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Abstract:
This paper analyzes the potential household demand for alternative fuel vehicles in Norway, by applying data from a stated preference survey. The alternative fuel vehicles we consider are liquid propane gas and electric powered vehicles in addition to a dual-fuel vehicle. In this survey each respondent, in a randomly selected sample, was exposed to 15 experiments. In each experiment the respondent is asked to rank three hypothetical vehicles characterized by specified attributes, according to the respondent's preferences. Several versions of a random utility model are formulated and estimated. They include the ordered logit model and a model with preferences that are correlated across experiments. The model is applied to predict changes in demand resulting from price changes, and to assess the willingness to pay for alternative fuel vechicles.

Keywords: Stated preference, random utility, alternative fuel vehicles, ordered logit model, serially dependent preferences.

JEL classification: C51, C93, D12.

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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 obvious reason for this effort is the acknowledgement that the world's resources of oil is rather limited. Furthermore, there is increasing public awareness about the problems caused by pollution from automobiles in many densely populated areas, and the fact that monoxide 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.

This paper analyzes the potential household demand for alternative-fuel vehicles in Norway based on data from a stated preference type of survey conducted by Statistics Norway. In stated preference surveys respondents are asked to express preferences for hypothetical products characterized by specific attributes. Such experiments have some advantages over market data. First, a detailed design of the new products can be presented to the consumers so as to obtain information about their attitudes towards new products and preferences over product attributes. This is in contrast to the use of existing market data to forecast potential demand which depends heavily on correct model specification and the requirement that agents value attributes similarly for different products. Also, more information can be elicited from a given agent in stated preference surveys since he/she can be asked to rank the products in preference order. On the other hand, hypothetical choice situations can be inferior to market data since the possibility of confusion or unstated assumptions cannot be ruled out. Furthermore, one may also argue that individuals do not necessarily behave the same way in laboratory experiments as they would in real markets with real products, since they are not liable for their choices in hypothetical experiments. This issue is known as the problem of external validity. Although academic research on external validity is rare, there are, however, a few studies (cf. Levin et al. (1983) and Pearmain et al. (1991)) that indicate considerable evidence of external validity. In the particular cases where the product under investigation is not available in the market, the analyst has, however, no other choice but to rely on hypothetical choice experiments.

So far, alternative fuel-vehicles have not been sufficiently developed to appear competitive. For example, the battery technology of electric cars necessitate frequent recharging and costly replacement. Thus, the shortcomings of current battery technology prevents electric vehicles from being attractive in the market other than possibly for short/medium range transportation purposes. An additional problem is that the current infrastructure on maintenance and fuel supply is exclusively oriented towards conventional fuel vehicles, i.e. gasoline and diesel vehicles.

Although the data collected from the present stated preference survey yields some insight in individuals attitudes towards altenative fuel vechicles, it is nevertheless difficult to get a clear picture of the structure of the preferences judging from summary statistics (from the survey) alone. One important reason for this is that the choice setting is rather complicated with alternatives being characterized by several attributes which vary across the experiments presented to the survey participants. Thus, summary statistics only reveals "average behavior" across different experimental conditions. To fully analyze the structure of the preferences, it is therefore necessary to formulate and estimate a behavioral model that enables us to identify parameters of the distribution of the preferences. A further advantage with the behavioral modelling approach is that it can be applied to perform policy experiments and to calculate compensating variation measures. Compensating variation measures are of interest to answer questions, such as: What are the respective amounts that must be added to the purchase price of a specific alternative fuel vehicle to obtain the same utility level, ceteris paribus, as the gasoline vehicle?

A major part of this paper is concerned with the formulation and estimation of several versions of a structural model for individual choice behavior. The models discussed are based on recent advances in the theory of discrete choice. The first version we discuss is known as the ordered logit model. 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 the ordered logit model it is assumed that the decision-maker ranks the alternatives presented according to a random utility index where the random components of the utility index 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 be dependent across experiments. The motivation for this extension 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). In addition to these models we also discuss the ordered logit model with random coefficients.

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

The organization of the paper is as follows: In the next section we describe the theoretical point of departure and the rationale behind the chosen modeling framework. Section 3 discusses the survey method and provides a descriptive analysis of the data. In section 4 the empirical specification is presented and the estimation results are displayed and discussed. Section 5 reports selected price elasticities and the distribution of compensating variation for alternative fuel technologies.

2 Stochastic choice models

In the traditional (algebraic) theories for choice behavior under certainty the consumer (agent) is assumed to be perfectly rational, i.e., his preferences are deterministic and satisfy a set of regularity and consistency conditions such as transitivity, continuity, etc. This point of departure has a rather long tradition in economics, although an increasing body of empirical evidence, as well as common daily life experience, suggest that agents often make decisions under conflict in the sense that they have difficulty with assessing the precise value of each alternative. Furthermore, their preferences may change from one moment to the next in a manner that is unpredictable (to the agents themselves). In psychology, this problem has long been recognized (cf. Tversky (1969)). Already Thurstone (1927) found that often when individuals are exposed to the same choice experiment they tend to make inconsistent choices. To account for this phenomenon, Thurstone introduced the (binary) Thurstone random utility model. In this model the agent's preferences over alternatives are represented by a normally distributed random utility function. This point of departure seems particularly appealing in the context of analyzing potential demand for products with which the consumers have little or no experience. There is by now a large literature on probabilistic choice models, mainly developed by psychologists, where an important concern is to provide a theoretical rationale for the structure of choice models consistent with the notion of stochastic preferences (cf. Luce (1959), Luce et al. (1965), Luce (1977), Suppes et al. (1989), McFadden, (1981)). In contrast, economists have mainly focused on problems related to econometric specification and estimation of stochastic choice models and been less concerned about theoretical foundation for the structure of this type of models.

A seminal contribution to the theory of probabilistic choice is Luce (1959) in which he introduces his well known choice axiom; "independence from irrelevant alternatives" (IIA). The IIA assumption represents a stochastic formulation of rational behavior: While the agent in each experiment is allowed to behave inconsistently, IIA states that when the choice experiments are replicated a large number of times the agent will "on average" behave consistently. The IIA property also implies a very tractable structure of the corresponding choice model, often called the Luce model. This is also the case for choice experiments with rankings, which is of particular relevance for the present study.

Based on empirical evidence the IIA assumption has often been critisized for being rather restrictive. Apart from the "red bus-blue bus" example (cf. Debreu (1960)), the grounds for rejecting IIA have, however, sometimes been somewhat superficially summarized. As is well known but not always remembered, the IIA property may very well hold on the individual level but fail to hold on "average" in a sample of heterogeneous agents where the observable individual characteristics are insufficient for controlling properly for this heterogeneity.

2.1 Stochastic models for ranking

The systematic development of stochastic models for ranking started with Luce (1959) and Block and Marschak (1960). Specifically, they provide a powerful theoretical rationale for the structure of the so-called ordered logit model. The theoretical assumptions that underly the ordered logit model can briefly be described as follows.

Let S denote the choice univers (i.e., the set of all alternatives) and let $C \subset S$ be the choice set of feasible alternatives. Let $\boldsymbol{\rho}_C = (\rho_1, \rho_2, \ldots, \rho_m)$ be the rank ordering of the alternatives in C, where m is the number of alternatives in C. This means that ρ_i denotes the element in C that has the ith rank. Moreover, let $\mathrm{P}(\boldsymbol{\rho}_C)$ denote the probability that the agent shall prefer rank ordering $\boldsymbol{\rho}_C$ of C, and let $\mathrm{P}_C(\rho_i)$ be the probability that the agent shall rank alternative i on top when C is the set of feasible alternatives. Recall that the empirical counterpart of these probabilities are the respective number of times the agent chooses a particular rank ordering to the total number of times the experiment is replicated.

Definition

The ranking probabilities constitute a random utility model if

$$\mathrm{P}(\boldsymbol{\rho}_C) = \mathrm{P}(U(\rho_1) > U(\rho_2) > \cdots > U(\rho_m))$$

for $C \subset S$, where $\{U(j), j \in S\}$, are random variables.

The following assumptions are central to the development below.

Assumption A1

The ranking probabilities are consistent with some random utility model.

Assumption A2 (Stochastic rationality)

The ranking probabilities satisfy the Independence from Irrelevant Alternatives (IIA) *property in the sense that for any $C \subset S$*

$$\mathrm{P}(\boldsymbol{\rho}_C) = \mathrm{P}_C(\rho_1)\mathrm{P}_{C\setminus\{\rho_1\}}(\rho_2)\cdots\mathrm{P}_{\{\rho_{m-1},\rho_m\}}(\rho_{m-1}). \tag{2.1}$$

Assumption A2 states that the agent's ranking behavior can (on average) be viewed as a multistage process in which he first selects the most preferred alternative, next he selects the second best among the remaining alternatives, etc. The crucial point here is that in each stage, the agent's ranking of the remaining alternatives is independent of the alternatives that were selected in earlier steps. In other words, they are viewed as "irrelevant".

Theorem 1

There exists positive scalars, $\{a(j), j \in S\}$, such that the ranking probabilities are given by the model,

$$\mathrm{P}(\boldsymbol{\rho}_C) = \prod_{i \in C} \frac{a(\rho_i)}{\sum_{k \in C \setminus \{\rho_0, \ldots, \rho_{i-1}\}} a(\rho_k)}, \tag{2.2}$$

for $C \subset S$, if and only if A1 *and* A2 *hold, where $\rho_0 \equiv \{\emptyset\}$. The scalars, $\{a(j), j \in S\}$, are uniquely determined apart from multiplication by a positive constant.*

Block and Marschak (1960, p.109) have proved Theorem 1, the first part of which is a generalization of a result in Luce (1959, p.72), cf. Luce and Suppes (1965). As an example consider the case when $C = \{1, 2, 3\}$ and $\boldsymbol{\rho}_C = (2, 3, 1)$. Then (2.2) reduces to

$$\mathrm{P}(2,3,1) = \frac{a(2)}{a(1) + a(2) + a(3)} \cdot \frac{a(3)}{a(1) + a(3)}. \tag{2.3}$$

The next question that naturally arose in the early sixties was to characterize the class of random utility that satisfy A2. One model that satisfies A2 is the independent extreme value random utility model for ranking, cf. Luce and Suppes (1965). Formally this model is described as follows: Let $U(j)$ be the utility of alternative j and assume that $U(j) = V_j + \varepsilon_j$ where $\varepsilon_j, j \in S$, are *i.i.d.* random variables with cumulative distribution function

$$\mathrm{P}(\varepsilon_j \le x) = \exp(-e^{-x}). \tag{2.4}$$

Then it is not hard to demonstrate (see Beggs et al. (1981), for example) that the assumptions above yield (2.2) with $V_j = \log a(j)$. Later, Strauss (1979) and Strauss and Robertson (1981) found a random utility representation that yields (2.2) when the independence assumption is relaxed.

Theorem 2

Suppose the utility function has the structure, $U_j = V_j + \epsilon_j$, where $\epsilon_j, j \in S$, are i.i.d. random variables with a strictly increasing distribution function. If S contains more than two elements than (2.2) holds, with $V_j = loga(j)$, if and only if (2.4) holds.

A proof of Theorem 2 is given in Yellott (1977).

In this paper the point of departure for developing an empirical model is A1 and A2. What remains to obtain a fully specified econometric model, is to specify the structure of the systematic component of the utility function and to derive the likelihood function under specific assumption about population heterogeneity.

2.2 Random utilities with serial dependence

When a sample of individuals is presented with a series of experiments (such as the experiment analyzed below) the problem of memory effect, and/or taste persistence arises. By this it is meant that the utility 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".

In this section we shall briefly describe a class of choice models that allows the random terms of the preferences to be serially dependent. This type of models was introduced by Dagsvik (1983, 1988) and further developed in Dagsvik (1995 a, b). Let $U_j(t)$ denote the agent's utility of alternative j at time t (experiment t) and assume that $U_j(t), t = 1, 2, .., j \in S$, are stochastic processes in discrete time. In Dagsvik (1995 a, b) it is demonstrated that particular behavioral assumptions are consistent with the utilities $\{U_j(t)\}$, being independent 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, cf. (2.5) below. The behavioral assumptions, which justify the utilities being extremal processes may be viewed as extentions of the IIA assumption to the intertemporal context. We refer to Dagsvik (1995a) for a precise description and interpretation of these assumptions. Under the extremal process hypothesis we can express the utility process $\{U_j(t)\}$, as

$$U_j(t) = \max(U_j(t-1) - \theta, V_j(t) + \epsilon_j(t)) \tag{2.5}$$

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 $\varepsilon_j(t), j \in S$, $t = 1, 2, ..$ are i.i.d. random variables with c.d.f. as in (2.4). From (2.5) it follows that

$$\exp(EU_j(t)) = \sum_{r=1}^{t} \exp(V_j(r) - (t-r)\theta) \tag{2.6}$$

for $t \geq 1$. Eq. (2.6) shows that θ is analogous to a rate of preference parameter. Specifically, the contribution from the period r-specific systematic utility component to the currrent 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

$$corr\,(\exp(-U_j(s)),\ \exp(-U_j(t))) = \frac{\exp(EU_j(s))}{\exp(EU_j(t))} \cdot \exp(-(t-s)\theta) \tag{2.7}$$

for $s \leq t$. Since by (2.6), $EU_j(t)$ is nondecreasing as a function of t it follows that the right hand side of (2.7) is always less than or equal to $\exp(-(t-s)\theta)$. When $\{V_j(\tau), \tau = 1,2,..\}$ varies little over time (2.6) implies that (2.7) reduces to $\exp(-(t-s)\theta)$ 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 $\theta > 5$, then the serial correlation is negligible. The implication from the hypothesis of taste persistence is that choices at different moments become dependent. As demonstrated by Dagsvik (1988), it follows from (2.5) that the choice process $\{J(t)\}$ defined by

$$J(t) = j \Leftrightarrow U_j(t) = \max_k U_k(t)$$

becomes a Markov chain. Furthermore, the state and transition probabilities, $P_j(t)$ and $Q_{ij}(t-1,t)$, are given by (cf. Dagsvik (1995 a))

$$P_j(t) \equiv P(J(t)=j) = \frac{\sum_{r=1}^{t} \exp(V_j(r) - (t-r)\theta)}{\sum_{k \in C} \sum_{r=1}^{t} \exp(V_k(r) - (t-r)\theta)} \tag{2.8}$$

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

$$Q_{ij}(t-1,t) \equiv P(J(t)=j \mid J(t-1)=i) = \frac{\exp(V_j(t))}{\sum_{k \in C} \sum_{r=1}^{t} \exp(V_k(r) - (t-r)\theta)} \tag{2.9}$$

for $j \neq i$, $t \geq 2$, $i,\ j \in C$, and

$$Q_{ii}(t-1,t) \equiv P(J(t)=i \mid J(t-1)=i) = 1 - \sum_{k \in C \setminus \{i\}} Q_{ik}(t-1,t) \tag{2.10}$$

for $t \geq 2$. Moreover, the conditional transition probability given that a transition occurs equals

$$\pi_{ij}(t-1,t) \equiv P(J(t)=j \mid J(t) \neq i, J(t-1)=i) = \frac{\exp(V_j(t))}{\sum_{k \in C \setminus \{i\}} \exp(V_k(t))} \tag{2.11}$$

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, $\{V_j(t)\}$, of the utility function without relying on assumption about the taste persistence parameter θ; for example assumptions about the distribution of θ across individuals.

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 (2.5). Unfortunately, this turns out to be rather difficult and it is so far an unsolved problem.

In the special case where the systematic utility components, $\{V_j(t)\}$, are constant over time (2.8) and (2.9) reduce to

$$P_j(t) = P_j = \frac{\exp(V_j)}{\sum_{k\in C} \exp(V_k)} \qquad (2.12),$$

$$Q_{ij}(t-1,t) = Q_{ij} = (1-e^{-\theta})P_j \qquad (2.13)$$

for $i \neq j$, and

$$Q_{ii}(t-1,t) = e^{-\theta} + (1-e^{-\theta})P_i. \qquad (2.14)$$

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 (2.13) and (2.14) that $\theta = 0$, corresponds to a perfectly rational agent in the sense that he makes consistent choices over "time".

3 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 individuals 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. The latter strategy is preferable since it yields more information than the former one.

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 vehicles 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 a to 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.

3.1 Experimental design

We shall now, in detail, consider the construction of the choice sets presented to the survey participants. Since the purpose of this analysis is to study how potential demand for future vehicles depends on attributes that are assumed to influence preferences, it is important that the experimental design, to a reasonable degree, is representative for the central part of the attribute space. The ideal situation would have been that these attributes, in conjunction with socio-economic characteristics such as income, gender, etc., were the only factors influencing individuals' preferences. However, it is not realistic to believe that this is the case. First of all, there are several aspects of the vehicles which we are unable to represent in our design. Second, responses are supposed to reflect future purchase decisions of the survey respondents and, hence, the quality of the data depends heavily on the ability of the respondents to make "realistic" decisions in hypothetical situations. This is inherently related to the problem of external validation. Since the respondents are not liable for their choices they might tend to make other choices in a hypothetical situation than they would do in a real situation. This might, for instance, be the case if they disregard their current and expected future budget constraints. Further, the introduction of hypothetical future alternatives requires strong assumptions about future engines, and distribution and storage[1] of fuel. Not only does this imply that estimation results and forecasts should be interpreted with caution, but also that respondents may reject the assumptions imposed in the experiment on the basis of their own knowledge and perceptions. Thus we risk to find ourselves in a situation where we cannot be sure about which assumptions the responses are based on. Hence, 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 dual-fueled (electricity and gasoline) vehicles which all are hypothetical vehicles in the sense that they at present hardly appear as competitive alternatives to con-

[1] In particular battery capacity.

ventional gasoline and diesel vehicles[2]. 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 is 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", "vehicle driving range between refueling/recharging", "top speed" and "fuel consumption" appeared to be the most important attributes. Attributes such as refueling/recharging time and availability, emission level and size of the vehicle were omitted as attributes in the choice sets. 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[3]. 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 asumptions we intended to reduce some of this heterogeneity.

As mentioned above we used four attributes to describe the vehicles. In Table 3.9 in Appendix II we report the range of the values used for each attribute. Since we used slightly different ranges in the two groups A and B we report both.

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 occured. 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 reasonably good *local* approximation of the utility function. To

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

[3]This description is given in Appendix II (in Norwegian only).

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.

Table A in Appendix II shows an example of a typical choice set. 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 the other half to 15 different choice sets with the fuel technologies, "hybrid", "lpg" and "gasoline". For a complete description of the choice sets, see Appendix II.

3.2 Description of data

The scope of this section is to provide a descriptive analysis of the data and tentatively draw some conclusions about how preferences for alternative fuel vehicles vary with socio-economic characteristics. Although the conclusions are suggestive, they provide information which is of interest as a basic for discussion and interpretation of various model specifications. For expository reasons, we focus mainly on group A in this section. Yet, for the sake of comparison, we frequently comment upon the corresponding results for group B. The results for group B are given in Appendix I.

Table 3.1.A displays the relative frequency of choice of fuel technology, for group A, by chosen rank and gender. When we compare first choices (most preferred vehicle) we see that both men and women choose the electric vehicle more frequently than the lpg vehicle and the lpg vehicle more frequently than the gasoline vehicle. Conditional on the experimental design of the survey, this reveals two interesting and important aspects of the attitudes towards alternative fuel vehicles. First, the results in Table 3.1.A seem to indicate a large "green" segment in the population. In Table 3.1.B (Appendix I), this tendency is even stronger. Second, Table 3.1.A shows that people, to a large extent, perceive the electric vehicle as an interesting alternative. Thus, a tempting conclusion is that there seems to be a large potential demand for "cleaner" vehicles, especially electric powered vehicles.

Table 3.1.A Fuel technology by chosen rank and gender. Per cent.*)

	First Choice			Second Choice			Third Choice		
Gender	Elec-tricity	Lpg	Gaso-line	Elec-icity	Lpg	Gaso-line	Elec-tricity	Lpg	Gaso-line
Females	52.1	26.1	21.9	22.3	46.5	31.2	25.6	27.4	46.9
Males	40.0	34.5	25.5	20.3	43.5	36.2	39.7	22.0	38.3
Total	46.1	30.2	23.7	21.3	45.0	33.7	32.6	24.8	42.6

*) Note that both conditional on choice rank and conditional on fuel technology the rows add up to 100. The figures have standard deviation between 1 and 2 per cents.

We also see from Table 3.1.A that females choose the electric vehicle as first choice more frequently than men. One interpretation might be that women in general are more concerned about environmental issues than men. An additional possible explanation is that some married women may be solely concerned with purchase of the household's second car intended for short range use. The results of Table 3.2.A demonstrate, however, that the purchase prices of the chosen vehicles by technology do not vary significantly by gender.

Table 3.4.A (and Table 3.4.B) clearly indicate a negative effect of purchase price on vehicle choice. According to traditional consumer theory, this is what one would expect to find. Note, however, that differences in mean purchase price over fuel technologies depend heavily on the attribute values and must be interpreted with caution.

Table 3.2.A Mean purchase price by fuel technology, chosen rank and gender. In 1000 NOK.

	First Choice			Second Choice			Third Choice		
Gender	Electr-icity	Lpg	Gaso-line	Electr-icity	Lpg	Gaso-line	Electr-icity	Lpg	Gaso-line
Females	178	179	165	201	194	176	212	206	183
Males	175	181	167	198	195	175	207	210	185
Total	177	180	166	200	194	175	209	208	184

No evident gender specific variation in purchase price of the chosen vehicles appears to be present. A similar pattern emerges if we condition on age groups. This can be seen from Tables 3.4.A and B, which display mean purchase price by fuel technology, chosen rank and age of respondent. However, the choices of individuals between 18 and 29 years of age seem to depend more heavily on purchase price than the choices of older individuals. This dependency is particularly evident for electric vehicles. An explanation might be that these individuals choose the electric vehicle, as first choice solely, when this vehicle has a lower price than the lpg and gasoline alternatives. The results of Table 3.3.A show, however, that the fraction of respondents that choose the electric vehicle as their first choice is lower for age group 18-29 than for age groups 30-49 and 50 and above. This result may be due to income differences between younger and older individuals. However, the above conclusion does not apply to group B, and thus its general validity is questionable.

Table 3.3.A Fuel technology by chosen rank and age. Per cent.

	First Choice			Second Choice			Third Choice		
Age	Electricity	Lpg	Gasoline	Electricity	Lpg	Gasoline	Electricity	Lpg	Gasoline
18–29	40.2	33.7	26.1	24.4	39.6	36.0	35.4	26.7	37.9
30–49	49.1	29.6	21.3	20.2	46.5	33.3	30.8	23.8	45.4
50–	46.5	28.2	25.3	20.4	47.3	32.3	33.1	24.5	42.4
Total	46.1	30.2	23.7	21.3	45.0	33.7	32.6	24.8	42.6

Table 3.4.A Mean purchase price by fuel technology, chosen rank and age. In 1000 NOK.

	First Choice			Second Choice			Third Choice		
Age	Electricity	Lpg	Gasoline	Electricity	Lpg	Gasoline	Electricity	Lpg	Gasoline
18–29	172	179	165	198	195	174	212	209	187
30–49	178	181	165	201	194	176	209	208	183
50–	179	181	169	200	194	175	207	206	183
Total	177	181	166	200	194	175	209	208	184

Since pollution from vehicles is acknowledged to be an increasing problem in many densely populated areas, we would expect that the proportion of the gasoline vehicle as first choice declines with the population density in the area of residence. The results of Table 3.5.A suggest, however, that residents in urban areas (here: urban relates to areas with more than 20000 inhabitants) tend to choose the gasoline vehicle as first choice more often than individuals residing in small towns and rural areas. In contrast, residents in rural areas (here: rural relates to areas with less than 2000 inhabitants) are more likely to choose the electric vehicle as their first choice. Although Table 3.5.A depicts a different picture than expected, the results do not necessarily imply that residents in densely populated areas are less concerned about emission from vehicles and general pollution problems than residents in rural areas.

Table 3.6.A indicates that mean purchase prices of the chosen electric vehicles decrease by increasing population density. However, this pattern is not present for the remaining fuel technologies. We can investigate the validity of the above conclusion further by computing

mean purchase price of the first choice (i.e. the mean purchase price across fuel technologies). This gives a value of 173.8 for the group > 20000, 176.8 for the group $2000 - 20000$ and 176.4 for the group < 2000. These results may reflect the fact that the supply of public transportation services is better in urban than in rural areas.

Table 3.5.A Fuel technology by chosen rank and area of residence. Per cent.

	First Choice			Second Choice			Third Choice		
Area of residence	Electr-icity	Lpg	Gaso-line	Electr-icity	Lpg	Gaso-line	Electr-icity	Lpg	Gaso-line
<2000	50.0	29.3	20.7	20.7	43.6	35.7	29.3	27.1	43.6
2000–20000	44.5	34.5	21.0	24.3	43.2	32.5	31.2	22.3	46.5
>20000	43.1	28.0	28.9	19.8	47.0	33.2	37.1	25.0	47.9
Total	46.0	30.2	23.8	21.3	44.8	33.9	32.7	25.0	42.3

Table 3.6.A Mean purchase price by fuel technology, chosen rank and area of residence.

In 1000 NOK	First Choice			Second Choice			Third Choice		
Area of residence	Electr-icity	Lpg	Gaso-line	Electr-icity	Lpg	Gaso-line	Electr-icity	Lpg	Gaso-line
<2000	179	180	165	200	194	174	210	207	184
2000–20000	177	182	168	200	195	174	209	207	182
>20000	175	180	166	200	193	177	209	209	185
Total	177	181	166	200	194	175	209	208	184

According to the above arguments, we should find that car owners on average choose more expensive vehicles than those who do not possess a car. However, the results of Table 3.8.A do not confirm this relationship. On the contrary, car owners tend to choose less expensive electric vehicles, whereas there is no evident differences for the other fuel technologies. Inspection of Table 3.7.A, which reports proportions of choices by fuel technology, chosen rank and car ownership, reveals that individuals (households) that do not own a car have stronger preferences for electric vehicles than car owners. This result suggests that the former group represents a "green" segment in the population. Moreover, potential demand for alternative vehicles, especially electric vehicles, is greatest among these individuals.

Table 3.7.A Fuel technology by chosen rank and car ownership. Per cent.

	First Choice			Second Choice			Third Choice		
Car owner	Electr-icity	Lpg	Gaso-line	Electr-icity	Lpg	Gaso-line	Electr-icity	Lpg	Gaso-line
Yes	44.1	31.5	24.4	21.7	44.1	34.2	34.2	24.4	41.4
No	55.5	24.2	20.4	19.7	49.3	31.1	24.8	26.5	48.5
Total	46.1	30.2	23.7	21.3	45.0	33.7	32.6	24.8	42.6

Table 3.8.A Mean purchase price by fuel technology, chosen rank and car ownership. In 1000 NOK.

	First Choice			Second Choice			Third Choice		
Car owner	Electr-icity	Lpg	Gaso-line	Electr-icity	Lpg	Gaso-line	Electr-icity	Lpg	Gaso-line
Yes	176	180	166	200	194	175	208	208	184
No	181	181	166	198	193	175	214	206	182
Total	177	181	166	200	194	175	209	208	184

4 Empirical specifications and estimation results

4.1 Specification with serially uncorrelated preferences

From the discussions above it is apparant that it is impossible to get a precise picture of the preference patterns in the sample from a descriptive analysis alone. As mentioned in the introduction, it is necessary to have a behavioral model in order to identify the structure of individuals' preferences.

The objective of this section is to elaborate on the theoretical model developed in section 2.1 to obtain an empirical model that relates to the particular durables which are the focus of our analysis; namely alternative fuel vehicles. 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 hypothetical vehicles, characterized by given attributes (see above). Let $\boldsymbol{Z}_j(t) = (Z_{1j}(t), Z_{2j}(t), \ldots, Z_{nj}(t))$ denote the vector of attributes of alternative j in experiment t. In our case the dimension of $\boldsymbol{Z}_j(t)$, n, equals 4, plus dummies that represent the different fuel technologies. As mentioned above we shall assume that each agent in our sample has preferences over alternative vehicle attributes that can be rationalized by a random utility model that satisfies A2. According to Theorem 2 we know then that we may specify the utilities as independent extreme value distributed variables. We assume now that the utility function of individual h has the structure

$$U_j^h(t) = V_{jh}(t) + \varepsilon_{jh}(t) = \boldsymbol{Z}_j(t)\boldsymbol{\beta}_h + \boldsymbol{\varepsilon}_{jh}(t) \tag{4.1}$$

where $\{\varepsilon_{jh}(t)\}$ are *i.i.* extreme value distributed random variables and $\boldsymbol{\beta}_h$ is a set of unknown parameters, not necessarily the same for every individual. As discussed in section 2.1 the random terms $\{\varepsilon_{jh}(t)\}$ may capture aspects of the evaluation process that are random to the consumer himself. In addition, these random terms may also capture the effect 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 (4.1) was chosen after a series of preliminary rounds in which different candidates of functional forms where 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 (4.1) 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, 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 $V_{jh}(t)$ 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 for individual h with parameter vector $\boldsymbol{\beta}_h$ is given by

$$\mathcal{L}_h(\boldsymbol{\beta}_h) = \prod_{t=1}^{15} \prod_{i \in C} \prod_{j \in C \setminus \{i\}} (P_{ijt}(\boldsymbol{\beta}_h))^{Y_{ij}^h(t)}, \tag{4.2}$$

where $P_{ijt}(\boldsymbol{\beta}_h)$ 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), (2.4) and (4.1) it follows that

$$P_{ijt}(\boldsymbol{\beta}_h) = \frac{\exp(\boldsymbol{Z}_i(t)\boldsymbol{\beta}_h)}{\sum_{r \in C} \exp(\boldsymbol{Z}_r(t)\boldsymbol{\beta}_h)} \cdot \frac{\exp(\boldsymbol{Z}_j(t)\boldsymbol{\beta}_h)}{\sum_{r \in C \setminus \{i\}} \exp(\boldsymbol{Z}_r(t)\boldsymbol{\beta}_h)}. \tag{4.3}$$

Recall that for group A the choice set equals; $C = \{$ Gasoline, Lpg, Electric vehicle$\}$, while in group B, $C = \{$Gasoline, Lpg, Hybrid vehicle$\}$. Note that since (4.3) 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 4.1 Parameter estimates*) of the age/gender specific utility function.

	Age					
	18-29		30-49		50-	
Attribute	Females	Males	Females	Males	Females	Males
Purchase price	-2.530	-2.176	-1.549	-2.159	-1.550	-1.394
(in 100 000 NOK)	(-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	1380	1110	2070	2325	1290	1455
# of respondents	92	74	138	150	86	96
log-likelihood	2015.1	1747.8	3140.8	3460.8	2040.9	2333.8

*) t-values in parentheses

Table 4.1 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. Most of the other parameters also decline by age. However, when we take the standard error into account this tendency seems 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 sceptic 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 results are displayed in Tables 4.2 and 4.3.

Table 4.2 Prediction performence of the model for group A. Per cent.

Gender	First Choice			Second Choice			Third Choice		
	Electricity	lpg	Gasoline	Electricity	lpg	Gasoline	Electricity	lpg	Gasoline
Females:									
Observed	52.1	26.1	21.9	22.3	46.5	31.2	25.6	27.4	46.9
Predicted	45.6	36.3	18.1	32.8	38.5	28.8	21.6	25.3	53.2
Males:									
Observed	40.0	34.5	25.5	20.3	43.5	36.2	39.7	22.0	38.3
Predicted	32.6	44.2	23.3	32.1	35.5	32.4	35.3	20.3	44.3

Table 4.3 Prediction performance of the model for group B. Per cent.

Gender	First Choice			Second Choice			Third Choice		
	Hybrid	lpg	Gasoline	Hybrid	lpg	Gasoline	Hybrid	lpg	Gasoline
Females:									
Observed	45.0	42.0	13.0	33.0	44.9	22.1	22.0	13.1	64.9
Predicted	43.0	40.3	16.7	36.9	37.8	25.3	20.1	21.9	58.0
Males:									
Observed	38.1	46.2	15.7	32.9	41.0	26.2	29.0	12.8	58.1
Predicted	35.3	45.2	19.5	37.4	35.0	27.6	27.3	19.8	52.9

The results in Table 4.3 show that for those individuals who receive choice sets that include the hybrid vehicle alternative (group B) the model fits the data reasonably well. For the other half of the sample for which the electric vehicle alternative is feasible (group A), Table 4.2 shows that the predictions fail by about 10 per cent points in four cases. Thus the model performs better for group B than for group A. The reason for this is the following: In the model versions estimated and reported in this paper it is assumed that the model parameters are the same for both groups A and B (within the respective age/gender groups). We have also estimated the model with different parameters for each group. We found that the estimates for the two groups (which are not reported here) differ[4]. In particular, the estimates for group B (the hybrid case) are considerably more precisely determined than the estimates for group A. The parameter estimates for group B are the ones that are the closer of the two sets of estimates to the estimates reported above. As a

[4]The reason why the two sets of estimates differ may be related to the design of the experiments. First, the range of attribute variations is different for each group. Second, the correlation pattern between the components in the attribute vectors are different for the two groups, cf. the discussion in section 3.1. Since the assumed functional form of the utility function is at best a linear approximation that only holds locally, one may therefore risk that estimates depend on the attribute range and correlation pattern. Yet, another explication is possible: there may be violation of IIA resulting from agents perceiving the electric vehicle alternative as less "similar" to the gasoline vehicle alternative than other alternative fuel technologies are. These issues will be examined in future research.

result, the predictions from the model tend to be better for group B than for group A.

4.2 Random coefficient specification

In general, the parameters may vary across individuals. In some cases this variation may be accounted for by introducing individual characteristics such as age, education, etc. It is, however, a common experience that the available observable characteristics are insufficient for removing all the heterogeneity in the systematic terms of the utility function. Note that, in our case, since we have data equivalent to 30 observations for each individual, it is, at least in principle, possible to estimate individual specific parameters. Thus, as an alternative approach we employ a random coefficient specification in which the parameter vectors of the individuals are viewed as independent draws from a multivariate probability distribution F, say. Consequently, the likelihood function will in this case take the form

$$\mathrm{E}\mathcal{L}_h(\boldsymbol{\beta}) \equiv \int \mathcal{L}_h(\boldsymbol{\beta})\mathrm{d}F(\boldsymbol{\beta}) \tag{4.4}$$

and the total log likelihood function becomes

$$\ln \mathcal{L} = \sum_h \ln(\mathrm{E}\mathcal{L}_h(\boldsymbol{\beta})). \tag{4.5}$$

The maximum likelihood procedure is now to estimate the parameters of F, or in case a semi-parametric approach is taken, a non-parametric estimate of F.

In the estimation of the model we consider three cases. In the first case the parameters are assumed to be distributed across individuals according to a multivariate normal distribution with components that are independent apart from the parameters related to the technology dummies. In the second case the parameters are assumed to be distributed according to a nonparametric distribution. Finally, we have also estimated individual specific parameters but these estimates turned out to be rather imprecise and are therefore not reported here. In the nonparametric case $F(\boldsymbol{\beta})$ is assumed to be a multinomial distribution with probability mass at points $\boldsymbol{\beta}_s, s = 1, 2, ..., d$, (say). Estimation of multinomial logit models with random coefficients distributed according to a multinomial distribution has been considered by Jain et al. (1994). In practice this may be a rather tricky task because the corresponding likelihood function often may have several local maxima and it may be difficult to locate every one of them. In the present case this turned out to be so, in fact we have found numerous local maxima. We therefore cannot guarantee that the estimation results we have found so far correspond to the global maximum of the likelihood. We have therefore abandoned the case with a nonparametric distribution of the parameters in this paper, but we will pursue the issue in the future.

A drawback with the normallity assumption is that when large coefficient heterogeneity is present a considerable proportion of the sample may get the wrong sign of the price coefficients since the normal distribution is symmetric about the mean. From Table 4.7 in Appendix III we realize that this is indeed what turns out to be the case here and we therefore conclude that this strategy is inappropriate. Other alternatives will be considered in future research.

4.3 Allowing for serially correlated preferences

In this section we shall consider the empirical specification and estimation of the model version discussed in subsection 2.2, where the utility functions are correlated across experiments.

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 for the first choices of individual h can be written as

$$L_h(\beta_h, \theta_h) = \prod_{t=2}^{15} \prod_{i \in C} \prod_{j \in C} \quad Q_{ij}^h(t-1, t)^{W_{ij}^h(t)} \prod_{j \in C} P_j^h(1)^{W_{\cdot j}^h(1)} \tag{4.6}$$

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

Recall that the likelihood function (4.6) corresponds to the observations on individuals' first choices. As mentioned in section 2.2, 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 assumption which is a crucial assumption in all the model versions discussed in this paper.

Table 4.4 Parameter estimates*) of the age specific utility functions, when the utilities are serially correlated.

	Age					
	18-29		30-49		50-	
Attribute	Females	Males	Females	Males	Females	Males
Purchase price	-3.256	-3.234	-2.496	-2.932	-2.590	-2.618
(in 100 000 NOK)	(-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	-1.583	-2.263	-1.679	-2.828	-1.420	-3.945
(liter per 10 km)	(-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	690	555	1035	1177	645	728
# of respondents	92	74	138	150	86	96
log-likelihood	1156.7	979.1	1710.7	1978.5	1046.0	1183.9

*) t-values in parentheses

The results displayed in Table 4.4 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. 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 (2.7) that there is practically no correlation between utilities that are two or more experiments apart. Note that the log-likelihood value reported in Table 4.4 should not be compared with the corresponding values in Table 4.1, since only observations on first choices are applied here.

As mentioned in section 2.2, it is possible to form a conditional likelihood function which does not depend on the taste persistence parameter θ. We have obtained estimates based on the conditional likelihood which are reported in Table 4.8 in Appendix III. In general the absolute value of most parameters increase but when taking the standard deviation into account the estimates in Table 4.8 are essentially not different from the once reported in Table 4.4. The penalty that follows from applying the conditional likelihood approach is a reduction of the sample by almost 50 per cent of the subsample consisting of data from first choices.

Table 4.5 Prediction performance of the model for group A with serially dependent utilities. Per cent

	First Choice			Second Choice			Third Choice		
Gender	Electri-city	lpg	Gaso-line	Electri-city	lpg	Gaso-line	Electri-city	lpg	Gaso-line
Females:									
Observed	52.1	26.1	21.9	22.3	46.5	31.2	25.6	27.4	46.9
Predicted	53.4	30.2	16.4	30.4	41.5	28.1	16.2	28.4	55.4
Males:									
Observed	40.0	34.5	25.5	20.3	43.5	36.2	39.7	22.0	38.3
Predicted	41.3	38.5	20.2	32.5	39.0	28.4	26.2	22.4	51.4

Table 4.6 Prediction performance of the model for group B with serially dependent utilities. Per cent

	First Choice			Second Choice			Third Choice		
Gender	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
Predicted	45.5	38.8	15.7	36.4	39.9	23.7	18.1	21.3	60.6
Males:									
Observed	38.1	46.2	15.7	32.9	41.0	26.2	29.0	12.8	58.1
Predicted	38.4	44.4	17.2	38.2	37.6	24.2	23.4	18.0	58.5

In Tables 4.5 and 4.6 we report how the model performs with respect to prediction. Recall that since we only apply data from individuals first choices 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. 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 (2.5) to update the utilities to the next period (experiment). The simulations are replicated a large number of times to eliminate simulation error.

The tables demonstrate that predictions are improved as regards to first choices (which are within-sample predictions), but that predictions for second and third choices (which are out-of-sample predictions) are not improved compared to the case with serially uncorrelated utilities.

5 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. A standard approach is to compute CV by applying the mean of the utility function only, (cf. Small and Rosen, (1981)). This ignores the heterogeneity in the model. 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.

Consider first the elasticities. For the purpose of computing elasticities of the choice probabilities note that by (2.12)

$$P_j = \frac{\exp(\boldsymbol{Z}_j \boldsymbol{\beta})}{\sum_r \exp(\boldsymbol{Z}_r \boldsymbol{\beta})}. \tag{5.1}$$

By straight forward calculus we obtain the following expressions,

$$\frac{\partial \log P_j}{\partial \log Z_{js}} = Z_{js}\beta_s(1 - P_j) \tag{5.2}$$

and

$$\frac{\partial \log P_j}{\partial \log Z_{ks}} = -Z_{ks}\beta_s P_j. \tag{5.3}$$

for $k \neq j$. Equation (5.2) expresses the own-attribute elasticity of P_j with respect to component Z_{js} while (5.3) expresses the corresponding formulae for the cross-attribute elasticity.

Table 5.1 Predictied technology choices by age and gender when attributes are equal for all technologies.

Technology	Age					
	18-29		30-49		50-	
	Females	Males	Females	Males	Females	Males
Electricity	0.27	0.22	0.25	0.19	0.30	0.18
Hybrid	0.36	0.37	0.42	0.33	0.41	0.28
Lpg	0.27	0.24	0.22	0.31	0.19	0.29
Gasoline	0.10	0.17	0.11	0.17	0.10	0.25

Table 5.1 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". These results could, however, not have been obtained from the survey data alone and they therefore provide a nice example of the usefulness of a structural modelling approach. The figures confirm the tentative conclusion in section 3.2 that women seem to be more concerned about environmental issues than men.

Table 5.2 Own purchase price elasticities by fuel technology and level of purchase price.

Technology	Purchase price (NOK)	Age					
		18-29		30-49		50-	
		Females	Males	Females	Males	Females	Males
Electricity	150 000	-3.56	-3.78	-2.81	-3.56	-2.72	-3.22
	200 000	-4.75	-5.05	-3.74	-4.75	-3.63	-4.29
Hybrid	150 000	-3.13	-3.06	-2.17	-2.95	-2.29	-2.83
	200 000	-4.17	-4.07	-2.90	-3.93	-3.06	-3.77
Lpg	150 000	-3.57	-3.69	-2.92	-3.03	-3.15	-2.79
	200 000	-4.75	-4.92	-3.89	-4.05	-4.20	-3.72
Gasoline	150 000	-4.40	-4.03	-3.33	-3.65	-3.50	-2.95
	200 000	-5.86	-5.37	-4.44	-4.87	-4.66	-3.93

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. This can be achieved by means of (5.2) and (5.3). Selected elasticities are computed in Table 5.2 based on the estimates given in Table 4.4. When large changes in attribute values are considered then the elasticity formulas (5.2) and (5.3) may give imprecise results due to the fact that the model is highly nonlinear. We have therefore given exact predition results for the case when purchase prices increase by 20 per cent, see Table 5.3.

Table 5.3 Relative change in predicted technology choice when the purchase price of gasoline vehicles increases by 20 per cent, from 150 000 NOK. Per cent.

Technology	Age					
	18-29		30-49		50-	
	Females	Males	Females	Males	Females	Males
Electricity	6.6	11.8	6.2	11.0	5.7	15.7
Hybrid	6.6	11.8	6.2	11.0	5.7	15.7
Lpg	6.6	11.8	6.2	11.0	5.7	15.7
Gasoline	-59.8	-57.6	-49.8	-54.0	-51.4	-47.2

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. Let us express the utility of fuel technology as $\boldsymbol{Z}_j^*\boldsymbol{\beta} + \mu_j + \epsilon_{jh}$, where $\boldsymbol{Z}_j^*$ represents the four attributes, "purchase price", "top speed", "driving range" and "fuel consumption", and $\{\mu_j\}$ denotes the technology specific constants. Recall that the random terms $\{\epsilon_{jh}\}$ are assumed to be i.i. extreme value distributed. Let $j = 1$ represent gasoline fuel technology and let Y_{jh} denote the CV (individual specific) associated with technology $j > 1$, defined as

$$\boldsymbol{Z}_1^*\boldsymbol{\beta} + \epsilon_{1h} = (Z_{j1}^* + Y_{jh})\beta_1 + \sum_{r=2}^{4} Z_{jr}^*\beta_r + \mu_j + \epsilon_{jh}, \tag{5.4}$$

where $\mu_{1h} = 0$ and Z_{j1}^* is the purchase price of technology j. We shall only consider cases in which $\boldsymbol{Z}_1^* = \boldsymbol{Z}_j^*$, so that (5.4) reduces to

$$Y_{jh} = \frac{\epsilon_{1h} - \epsilon_{jh} - \mu_j}{\beta_1}. \tag{5.5}$$

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

$$P(Y_{jh} \leq y) = \frac{1}{1 + \exp(-\mu_j - \beta_1 y)}. \tag{5.6}$$

Moreover (5.6) implies that

$$E(Y_{jh}) = -\frac{\mu_j}{\beta_1} \tag{5.7}$$

and

$$var(Y_{jh}) = \frac{\pi^2}{3\beta_1^2}. \tag{5.8}$$

In Table 5.4 we present estimates, based on (5.7) and (5.8), for the mean and the standard deviation of CV for the different technologies for each combination of age and gender.

Table 5.4 Mean and standard deviation in the distribution of compensating variation for different technologies. NOK

	Age					
	18-29		30-49		50-	
Fuel	Females	Males	Females	Males	Females	Males
Electric, mean	-32000	-8000*	-32000	-3000*	-42000	12000*
Electric, standard deviation	56000	56000	72000	62000	70000	69000
Hybrid, mean	-41000	-24000	-52000	-22000	-53000	-5000
Hybrid, standard deviation	56000	56000	72000	62000	70000	69000
Lpg, mean	-32000	-11000	-28000	-20000	-24000	-6000
Lpg, standard deviation	56000	56000	72000	62000	70000	69000

Note that the figures with the $_*$-label are derived from parameter estimates that are not significantly different from zero. Consequently we cannot claim that these figures differ significantly from zero.

Similarly to Table 5.1, the CV estimates in Table 5.4 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 32 000 NOK higher than the purchase price of the gasoline vehicle. For males the results are ambiguous. Moreover, for females the hybrid alternative seems to be the most attractive one. Young males seem to find the hybrid alternative the most attractive one. Note, however, that the standard deviations in the distribution of CV are very large which means that the compensating values may vary drastically across individuals and /or across time.

Table 5.5 Fractions of individuals with negative compensating variation.

Technology	Age					
	18-29		30-49		50-	
	Females	Males	Females	Males	Females	Males
Electricity	0.74	0.57	0.69	0.52	0.75	0.42
Hybrid	0.79	0.69	0.79	0.66	0.80	0.53
Lpg	0.74	0.59	0.67	0.65	0.65	0.54

In Table 5.5 we report the fraction of individuals with negative CV, as predicted by the model. 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 (5.6) with $y = 0$.

6 Conclusion

In this paper we have analyzed the demand for alternative fuel vehicles. The empirical results are based on a "stated preference" type of survey conducted on a sample of Norwegian individuals. Different random utility models are formulated and estimated. They include models with serially uncorrelated as well as serially correlated utility functions.

The empirical results show that alternative fuel vehicles appear to be fully competitive alternatives compared to conventional gasoline vehicles. As regards electric vehicles, it 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 men, more than women, may have doubts about whether or not it will be possible to provide a sufficiently convenient infrastructure for servicing and refueling for electric vehicles in the near future. Furthermore, the hybrid alternative appears to be the most preferred technology among females and young males while males above 30 years of age seem more or less indifferent between the hybrid and the lpg alternative.

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Appendix I

Table 3.1.B Fuel technology by chosen rank and gender. Per cent.

	First Choice			Second Choice			Third Choice		
Gender	Hybrid	Lpg	Gaso-line	Hybrid	Lpg	Gaso-line	Hybrid	Lpg	Gaso-line
Females	45.0	42.0	13.0	33.0	44.9	22.1	22.0	13.1	64.9
Males	38.1	46.2	15.7	32.9	41.0	26.2	29.0	12.8	58.1
Total	41.4	44.2	14.4	33.0	42.8	24.2	25.6	13.0	61.4

Table 3.2.B Mean purchase price by fuel technology, chosen rank and gender. In 1000 NOK.

	First Choice			Second Choice			Third Choice		
Gender	Hybrid	Lpg	Gaso-line	Hybrid	Lpg	Gaso-line	Hybrid	Lpg	Gaso-line
Females	243	209	197	248	222	209	252	238	216
Males	243	209	198	246	223	208	252	240	217
Total	243	209	198	247	223	208	252	239	216

Table 3.3.B Fuel technology by chosen rank age of respondent. Per cent.

	First Choice			Second Choice			Third Choice		
Age	Hybrid	Lpg	Gaso-line	Hybrid	Lpg	Gaso-line	Hybrid	Lpg	Gaso-line
18–29	39.4	44.4	16.2	32.5	40.1	27.4	28.1	15.5	56.4
30–49	42.2	44.3	13.5	32.5	45.4	22.1	25.3	10.3	64.4
50–	41.9	43.8	14.3	34.2	41.3	24.5	23.9	14.9	61.2
Total	41.4	44.2	14.4	33.0	42.8	24.2	25.6	13.0	61.4

Table 3.4.B Mean purchase price by fuel technology, chosen rank and age. In 1000 NOK.

	First Choice			Second Choice			Third Choice		
Age	Hybrid	Lpg	Gaso-line	Hybrid	Lpg	Gaso-line	Hybrid	Lpg	Gaso-line
18–29	243	208	196	247	222	209	252	238	217
30–49	243	208	197	247	223	207	253	246	216
50–	243	211	201	248	222	210	251	232	215
Total	243	209	198	247	223	208	252	239	216

Table 3.5.B Fuel technology by chosen rank and area of residence. Per cent.

Area of residence	First Choice Hybrid	Lpg	Gasoline	Second Choice Hybrid	Lpg	Gasoline	Third Choice Hybrid	Lpg	Gasoline
<2000	45.1	42.2	12.7	30.3	47.8	21.9	24.6	10.0	65.4
2000–20000	41.1	43.3	15.6	33.3	43.8	22.9	25.6	12.9	61.5
>20000	38.7	45.9	15.4	34.6	38.7	26.7	26.7	15.4	57.9
Total	41.5	44.0	14.5	32.8	43.0	24.2	25.7	13.0	61.3

Table 3.6.B Mean purchase price by fuel technology, chosen rank and area of residence. In 1000 NOK.

Area of residence	First Choice Hybrid	Lpg	Gasoline	Second Choice Hybrid	Lpg	Gasoline	Third Choice Hybrid	Lpg	Gasoline
<2000	243	208	199	247	223	208	252	241	215
2000-20000	243	208	198	246	224	208	252	237	217
>20000	242	210	197	247	221	209	253	239	217
Total	243	209	198	247	223	208	252	239	216

Table 3.7.B Fuel technology by chosen rank and car ownership. Per cent.

Car owner	First Choice Hybrid	Lpg	Gasoline	Second Choice Hybrid	Lpg	Gasoline	Third Choice Hybrid	Lpg	Gasoline
Yes	41.1	44.5	14.4	32.3	42.6	25.1	26.6	12.9	60.5
No	42.7	42.5	14.8	37.3	44.2	18.5	20.0	13.3	66.7
Total	41.4	44.2	14.4	33.0	42.8	24.2	25.6	13.0	61.4

Table 3.8.B Mean purchase price by fuel technology, chosen rank and car ownership. In 1000 NOK.

Car owner	First Choice Hybrid	Lpg	Gasoline	Second Choice Hybrid	Lpg	Gasoline	Third Choice Hybrid	Lpg	Gasoline
Yes	243	209	198	247	223	208	252	240	216
No	244	210	198	246	221	209	253	236	216
Total	243	209	198	247	223	208	252	239	216

Appendix II

Table A Choice sets.

Choice set	Fuel technology	Price 1000 NOK	Top speed Km/h	Driving range Kilometers	Fuel consumption Liter per km.
1	Electric	210	100	500	0.1
	Lpg	160	140	500	0.3
	Gasoline	140	160	500	0.6
2	Electric	130	100	300	0.2
	Lpg	200	140	400	0.5
	Gasoline	170	140	500	0.8
3	Electric	250	120	300	0.2
	Lpg	200	180	400	0.5
	Gasoline	210	180	500	1.0
4	Electric	170	110	300	0.2
	Lpg	225	180	400	0.4
	Gasoline	170	160	500	0.7
5	Electric	170	100	300	0.1
	Lpg	160	140	400	0.5
	Gasoline	210	160	500	0.8
6	Electric	210	120	300	0.2
	Lpg	200	160	400	0.5
	Gasoline	140	140	500	0.7
7	Electric	130	100	300	0.1
	Lpg	225	160	500	0.4
	Gasoline	170	160	500	1.0
8	Electric	250	110	400	0.1
	Lpg	160	160	300	0.5
	Gasoline	210	180	400	1.0
9	Electric	250	120	400	0.2
	Lpg	200	160	400	0.4
	Gasoline	170	140	500	0.7

Table A Choice sets. Continued ...

Choice set	Fuel technology	Price 1000 NOK	Top speed Km/h	Driving range Kilometers	Fuel consumption Liter per km.
	Electric	170	100	300	0.1
10	Lpg	200	160	500	0.5
	Gasoline	160	140	400	1.0
	Electric	210	120	400	0.2
11	Lpg	160	180	400	0.5
	Gasoline	170	160	400	0.8
	Electric	130	100	300	0.1
12	Lpg	200	140	400	0.3
	Gasoline	210	180	400	0.8
	Electric	170	100	400	0.1
13	Lpg	225	180	500	0.3
	Gasoline	170	140	500	0.7
	Electric	225	130	400	0.3
14	Lpg	160	180	400	0.5
	Gasoline	140	160	500	0.8
	Electric	210	100	400	0.1
15	Lpg	225	160	400	0.4
	Gasoline	210	160	500	0.7

Table B Choice sets.

Choice set	Fuel technology	Price 1000 NOK	Top speed Km/h	Driving range Kilometers	Fuel consumption Liter per km.
	Hybrid	250	180	600	0.4
1	Lpg	220	160	500	0.4
	Gasoline	250	200	500	0.8
	Hybrid	225	140	500	0.2
2	Lpg	275	180	500	0.3
	Gasoline	200	180	400	0.8
	Hybrid	300	160	600	0.3
3	Lpg	190	150	400	0.3
	Gasoline	250	150	500	0.6
	Hybrid	275	160	500	0.2
4	Lpg	250	180	400	0.5
	Gasoline	175	150	400	0.6
	Hybrid	250	160	500	0.3
5	Lpg	210	160	500	0.4
	Gasoline	200	160	500	1.0
	Hybrid	225	140	500	0.2
6	Lpg	210	160	400	0.5
	Gasoline	200	160	500	1.0
	Hybrid	225	170	500	0.4
7	Lpg	190	160	400	0.4
	Gasoline	175	150	400	0.6
	Hybrid	250	170	400	0.4
8	Lpg	190	150	400	0.4
	Gasoline	175	150	400	0.6
	Hybrid	275	160	600	0.2
9	Lpg	250	180	500	0.5
	Gasoline	250	180	600	1.0

Table B Choice sets. Continued ...

Choice set	Fuel technology	Price 1000 NOK	Top speed Km/h	Driving range Kilometers	Fuel consumption Liter per km.
10	Hybrid	225	140	500	0.3
	Lpg	190	150	400	0.5
	Gasoline	200	160	400	0.5
11	Hybrid	275	160	600	0.3
	Lpg	220	160	500	0.4
	Gasoline	200	150	500	0.6
12	Hybrid	225	160	500	0.4
	Lpg	210	160	400	0.3
	Gasoline	200	150	500	0.8
13	Hybrid	250	160	500	0.4
	Lpg	275	180	500	0.5
	Gasoline	250	150	400	0.6
14	Hybrid	225	140	400	0.3
	Lpg	210	160	400	0.4
	Gasoline	200	170	600	1.0
15	Hybrid	225	140	600	0.2
	Lpg	190	150	400	0.3
	Gasoline	250	170	500	0.8

Table 3.9 Attribute ranges

Attribute	Group A	Group B
Purchase price (in 1000 NOK)	[130 , 250]	[175 , 300]
Top speed (km/h)	[100 , 180]	[140 , 200]
Driving range (km)	[300 , 500]	[400 , 600]
Fuel consumption (liter/10 km)	[0.1 , 1.0]	[0.2 , 1.0]

Table 3.10 Attribute means

	Group A			Group B		
Attribute	Electricity	Lpg	Gasoline	Hybrid	Lpg	Gasoline
Purchase price (in 1000 NOK)	192	193	177	247	219	212
Top speed (km/h)	109	161	157	156	163	162
Driving range (km)	353	420	473	520	440	473
Fuel consumption (liter/10 km)	0.15	0.43	0.81	0.31	0.41	0.75

Kort 1A

Ta hensyn til følgende informasjon når du vurderer alternativene:

1. Oppladningstiden for et tomt (flatt) batteri i en el-bil vil være ca. 3-4 timer når en benytter en vanlig stikkontakt. Det eksisterer i dag teknologi som gjør det mulig å fullade et tomt batteri på 20 minutter. Dette må gjøres ved spesielle ladestasjoner (bensinstasjoner).
2. El-bilen det her er snakk om er ikke nødvendigvis av samme type som de som er på markedet idag.
3. Med kjørelengde for el-biler menes hvor langt man kan kjøre på et fullt ladet batteri før man må lade opp batteriet på el-bilen igjen. For bensin og gass drevne biler er dette lik den distansen man kan kjøre på en full tank (både by- og landeveiskjøring).
4. Drivstoff kostnader pr. mil er regnet i liter bensin pr. mil. For el-bil er el-kostnadene pr. mil (inkludert batteri skift) omregnet til liter bensin pr. mil. Tilsvarende er kostnadene pr. mil for gassbilen omregnet i liter bensin pr. mil.
5. Gassbilen forurenser mindre enn en bensinbil med katalysator. Bruk som utgangspunkt at tilgjengeligheten på gass vil være den samme som for bensin i fremtiden.
6. Om bilen er drevet av bensin, gass eller elektrisitet har ingen betydning for bilens størrelse, utseende eller levetid.

Kort 1B

Ta hensyn til følgende informasjon når du vurderer alternativene:

1. Gassbilen forurenser mindre enn en bensinbil med katalysator. Bruk som utgangspunkt at tilgjengeligheten på gass vil være den samme som for bensin i fremtiden.
2. En hybrid bil er en el-bil som har et diesel/bensin aggregat som kan lade bilens batteri under kjøring. Batteriet på bilen kan også lades opp på vanlig måte som f.eks. via motorvarmer uttak. Hybridbilen omregnet i liter bensin pr. mil.
3. Drivstoff kostnader pr. mil er regnet i liter bensin pr. mil. For hybridbilen er kostnadene pr. mil (inkludert batteriskift) omregnet til liter bensin pr. mil. Tilsvarende er kostnadene pr. mil for gassbilen omregnet i liter bensin pr. mil
4. Om bilen er drevet av bensin, gass eller elektrisitet har ingen betydning for bilens størrelse, utseende eller levetid.

Appendix III

Table 4.7 Parameter estimates*) of the utility function. Random coefficient models.

	Females		Males	
Attribute	Expectation	St.dev.	Expectation	St.dev.
Purchase price	-4.51	3.51	-5.09	2.97
(in 100 000 NOK)	(-16.1)	(14.0)	(-22.1)	(14.9)
Top speed (km/h)	-0.51	1.40	0.42	2.13
	(-1.9)	(1.8)	(1.5)	(5.5)
Driving range (km)	1.49	4.80	3.16	3.47
	(2.5)	(5.6)	(6.0)	(3.9)
Fuel consumption	-2.44	3.35	-4.10	4.08
(liter per 10 km)	(-6.4)	(6.7)	(-11.7)	(11.7)
Dummy, electric	2.47	4.56	0.35	4.17
	(5.5)	(11.7)	(0.8)	(12.6)
Dummy, hybrid	2.46	3.84	1.15	3.27
	(7.9)	(6.7)	(4.4)	(15.6)
Dummy, lpg	1.77	3.5	1.11	2.59
	(8.0)	(7.3)	(6.5)	(14.4)
Covariance		3.36		2.33
		(5.9)		(12.32)
# of observations	4740		4890	
# of observations	316		326	
log-likelihood	1701.5		1942.3	

*) t-values in parentheses.

Table 4.8 Parameter estimates*) based on conditional likelihood.

	Age					
	18-29		30-49		50-	
Attribute	Females	Males	Females	Males	Females	Males
Purchase price	-3.592	-4.126	-3.050	-3.360	-3.365	-3.206
(in 100 000 NOK)	(-11.0)	(-10.6)	(-10.9)	(-13.4)	(-8.7)	(-8.9)
Top speed (100 km/h)	1.204	1.931	-0.646	0.875	0.226	2.063
	(1.7)	(2.6)	(-1.0)	(1.5)	(0.3)	(2.7)
Driving range (1 000 km)	6.835	5.367	4.176	7.394	3.938	6.617
	(4.4)	(3.1)	(3.0)	(5.8)	(2.1)	(3.5)
Fuel consumption	-2.263	-2.720	-1.150	-2.553	-0.857	-5.025
(liter per 10 km)	(-3.0)	(-3.4)	(-1.7)	(-4.2)	(-0.9)	(-5.4)
Dummy, electric	1.603	0.632	1.247	1.043	2.183	0.060
	(3.4)	(1.1)	(2.8)	(2.8)	(3.6)	(0.1)
Dummy, hybrid	1.152	0.971	1.948	0.791	1.951	-0.256
	(3.0)	(2.3)	(5.4)	(2.6)	(4.0)	(-0.6)
Dummy, lpg	1.113	0.563	0.981	1.074	1.121	0.032
	(4.3)	(1.9)	(4.1)	(5.3)	(3.4)	(0.1)
# of observations						
# of respondents						
log-likelihood	409.8	301.1	507.2	634.8	292.2	326.5

*) t-values in parentheses

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