.4	-754.7	-936.7
Log-likelihood, model 5	-965.5	-778.8	-1244.1	-1479.1	-706.0	-850.2
McFadden's ρ^2, model 1	0.19	0.12	0.15	0.17	0.12	0.10
McFadden's ρ^2, model 2	0.22	0.14	0.17	0.19	0.15	0.12
McFadden's ρ^2, model 3	0.24	0.20	0.25	0.20	0.26	0.25
McFadden's ρ^2, model 4	0.33	0.34	0.41	0.37	0.47	0.41
McFadden's ρ^2, model 5	0.36	0.36	0.45	0.42	0.50	0.47

From Tables 5.6 and 5.7 we realize that as regards to first choices (which are within-sample predictions for Models 1 to 5) that the prediction performance is more or less the same for all three models. However, from Table 5.8 it follows that the fit is best for Model 5 and Model 4 fits the data better than Model 3 in the case where the fit is evaluated by the loglikelihood and McFadden's ρ^2. The explanation why the results of Table 5.8 differ from the results of Tables 5.6 and 5.7 is that the predictions of Tables 5.6 and 5.7 do not account for as much micro information as the likelihood function. A more interesting way of evaluating the models is to consider the prediction performance for the second and third choices, which are out-of-sample predictions (for Models 2 to 5). We realize that, except in a few cases, Model 5 clearly has the best performance. If we take into account the standard deviations due to the limited sample sizes, we realize that only in 6 out of 24 cases are the out-of-sample predictions of Model 5 off by more than two standard deviations. Note that here we have neglected the contribution to the standard errors that is due to uncertain parameter estimates. If the prediction uncertainty were taken into account it is likely that the prediction confidence interval (based on two standard deviations on either side) would overlap all corresponding observed shares.

Since Model 5 fits the data better in terms of the Goodness-of-fit measures of Table 5.8 and has the best prediction performance, we conclude that it is our preferred model specification.

6. Elasticities and the willingness to pay for alternative fuel vehicles

By means of the estimated model it is possible to compute elasticities and compensation variation measures. In our context compensating variation (CV) means the amount that must be added to the purchase price of a specific vehicle technology to obtain the same utility, ceteris paribus, as the reference technology. Since we have formulated and estimated a random utility model it is possible to take the random taste-shifters into account when computing CV. In this way CV also becomes random and one must derive the corresponding distribution function. In our case this turns out to be simple due to the fact that the mean utility function is linear and the random terms are extreme value distributed. If the random terms of CV are interpreted as random to the agent himself the distribution function of CV describes the likelihood of the different levels of CV. If however, the randomness is solely attributed to unobserved population heterogeneity this distribution function describes how CV vary across the population due to unobservables that are perfectly known to the agents. See for example Hanemann (1996) for a presentation of this kind of approach.

For the purpose of predicting technology choices probabilities note that by (3.10)

(6.1)
$$P_j = \frac{\exp\left(\mathbf{Z}_j\beta + \mu_r\right)}{\sum_r \exp\left(\mathbf{Z}_r\beta + \mu_j\right)}.$$

For Model 5 the corresponding choice probabilities are obtained by taking the mean of P_j given in (6.1) with respect to the technology parameters.

Table 6.1 shows the predicted fractions of individuals in each age/gender group that would choose the respective technologies when the observable attributes are equal for all technologies. Thus, the results in this table can be interpreted as an aggregate measure of the distribution of “pure technology preferences”.

Table 6.1. Predicted technology choices by age and gender when attributes are equal for all technologies. (Model 5)

Technology	Model	Age/gender					
		18-29		30-49		50-	
		Females	Males	Females	Males	Females	Males
Electric	Model 3	0.27	0.22	0.25	0.19	0.30	0.18
	Model 4	0.24	0.20	0.21	0.15	0.35	0.16
	Model 5	0.36	0.27	0.37	0.27	0.36	0.23
Hybrid	Model 3	0.36	0.37	0.42	0.33	0.41	0.28
	Model 4	0.36	0.36	0.41	0.36	0.38	0.30
	Model 5	0.34	0.38	0.36	0.31	0.37	0.31
Lpg	Model 3	0.27	0.24	0.22	0.31	0.19	0.29
	Model 4	0.29	0.26	0.26	0.32	0.19	0.29
	Model 5	0.21	0.18	0.17	0.25	0.13	0.24
Gasoline	Model 3	0.10	0.17	0.11	0.17	0.10	0.25
	Model 4	0.11	0.18	0.12	0.17	0.08	0.25
	Model 5	0.09	0.17	0.10	0.17	0.14	0.22

By means of elasticities one can compute the effect from (marginal) changes in one or several attributes. For example, one may be interested in assessing the impact of indirect taxation through the purchase price of conventional fuel vehicles so as to make the alternative fuel vehicles more competitive.

Table 6.2. Aggregate own purchase price elasticities by fuel technology with taste persistence and random technology parameters (Model 5)

Technology	Age/gender					
	18-29		30-49		50-	
	Females	Males	Females	Males	Females	Males
Electric	-1.52	-0.92	-0.92	-1.37	-1.19	-1.26
Hybrid	-1.53	-1.14	-1.14	-1.61	-1.27	-1.32
Lpg	-2.78	-2.00	-2.00	-2.40	-2.54	-1.88
Gasoline	-2.41	-1.70	-1.70	-2.18	-1.71	-1.32

Table 6.3. Mean own purchase price elasticities by fuel technology with taste persistence and random technology parameters (Model 5)

Technology	Age/gender					
	18-29		30-49		50-	
	Females	Males	Females	Males	Females	Males
Electric	-2.80	-3.34	-2.41	-3.34	-3.03	-3.18
Hybrid	-2.89	-2.84	-2.64	-3.16	-2.98	-2.84
Lpg	-3.46	-3.76	-2.87	-3.44	-4.12	-3.14
Gasoline	-3.99	-3.80	-3.45	-3.80	-4.07	-3.22

In Tables 6.2 and 6.3 we have computed aggregate- and mean own price elasticities based on Model 5. By aggregate elasticities we mean elasticities of the mean choice probabilities across technology parameters (random) with respect to price. The mean elasticities are obtained by first computing elasticities conditional on technology parameters and subsequently evaluate the mean across the technology parameters. From the tables we see that the aggregate elasticities are considerably smaller than the mean ones. This is due to unobserved heterogeneity in the preference for technology. While the mean elasticities are interesting for assessing the strength of individual responses to price changes, the aggregate elasticities may be more interesting in the context of (macro) policy interventions. From these tables we note that, apart from women more than 50 years of age, the mean own purchase price elasticities are highest (in terms of absolute value) for Gasoline vehicles. However, for the aggregate elasticities we note that the elasticities have highest absolute value for the Lpg technology. One reason for this is that the relative variance of the technology parameter of the Gasoline vehicle is greater than for the other vehicles. In contrast, the relative variance of the technology parameter of the Lpg vehicle is rather small.

A major disadvantage with electric vehicles is the limited driving range. Until recently most electric vehicles had a driving range of about 100 km although current development of battery technology seems promising as to the possibility of substantially increasing the driving range in the near future. The estimates seem to confirm that "driving range" is an important attribute. In Table 6.4 we have applied the estimated model to predict the choice frequencies for various levels of "driving range" of electric vehicles, based on the estimates of Table 5.5, while it is set equal to 500 km for all other technologies, and the other attributes are equal across all technologies. The results of Table 6.4 seem to indicate that "driving range" is an important attribute.

Table 6.4. Predicted choice frequencies of electric vehicles by levels of driving range for electric vehicles when the driving range is 500 km for the other technologies and other attributes are equal for all technologies. Random technology parameters and taste persistence (Model 5)

	Age					
Driving range	18-29		30-49		50-	
for electric vehicles	Females	Males	Females	Males	Females	Males
500	0.36	0.27	0.36	0.27	0.37	0.23
350	0.27	0.20	0.32	0.23	0.33	0.18
250	0.22	0.16	0.30	0.20	0.31	0.15
150	0.17	0.13	0.27	0.18	0.29	0.13
100	0.15	0.11	0.26	0.17	0.28	0.12

Consider now the following scenario: we compare alternative fuel vehicle j to a conventional gasoline vehicle. Both vehicles have the same Z-attributes. We shall demonstrate how the distribution of CV can be obtained. Recall that the random terms $\{\varepsilon_{jh}\}$ are assumed to be i.i. extreme value distributed. Let $j=1$ represent gasoline fuel technology, and let K_{jh} denote the CV (individual specific) associated with technology $j>1$, defined as

$$\mathbf{Z}_1\beta+\mu_{1h}+\varepsilon_{1h}=\left(Z_{j1}+K_{jh}\right)\beta_1+\sum_{r=2}^{4}Z_{jr}\beta_r+\mu_{jh}+\varepsilon_{jh}, \tag{6.2}$$

where Z_{j1} is the purchase price of technology j. We shall only consider cases in which $\mathbf{Z}_1=\mathbf{Z}_j$, so that (6.2) reduces to

$$K_{jh}=\frac{\varepsilon_{1h}-\varepsilon_{jh}-\mu_{jh}+\mu_{1h}}{\beta_1}. \tag{6.3}$$

Since ε_{1h} and ε_{jh} are independent and (type III) extreme value distributed it follows that the distribution of $\varepsilon_{1h}-\varepsilon_{jh}$ is logistic. Thus

$$P\left(K_{jh}\le y\right)=E\left(\frac{1}{1+\exp\left(-\mu_{jh}+\mu_{1h}-\beta_1 y\right)}\right) \tag{6.4}$$

where the expectation is taken with respect to $\mu_{jh}-\mu_{1h}$.

Table 6.5. Mean and standard deviation in the distribution of compensating variation for different technologies with random technology parameters and taste persistence. (Model 5). NOK

Fuel	Age					
	18-29		30-49		50-	
	Females	Males	Females	Males	Females	Males
Electric, mean	45 000	7 000	67 000	9 000	65 000	2 000
Electric, standard deviation	76 000	85 000	129 000	98 000	116 000	131 000
Hybrid, mean	47 000	28 000	79 000	22 000	69 000	33 000
Hybrid, standard deviation	67 000	76 000	101 000	81 000	108 000	117 000
Lpg, mean	39 000	14 000	52 000	29 000	40 000	33 000
Lpg, standard deviation	59 000	58 000	95 000	66 000	97 000	101 000

Similarly to Table 6.1, the CV estimates in Table 6.5 indicate a marked difference between males and females with respect to preferences over alternative fuel technologies. Females are more positive towards alternative fuel vehicles than males. For electric vehicles females would—on average—prefer an electric to a gasoline vehicle even if the purchase price of the electric vehicle is up to 45 000 NOK higher than the purchase price of the gasoline vehicle, provided that the other attributes are equal. For males the results are ambiguous. Moreover, for females the hybrid alternative seems on average to be the most attractive one. Note, however, that the standard deviations in the distributions of CV are very large which means that the compensating values may vary drastically across individuals and/or across time.

Table 6.6. Fractions of individuals with negative compensating variation. Random technology parameters and taste persistence. (Model 5)

Technology	Age					
	18-29		30-49		50-	
	Females	Males	Females	Males	Females	Males
Electric	0.72	0.53	0.70	0.53	0.71	0.50
Hybrid	0.76	0.64	0.79	0.63	0.74	0.61
Lpg	0.75	0.60	0.71	0.68	0.66	0.63

In Table 6.6 we report the fraction of individuals with negative CV. That is, these figures express the fractions of individuals which would prefer the respective alternative technologies to a gasoline vehicle when the (observable) attributes are equal for all technologies. These figures are obtained by means of (6.4) with $y = 0$.

For example, 75 per cent of young females would prefer the electric to the gasoline vehicle, if the (observed) attributes were equal for both alternatives. The corresponding figure for young males is 60 per cent.

7. Concluding remarks

In this paper we have applied probabilistic choice models to analyze the demand for alternative fuel vehicles. The empirical analysis is based on a “stated preference” type of survey conducted on a sample of Norwegian individuals. Different random utility models are formulated and estimated. Not surprisingly the model with taste persistence and random technology parameters (Model 5) provides the best fit to the data. Moreover, when the technology parameters are allowed to be random effects the taste persistence effect more or less vanishes. The empirical study is simple in the sense that we have focused on a limited set of attributes and linear specifications of the utility function. Due to the fact that we have data on rank orderings it is possible to check out-of-sample model prediction performance. The results show that our preferred model (Model 5) performs rather well as regards out-of-sample predictions. The empirical results also show that alternative fuel vehicles appear to be fully competitive alternatives compared to conventional gasoline vehicles, provided the attribute values are the same given that a suitable infrastructure for maintenance and refueling has been established. In addition to purchase price, driving range seems to be an important attribute. The results indicate that unless the limited driving range for electric vehicles is increased substantially this technology will not be fully competitive in the automobile market. As regards electric vehicles, it furthermore seems that (on average) men are more reserved towards this technology than women. This may reflect the fact that so far there is considerable uncertainty about the battery technology, and the responses from men, more than from women, may be affected by doubts about whether or not it will be possible to obtain acceptable levels of driving range and sufficiently convenient infrastructure for servicing and refueling for electric vehicles in the near future.

Footnotes

[1] The battery technology seems at present, however, to develop rather rapidly.

[2] The notation C\A means the set of elements in C that are not in A.

[3] Sometimes researchers refer to the Central Limit Theorem as a justification for the probit model. However, the Central Limit Theorem does not immediately apply in this context. For example, the utility of a collection of elemental alternatives (aggregate alternative) equals the maximum of the utilities of the elemental alternatives. Thus, the maximum functional plays an essential role in this context which leads to the extreme value distribution instead of the normal distribution.

[4] Unfortunately, the proofs of the results summarized here are too long and complicated to be reviewed here, even in an appendix.

[5] Apart from the Netherlands, where lpg-fueled vehicles are quite common, this is the situation in other countries.

[6] A complete description of the choice sets and the choice context is given in Dagsvik et al. (1996).

[7] The CPU time on a Sun Sparc Ultra 2 Station implied by M = 1000 is about 30-50 h. If M is chosen equal to 300 we obtain results that are close to the ones obtained with M = 1000.

References

Beggs, S., S, Cardell and J. Hausman (1981): Assessing the Potential Demand for Electric Cars. *Journal of Econometrics* **16**, 1-19.

Ben-Akiva, M. and S.R. Lerman (1985): *Discrete Choice Analysis*. MIT Press, Cambridge.

Block, H., and J. Marschak (1960): Random Orderings and Stochastic Theories of Response. In Olkin et al. (eds.): *Contributions to Probability and Statistics*. Stanford: Stanford University Press.

Brownstone, D., D. Bunch, T. Golob and W. Ren (1996): Transaction Choice Models for Forecasting Demand for Alternative Fuel Vehicles. *Research in Transportation Economics* **4**, 87-129.

Brownstone, D. and K. Train (1999): Forecasting New Products Penetration with flexible Substitution Patterns. *Journal of Econometrics* **28** (Forthcoming).

Bunch, D.S., M. Bradley, T.F. Golob, R. Kitamura and G.P. Occhiuzzo (1991): Demand for Clean-fuel Personal Vehicles in California: A Discrete-Choice Stated Preference Survey. University of California, Davis and Irvine.

Calfee, J.E. (1985): Estimating the Demand for Electric Automobiles using Fully Disaggregated Probabilistic Choice Analysis. *Transportation Research* **19B**, 287-302.

Dagsvik, J.K. (1983): Discrete and Dynamic Choice: An Extension of the Choice Models of Luce and Thurstone. *Journal of Mathematical Psychology*, **27** 1-43.

Dagsvik, J.K. (1988): Markov Chains Generated by Maximizing Components of Multidimensional Extremal Processes. *Stochastic Processes and their Applications* **28**, 31-45.

Dagsvik, J.K. (1995): The Structure of Intertemporal Models for Myopic Choice with Random Preferences. Memorandum, 11/95, Department of Economics, University of Oslo.

Dagsvik, J.K. (2000): Discrete Choice in Continuous Time: Implications of an Intertemporal Version of the IIA Property. To appear in *Econometrica*.

Dagsvik, J.K., D.G. Wetterwald and R. Aaberge (1996): Potential Demand for Alternative Fuel Vehicles. Discussion Papers, no. 165, Statistics Norway.

Golob, T.F., R. Kitamura and G. Occhiuzzo (1991): The Effects of Consumer Beliefs and Environmental Concerns on the Market Potential for Alternative Fuel Vehicles. Mimeo, University of California, Davis and Irvine.

Hanemann, W.M. (1996): Welfare Evaluations with Discrete Choice Models. Working Paper no. 792, Giannini Foundation of Agricultural Economics, University of California, Berkeley.

Hausman, J. and D. McFadden (1984): A Specification Test for the Multinomial Logit Model. *Econometrica*, **52**, 1219-1240.

Hensher, D.A. (1982): Functional Measurement, Individual Preferences and Discrete-Choice Modeling: Theory and Application. *Journal of Economic Psychology* **2**, 323-335.

Jain, D.C., N.J. Vilcassim, and P.K. Chintagunta (1994): A Random-Coefficient Logit Brand-Choice Model Applied to Panel Data. *Journal of Business & Economic Statistics*, **12**, 317-328.

Keane, M.P. (1997): Modeling Heterogeneity and State Dependence in Consumer Choice Behavior. *Journal of Business & Economic Statistics*, **15**, 310-327.

Levin, I.P., J.J. Louviere, A.A. Schepanski and K.L. Norman (1983): External Validity Tests of Laboratory Studies of Information Integration. *Organizational Behavior and Human Performance* **31**, 173-193.

Luce, R.D. (1959): *Individual Choice Behavior*. New York: Wiley.

Luce, R.D. and P. Suppes (1965): Preference, Utility and Subjective Probability. In R.D. Luce, R.R. Bush and E. Galanter (eds.): *Handbook of Mathematical Psychology, Vol. III*, New York: Wiley.

Mannering, F.L. and K. Train (1985): Recent Directions in Automobile Demand Modeling. *Transportation Research* **19B**, 265-274.

Morikawa, T. (1994): Correcting State Dependence and Serial Correlation in the RP/RS Combined Estimation Method. *Transportation*, **21**, 153-166.

Pearmain, D., J. Swanson, E. Kroes and M. Bradley (1991): *Stated Preference Techniques: A Guide to Practice*. Richmond/Haag: Steer Davis Gleave/Hague Consulting Group.

Resnick, S. and R. Roy (1990): Multivariate Extremal Processes, Leader Processes and Dynamic Choice Models. *Advances in Applied Probability* **22**, 309-331.

Small, K.A. and H.S. Rosen (1981): Applied Welfare Economics with Discrete Choice Models. *Econometrica* **49**, 105-130.

Train, K. (1980): The Potential Market for Non-gasoline-powered Vehicles. *Transportation Research* **14A**, 405-414.

Yellott, J.I. (1977): The Relationship between Luce's Choice Axiom, Thurstone's Theory of Comparative Judgment, and the Double Exponential Distribution. *Journal of Mathematical Psychology* **15**, 109-144.