European Transport \ Trasporti Europei n. 40 (2008): 4-32

Choice of season cards in public transport: a study of a Stated Preference experiment

Vincent van den Berg [1*], Eric Kroes [1, 2], Erik T. Verhoef [1, 3]

[1] *Department of Spatial Economics, VU University, Amsterdam, The Netherlands*

[2] *Significance BV, The Hague, The Netherlands*

[3] *Tinbergen Institute, Amsterdam/Rotterdam, The Netherlands*

Abstract

This paper studies a Stated Preference (SP) experiment on the choice of type of (Rail) season card, conducted among current Dutch Railways season cardholders. They were asked to choose from the following three alternatives: (1) an unrestricted season card, (2) a cheaper season card with peak travel and travel frequency restrictions, and (3) not buying a season card. Multinomial logit (MNL), nested logit and mixed logit models are used to analyse their choices. It is found that MNL underestimates the price sensitivities (as measured by the price elasticities) of the respondents and overestimates their Willingness-to-Pay (WTP) for reductions in the restrictions. The mixed logit estimation shows that there are (unobserved) differences in the marginal utilities of the price of the card (response heterogeneity), and the utility of owning a season card (preference heterogeneity). In the Netherlands a large share of commuters and business travellers receive travel cost compensation from their employer. However, empirical studies often do not control for the effect of travel cost compensation. We find, as expected, that travel cost compensation has a large impact on the price sensitivities and choices of the respondents.

Keywords: SP experiment; Rail season card; Travel cost compensation; Public transport demand.

---

1. Introduction

Season cards are often used in public transport systems as one of the ticket types. Of the total passenger kilometres of the Dutch Railways (NS) in 2005, about 32% was by season cardholders. Furthermore, season cardholders are most likely relatively frequent train users, as this group predominantly consists of commuters (Steer Davies Gleave, 2006a). Hence, this group of travellers is very important in public transport. With a season card a person can travel free of extra charge by public transport and for this the person pays a certain amount per period.

* Corresponding author: Vincent van den Berg (vberg@feweb.vu.nl)

However, the empirical study of the preferences of season cardholders has been very limited. This paper studies a Stated Preference (SP) experiment, performed on current Dutch Railways season cardholders, on the choice of rail season card. The SP experiment was designed and carried out by Steer Davies Gleave (2007). In the experiment, the respondents chose between three alternatives: (1) a conventional *unrestricted season card*, which is the same as their current one but more expensive, (2) a (hypothetical) card which is cheaper than their current card, but has restrictions on allowed travel frequency and travel during the rush hour, and (3) the *no card* alternative (i.e. not buying a season card).

An interesting aspect of the used survey is that it contains information on the proportion of the card's price that is paid by the respondent. This makes it possible to control for the effect of travel cost compensation by third parties. This is important, as a large share of the Dutch travellers get their travel costs (partly) compensated by third a party (Steer Davies Gleave, 2006b). Empirical studies of price sensitivities of travellers often do not control for such travel cost compensation, despite the fact that it is often named as a reason for why (absolute) transport demand elasticities are so low.

Table 1 shows that 58% of the respondents get the price of the season card fully compensated, whereas only 9% get nothing compensated. The remainder of the respondents is partly compensated. It seems unlikely that a respondent that is currently fully compensated would be just as price sensitive as a comparable respondent who is not compensated. The used survey enables us to control for such differences.

Table 1: Distribution of the proportion of the price of the season card respondents pay of themselves.

Proportion of the price paid by the respondent	*Number of respondents*	*Percentage of the respondents*
0%	328	57.7%
1%-25%	76	13.4%
26%-50%	56	9.9%
51%-75%	35	6.2%
75%-99%	21	3.7%
100%	52	9.2%

Multinomial logit (MNL), nested logit and mixed logit estimations are used to study the responses in the SP experiment. The two card alternatives both entail owning a card and hence both produce the utility of owning a season card. It is found that the value of this shared utility component differs substantially over the respondents. In MNL estimations the alternative specific constants (ASC's) measure (after controlling for the effect of the other variables) the average utility of owning a *restricted* or *unrestricted card*. Deviations from this average remain in the unobserved elements. The unobserved utilities of the two card alternatives are thus most likely related, as both contain the individual utility of owning a season card, and this violates the IID assumption of MNL. Nested logit and mixed logit estimations can control for this.

From the estimations, elasticities to changes in the price and Willingness-to-Pay for changes in the card's restrictions are calculated. Large and interesting differences are found between the elasticities and WTP's from the MNL, the nested logit and the mixed logit estimations.

It is common to find in the empirical literature that MNL gives incorrect estimates, when unobserved heterogeneity is present. For instance, Bhat (1998) notes that if there is heterogeneity in the preferences for the alternatives (i.e. heterogeneous ASC's) or response heterogeneity (i.e. heterogeneous marginal utilities), then ignoring this could lead to biased parameter estimates and choice probabilities. He found that for his dataset with MNL the WTP's were larger and the elasticities lower than with mixed logit. Hence, the conclusion was that MNL underestimated the price sensitivity.

Bhat (2000a) found that MNL severely underestimates the WTP's for *out-of-* and *in-vehicle travel time* and overestimates the "cost" elasticities, compared with his mixed logit which controlled for observed and unobserved heterogeneity. Train (1998) found for his data that the compensating variations for the attributes are slightly to substantially larger with mixed logit than with MNL. He also found that the compensating variations from his mixed logit with correlated parameters are smaller than those found by MNL and mixed logit. He concludes that there probably is no general conclusion whether MNL gives good estimates for the Willingness-to-Pay and that the performance of MNL will be different for each dataset.

This compares with the results of a theoretical study of Horowitz (1980), who used datasets created by Monte Carlo simulation. He found that ignoring heterogeneous marginal utilities causes no bias in ratio of coefficients (i.e. WTP's) from MNL estimations. He did find, however, that ignoring heterogeneity causes the choice probabilities to be biased. He also found that correlated unobserved elements (i.e. a nested structure) cause the probabilities to be biased.

With MNL and nested logit it is only possible to control for observed heterogeneity. In this respect, it is important that the used survey has data on travel cost compensation, which we expect to have a substantial effect on the marginal utility of price.

This paper studies whether the WTP's and elasticities from MNL are also biased for our data, as was found in other empirical studies. It also studies what the effect is of travel cost compensation on the price sensitivity and choice probabilities of the respondents.

The next section discusses the SP experiment. Section 3 discusses the different methods we use. Thereafter, section 4 describes the season card utility functions. Section 5 analyses the MNL estimations. Section 6 discusses the nested logit estimation. Section 7 discusses the mixed logit estimation and Section 8 concludes.

2. Discussion of the season card stated preference experiment

This section discusses the used Stated Preference (SP) exercise. This paper uses the dataset from an SP season card experiment, in which 626 current Dutch Railways (NS) season cardholders participated. This NS *tariff structure review stated preference survey* was designed and carried out by Steer Davies Gleave (2007).

The season card SP experiment was part of a larger survey, which also studied the preferences of discount card holders and single ticket travellers. The experiments were conducted among on members of the NS internet panel. Of the 13000 invitations send out for the entire survey, a total of 4571 respondents completed their SP experiment(s) and questionnaires, resulting in a response rate of 35%. The survey was carried out in June and July 2006 (Steer Davies Gleave, 2006a). Note that the experiment does not cover people who might become cardholders in the future. Hence, the results of this paper are not representative for the entire population of potential cardholders.

In the experiment, the respondents were asked to choose between three alternatives: (1) an *unrestricted season card*, which is the same as their current season card but more expensive, (2) a cheaper card, with travel frequency and rush hour travel restrictions and (3) *no card* (i.e. do not buy a season card). The experiment was based on an orthogonal, fractional factorial design and there was no correlation between any of the design variables. The experiment had 32 different choice cards. To limit the risk of loss of concentration of the respondents, each respondent was shown only eight cards, each of which was randomly selected from the total of 32 (Steer Davies Gleave, 2006b).

Background questions were asked on for instance age, trip purpose and in-vehicle travel time of their most frequent trip, the price of their current card, and the proportion of the price of their season card that they pay themselves. The price of the current season card was used as a benchmark in the creation of the choice cards. Table 2 gives a description of the SP experiment, and Figure A.1 in the appendix gives an example choice card. Note that the order in which the alternatives were presented was randomly determined for each choice card.

Table 2**:** Description of the season card choice experiment

Alternatives	*Design variables*	*Levels of the design variables*
1 Unrestricted season card	Price difference between the two types of season card's	10%, 20%, 30% and 40% of the current price
2 Restricted season card	Travel moment restrictions	0 min, 30 min, 60 min and 90 min from 8:00 or 17:00
3 No card	Maximum 5 days of travel per week	Yes a maximum or no maximum of 5 days per week

Note: source Steer Davies Gleave (2006b)

There are four levels for the *price difference* design variable (10%, 20%, 30% and 40% of the current price). The price difference was divided over an increase, relative to the current price, for the *unrestricted card* and a lowering for the *restricted card*. This so called "split" of the *price difference* was randomly generated. The design variable was, hence, the *price difference* between the two alternatives as a percentage of the current price (Steer Davies Gleave, 2006b). For example, with a 30% price difference and a 2:1 split, the *unrestricted card* is 20% more expensive than the current card and the *restricted card* 10% cheaper.

The *restricted season card* was invalid during the peak, the start and end of which were varied independently. A holder of this card thus would have to travel outside the restricted periods, or buy a single train ticket to travel during the restricted period or travel by a different mode. The start and end points of the AM and PM restricted periods varied independently around the references times of 8:00 and 17:00. Each of the four *travel moment restriction* variables has four levels, 0, 30, 60 and 90 minutes. In half of the choice cards, the *restricted card* had the limitation of maximum 5 days travelling per week with the card. In the analysis this experiment, the prices of the yearly season cards were divided by twelve, to obtain monthly prices (Steer Davies Gleave, 2006b). The average monthly *price* of the current season card of the respondents was 170 euros.

The respondents were asked, for the outward and return trip, if they could arrive earlier and later, and if so by how much. The possible answers are not earlier (later), max 30 minutes, max one hour, and more than an hour earlier (later).

Figure 1 shows how often the three alternatives were chosen. It is clearly visible that the *unrestricted card* is the most popular.

Figure 1: Choice frequency of the alternatives in the SP experiment.

3. Estimation methodology

This study uses random utility maximization models. The utility function (U_{iqt}) for alternative i of respondent q in choice situation t is stated in (1). It has two parts, a deterministic part (V_{iqt}) and an additive random part (ε_{it}), which is unknown to the observer. MNL bases its calculations on the assumption that the unobserved elements are independently and identically distributed (IID) and have the distribution form Extreme Value Type 1 (EV1) (Koppelman and Sethi, 2000).

The deterministic utility function of alternative *i,* for individual q in choice situation *t,* is represented by (2). It is determined by a vector of k attributes (x_{iqt}) and their parameters (vector β_i). With MNL only one fixed parameter for each variable can be estimated. It is possible that the individual respondent (q) faces several choice situations (indicated by subscript t). The T in superscript indicates that the vector is transposed. Note that $\beta_i^T x_{iqt}$ may also contain an alternative specific constant (ASC$_i$). Individual characteristics (z_q) and their vector of parameters (δ_i) can be added to V_{iqt}. These variables are added to control for observed heterogeneous preferences for the alternatives, by differentiating the ASC's over observed characteristics. Matrix Ψ_i gives the effect of the characteristics on the marginal utilities of the attributes. This, hence, enables a control for observed heterogeneous responses to the attributes.

$$\mathrm{U}_{iqt} = \mathrm{V}_{iqt} + \varepsilon_{\mathrm{iqt}} \quad (1)$$

$$\mathrm{V}_{iqt} = (\beta_i + \Psi_i z_{iq})^{\mathrm{T}} x_{qt} + \delta_i^{\mathrm{T}} z_{iq} \quad (2)$$

$$E_{x_{ikqt}}^{P_{iqt}} = \frac{\partial P_{iqt}}{\partial x_{ikqt}} \frac{x_{ikqt}}{P_{iqt}} = \beta_{ikq}(1 - P_{iqt}) x_{ikqt} \quad (3)$$

The direct micro (choice situation specific) elasticity for Multinomial Logit (MNL) is given by (3). It can be interpreted as the elasticity of the probability that individual q, in choice situation *t,* chooses alternative *i,* with respect to a change in the kth attribute.

This formula gives a different elasticity for each respondent and in each choice situation. To aggregate the micro elasticities we calculate the choice probability weighted average of all the micro elasticities of all respondents and the multiple choice situations they face. An alternative would be to calculate the normal average or to use the average (sample) values of the variables and marginal utilities. Louviere, Hensher and Swait (2000) warn against the usage of the using sample averages and calculating the unweighted average. Logit estimations are non-linear, thus the estimated logit function need not to pass through the point defined by the sample averages. The unweighted average ignores that situations (and persons) with a higher choice probability have a larger influence on total demand.

Nested logit is a popular alternative for MNL. It to some extent relaxes the assumption of independently distributed unobserved elements. Nested logit allows for correlation between the utilities of alternatives in predefined "nests". This correlation comes from unobserved factors that influence the utility of the alternatives in the nest in the same manner. In our study there are three alternatives, (1) an *unrestricted card*, (2) a cheaper card with restrictions, and (3) do not buy a season card (i.e. the *no card* alternative). It seems likely that the two alternatives that entail owning a card have some unobserved similarities, and are hence in the "season card" nest. The (hypothetical) *restricted card* is by design the *unrestricted card* with a lower *price* and some validity restrictions added. This implies a nest tree with two levels. The scale parameters of the alternative level (μ_i) are normalised to one. Thus this study uses the version of nested logit with the scale parameters of the alternative level normalised to one and hence only the nest level scale parameters estimated.

Under the said normalisation, the deterministic utility of nest l is $V_{lqt} = \lambda_l * IV_{lqt}$. The IV_{lqt} is the "Inclusive Value" variable and is equal to the natural logarithm of the sum of the exponentials of the deterministic utilities of all alternatives in the nest (i.e. it is the log sum). The λ_l is the scale parameter for the branch level. The correlation of the utility functions of two nested alternatives is $corr(V_j\text{-}V_i)=1-(\lambda_l)^2$. The closer λ_l is to one, the lower the correlation. If the parameter is not significantly lower than one, the model can be estimated by MNL (Louviere, Hensher and Swait, 2000). The (choice situation specific) micro elasticity for nested logit, when the μ_i's are normalized and there are two levels, is following Greene (2002) given by

$$E^{P_{iqt}}_{X_{ikqt}} = \lambda_l * \beta_{ikq} P_{qt}(i|l)(1 - P_{qt}(l)) x_{ikqt} + \beta_{ikq}(1 - P_{qt}(i|l)) x_{ikqt}. \tag{4}$$

The $P_{qt}(i|l)$ is the conditional choice probability of alternative i, conditional on its nest l being chosen. The $P_{qt}(l)$ is the choice probability of nest l. The total (unconditional) choice probability ($P_{qt}(i)$) is the product of the conditional choice probability of i and the choice probability of its nest (Greene, 2002).

MNL and nested logit both suffer from their respective IID assumptions and that they can only control for observed heterogeneity. Mixed logit can allow non-IID unobserved elements and can control for unobserved heterogeneity (Bhat, 2000b).

The utility function for mixed logit is given by (5). The x_{iqt} is a vector of attributes and β_{iq} a vector of individual parameters, which is the same for respondent q over all choice situations. The individual marginal utility of attribute k is determined by (6). The β_{ik} is the fixed parameter and η_{iqk} is the random individual component of the parameter. We thus used a *panel* version of mixed logit. Note that Revelt and Train (1998) developed the panel formulation of mixed logit. The panel version of mixed logit controls for the fact that we use an experiment with repeated choices and thus that the unobserved elements will (most likely) be similar for a respondent over the choice situations. In contrast, the non-panel version would assume that the unobserved random elements of the marginal utility of price will be completely different for a respondent from one choice situation to the next.

$$U_{iqt} = \beta^{T}_{iq} x_{iqt} + \varepsilon_{iqt} \tag{5}$$

$$\beta_{iqk} = \beta_{ik} + v^{T}_{ik} z_q + \beta_{sd\_ik} * \eta_{iqk} \tag{6}$$

The distribution form of the random part has to be predefined. With mixed logit it is also possible to take into account systematic differences in the parameters. For this, a vector of background variables (z_q) is multiplied by vector υ_{ik}, which determines the effect of the background variables on the parameter. The ASC is part of $\beta^{T}_{iq} x_{iqt}$, hence it is possible to differentiate the ASC's over individuals (Hensher, Rose and Greene, 2005).

We use two types of distribution shapes of the random component in this paper. The first is the triangular distribution and the second the lognormal. The lognormal distribution has the useful property that the marginal utilities are constrained to have the same sign for all respondents. This is useful for variables for which it is implausible to have negative or positive effects on utility[1].

The mixed logit choice probability formula of equation (7) has an open-form integral in it. Consequently, this probability can generally not be calculated directly and has to be approximated by simulation (Train, 2003). Values for the random elements (the η_{iqk}'s) are drawn and then using the values of the variables and the predefined distributions of the random elements, the conditional probabilities (L_{iqt}) are calculated. These probabilities are conditional on the draws of the random elements and hence the simulated outcome is different for each draw. Therefore, the process is repeated for many draws for each choice situation and the average probabilities are used as approximations of the choice probabilities.

$$P_{iqt} = \int_{\beta_{iq}} \frac{\exp(V_{iqt})}{\sum_j \exp(V_{jqt})} f(\eta_{iq})\, d\eta_{iq} = \int_{\beta_{iq}} L_{iqt} f(\eta_{iq})\, d\eta_{iq} \tag{7}$$

An important question is what number of repetitions results in a reasonably accurate and stable simulated outcome. The simulation for mixed logit traditionally uses pseudo-random draws. This method has the disadvantage that it requires a very large number of repetitions to get stable results (Hensher, Rose and Greene, 2005). Bhat (2000b) proposes the use of Halton draws. Halton sequences are generated from number theory and are more uniformly spread than the pseudo-random draws. This causes the estimation to be stable with fewer repetitions. For this reason, we only used Halton draws. We used LIMDEP/NLOGIT to estimate the models in this paper, using maximum (simulated) likelihood and for our final mixed logit estimation we used 2500 Halton draws.

---

[1] It is not directly possible to estimate negative coefficients with this distribution. However, this is easily be solved by multiplying the variable, which should have a negative marginal utility, by minus one.

The *choice situation specific* (micro) elasticity with mixed logit is given by equation (8). This elasticity has two parts that are in open-form integrals. One part gives the derivative of the probability to the independent variable and the second gives the choice probability (Train, 2003). To approximate these we perform a second simulation using 100 Halton draws. Each draw results in a different derivative and probability for the same choice situation for the same person. The average derivatives and probabilities are then used as approximations and used to calculate the choice situation specific (micro) elasticities. These are then, following Louviere, Hensher and Swait (2000), aggregated by calculating the choice probability weighted average.

The Halton draws used the primes 2 and 3. The simulation with a 100 draws was very stable. When we ran the same code using different sets of primes the aggregate elasticities only differed from each other by a few thousands.

$$E^{P_{iqt}}_{x_{ikqt}} = \frac{\partial P_{iqt}}{\partial x_{ikqt}} \frac{x_{ikqt}}{P_{iqt}} = {}_{\beta_{iq}} \mathrm{L}_{iqt}(1-\mathrm{L}_{iqt})\beta_{ikq} f(\eta_{iq})\,\mathrm{d}\eta_{iq} \; \frac{x_{ikqt}}{{}_{\beta_{iq}} \mathrm{L}_{iqt} f(\eta_{iq})\,\mathrm{d}\eta_{iq}} \tag{8}$$

4. Utility functions for the season cardholders

This section describes the used deterministic utility function (V_{iqt}) for each alternative (i=1,2,3) for respondent q in choice situation t. In the first two alternatives, the respondent continues to own a season card. Accordingly, the utility functions of these two contain the benefit of owning a card. The price sensitivity, as measured by the parameter of the *price* attribute, is assumed to be the same for both alternatives. To control for differences in the proportion of the price that respondents pay themselves, the *price* variable is interacted with the *proportion paid* by the respondent and the *proportion paid by others* variables, to obtain two price attributes.

The coefficient for "*price paid by a third party"* will be zero if the respondent does not care about the money spend by the third party. However, it could for example be the case that an employee fears that increases in the amount paid by the employer will induce him to make the compensation policy less generous, or that she fears a negative relation between the travel compensation and the wage. Than in those cases the coefficient will be negative.

In (9a-c), the β_{p2q} is the coefficient of "price*proportion paid" (representing "own" expenses) and β_{p3q} is the coefficient of the other interacted *price* variable (representing the amount spend by the third party). It is expected that β_{p3q} is negative, though smaller in absolute sense than β_{p2q}. If the utility of individual q of owning a card is subtracted from each alternative, this results in the following utility functions:

$$V(1\text{=unrestricted card})_{qt} = \beta_{p2q} * \text{price}_{1qt} * \text{proportion paid}_q + \beta_{p3q} * \text{price}_{1qt}(1\text{-proportion paid}_q), \tag{9a}$$

$$V(2\text{=restricted card})_{qt} = \beta_{p2q} * \text{price}_{2qt} * \text{proportion paid}_q + \beta_{p3q} * \text{price}_{2qt}(1\text{-proportion paid}_q) + \sum_{1}^{5} \gamma_n * \text{restriction}_{nqt} + \text{ASC\_2}_q, \tag{9b}$$

$$V(3\text{=no card})_{qt} = -\beta 1_q * \text{owning a card}_q = \text{ASC\_3}_q. \tag{9c}$$

In (9a-c), the constant of the *no card* alternative (ASC_3_q) is defined as minus the utility of owning a card, and therefore measures the utility of owning a card (irrespective of whether or not it is restricted). The five "restriction variables" are added to the *restricted card*'s utility function. There are two variables measuring the beginning and end of the restrictions in the morning, two that do the same for the afternoon, and one dummy variable for if the *restricted card* has a maximum of five days per week of free of extra charge of travelling. The last restriction is a travel frequency restriction, whereas the earlier four are travel moment restrictions. These four variables are measured in minutes from some reference point.

These reference points can be measured in two ways. With the first method the reference points are 8:00 in the morning and 17:00 for the afternoon. If the two variables are zero there is no travel restriction. This measurement gives the travel moment restrictions as they were shown in the choice cards to the respondents.

The second type follows the specification proposed by Steer Davies Gleave (2006b), and is centred around the times the respondent reported currently to start and finish her (most frequent) round trip. Suppose that the respondent gets on the train at 8:00 AM for the outbound journey, at 18:30 for the return journey and her trip takes 30 minutes both ways. Further, suppose that the *restricted card* is invalid between 7:00-8:30 and 16:00-18:00. Then, if the respondent wants to travel with the *restricted card*, she should displace her outbound travel moment to 60 minutes earlier or to 30 minutes later. Accordingly, the displacement times earlier and later are 60 and 30 minutes. The start of the return journey does not need alteration and thus the values for displacement times for the return trip are zero. The displacement times earlier for the outbound and return trip are centred around the current arrival times, whereas the displacement times later are centred around the current departure times.

As the restrictions are defined in minutes before and after a desired moment, they should give disutility and hence their parameters are hypothesized to be negative. There might also be some constant disutility of the restricted option. For instance, because the *restricted card* limits travel flexibility. This fixed disutility is measured by the ASC_2 of the *restricted card*.

The parameters of the two *proportion paid* interacted *price* variables can combined to form the total marginal utility of *price* by calculating

$$\beta_{price\ q} = \beta_{p2q} * \text{proportion paid}_q + \beta_{p3q}(\text{1-proportion paid}_q)\ .$$

It is possible to control further for different responses to changes in the attributes, by differentiating the β_{p2q} and β_{p3q} parameters. It seems likely that the coefficients for the *price* variables also differ over the respondents for unobserved reasons. It is also plausible that people with inflexible travel moments receive more disutility from the travel moment restrictions. The utility of owning a card differs over the respondents and it is likely that part of this remains unobserved. Examples of unobserved differences are accessibility of the origin train station, accessibility of the final destination from the destination rail station and relative preference for rail travel.

5. MNL estimations

Of the 626 respondents who completed the season card experiment, 568 respondents are actually used in this study. The other 58 respondent were filtered out because they reported that their most frequent trip made by the season card was for other purposes than commuting, going to school or a business trip. The focus in this study is on these three groups of “scheduled” travellers. Eight choice cards were shown to each respondent, hence there are 4544 observations.

As explained the four travel moment restriction variables are formulated, following the specification of Steer Davies Gleave (2006b), in the “displacement time” format[2]. The advantage of the displacement time variables is that they make the effect of the restrictions more person specific, so that their value is more likely to reflect the concerns of the individual. Note that these displacement time variables cannot be directly used to measure schedule delay valuation. Even with the *restricted card*, respondents can travel in the restricted period by single standard tickets or by car.

Table 3 shows the basic MNL estimation. This model does not yet control for the proportion of the price that respondents pay themselves. Coefficients for the three alternatives are depicted in separate columns. All six coefficients of the attributes are of the expected sign, and significant at the one percent level.

Among the displacement time attributes, the later restriction of the outbound trip moment gives more disutility than the displacement time earlier of the outbound trip. In contrast, for the return trip the displacement time earlier gives more disutility than later. This probably reflects the fact that the scheduling constraints at the destination (e.g. work) are more tight than at the origin (e.g. at home).

Both ASC’s are significantly negative. The control variables make the ASC’s group specific and hence control for heterogeneous preferences. The *inflexible travel moment* variable is a count variable for how often out of four questions the respondent answered that she could not change her travel moments of the most frequent trip. Thus, if she could start the outbound trip later or earlier, and if she could leave earlier or later for the return trip. The higher the value of this variable, the more inflexible she is and the less attractive the *restricted card*. This variable has a very significant negative effect on the utility of the *restricted card*.

Dummies reflecting the *journey length* (in-vehicle travel time of the most frequent trip) are added to all MNL estimations. Note that these are not attributes, but background variables. The *journey lengths* were reported in minutes. The variable is represented by five dummies; 15 minutes or less, 16 to 30 minutes, 31 to 45 minutes, 46 to 90 minutes and more than 90. The respondents with 15 minutes or less are the reference group. An advantage of using dummies is that it enables the study of non-linear effects. Respondents with journeys that are shorter than 16 minutes are more likely to choose the *no card* alternative. Presumably, for these shorter trips there is more competition from more alternative modes of transport. The effect on the *restricted card* alternative is more unclear. Only the 46 to 90 minutes dummy has a significant effect. This indicates that this group has more difficulty coping with the restrictions.

---

[2] In an estimation not shown in this paper, the final MNL model was re-estimated using the absolute travel moment restrictions (i.e. relative to absolute clock times) instead of the displacement time variables. The replacement had very little effect on the coefficients of the other attributes. The only substantial effect was of the ASC of the restricted card alternative.

The car dummy is 1 if the household of the respondent owns one or more cars. It has a slightly significant effect in the *restricted card*'s utility function. Persons with a car available are more willing to accept the restrictions. Car availability does not affect the constant of the third *no card* alternative. This indicates that car availability does not alter the utility of owning a season card, though it does alter the possibility of coping (once in a while) with the restrictions. Finally, a categorical variable on the weekly frequency of the most often made trip is added. This variable controls for the fact that persons who travel more, should receive different utilities from the alternatives. The surprising result is that the variable has no effect in the MNL estimations, whereas we expected that a season card is more valuable for travellers with higher trip frequencies.

Table 3: Estimation of the season card choice with one price variable.

		Season Card (1)		*Card with restrictions (2)*		*No card (3)*	
		Coeff.	t-statistic	Coeff.	t-statistic	Coeff.	t-statistic
Attributes							
Price (generic)		-0.0026***	-6.14	-0.0026***	-6.14		
Displacement time outbound trip earlier				-0.0085***	-3.70		
Displacement time outbound trip later				-0.0187***	-9.31		
Displacement time return trip earlier				-0.0119***	-6.35		
Displacement time return trip later				-0.0097***	-4.60		
Max 5 days travel				-0.2573***	-2.75		
Control variables							
Inflexible travel moment				-0.1311***	-3.91		
Journey time in minutes dummies:	15 min or less			Reference Group		Reference Group	
	16 to 30 min			0.1250	0.84	-0.7405***	-4.62
	31 to 45 min			-0.1426	-0.87	-0.8059***	-4.55
	46 to 90 min			-0.3425**	-1.96	-0.6717***	-3.69
	More than 91 min			-0.1398	-0.85	-0.8373***	-4.50
Car in household				0.1853*	1.76	-0.0221***	-0.20
Frequency trip				0.0199	0.24	-0.0862	-0.94
ASC				-0.9081***	-4.36	-2.7363***	-11.03
Respondents 568		Choice cards per respondent 8		log-likelihood -2840.65		Adjusted Rho^2 0.5731	

Note: ***, ** and *, respectively indicate significance of the coefficient at the 1%, 5% and 10% level. The Adjusted Rho^2 is calculated as (LL(estimation)-number of parameters) / LL(0), where LL(0) is the log-likelihood for an estimation with all parameters fixed at zero.

Table A.1 in the appendix shows the estimation following the specification of (9a-c), with two *price* interacted with *proportion paid* by the respondent variables. The log-likelihood for this estimation is much higher than for the estimation of Table 3. Respondents react much stronger to prices if they pay a higher proportion themselves. There is a marked difference in the price sensitivities of those who pay little themselves and those who pay a large share. The coefficient of *Price*proportion paid* is much larger in absolute sense than the coefficient of *Price*proportion paid by others*. However, the effect of *Price*proportion paid by others* is also significantly negative. Travel cost compensation has therefore the expected large effect on the price sensitivities. However, even respondents who currently are fully compensated are not completely price insensitive. Whether this is because they do care about what third part pays, or because they fear changes in the compensation policy following price increases, is unknown. In any case, these results suggest that cost compensation has a large effect on the decision of purchasing a season card.

Control dummies on occupation and purpose of the most frequent trip have no effect in the estimations. Interacting the attributes with the occupation, trip length, and purpose of trips variables does not alter the results. Especially interesting is that car ownership of the respondent's household does not alter the price sensitivity. We expected that with an easily available alternative mode one would expect that the respondent would be more price sensitive.

The estimation of Table A.2 tests whether there is a different valuation of the season card over the age groups. The 30 to 39 and 50 to 59 year olds value the season card significantly less than the 60 and older group. For the 18 and younger, 20 to 29 and the 40 tot 49 no effect is found. Note that the coefficients for the dummies for the age categories are not significantly different from each other.

It seems possible that the effects of the *price* and *travel restrictions* variables differ with the gender of the respondent. The results of the final MNL specification are shown in Table 4. It interacts the gender dummy (one for women) with *price*proportion paid* and adds gender dummies to the utility functions. The *price*(proportion paid)*gender* interaction variable has a significant positive effect on utility. This indicates that women are less price sensitive than men. Conversely, the gender dummies alone have no direct effect. This predicts that there is no difference in the valuation of the alternatives over gender. There is again a clear difference in the price sensitivities of those who pay little themselves and those who pay a large share of the price of the season card.

Interacting the restriction attributes with background variables does not lead to statistical improvements. It was expected that respondents with more restricted travel moments value travel moment restrictions more. This was tested by interacting the displacement time variables with their respective answers on the question on how much the travel moment could be changed. An example should make this arrangement clearer. The displacement outbound trip later variable was interacted with the answer to the question how much the respondent could start her most frequent outbound trip later. However, we found that the interacted displacement time variables have no effect on the utility of the restricted card. Similarly, car ownership, age, purpose of the trip and occupation do not differentiate the marginal utilities of the attributes. Interacting the gender dummy with the other attributes also does not improve matters.

The effect of proportion paid on the price sensitivity is very large. However, interpreting the resulting coefficients is difficult. When the price is raised, it is uncertain how much of this raise is paid by the individual and how much by the third party. The proportion paid could remain constant. The respondent could have to pay the entire increase herself. It is also possible that following the increase the respondent will convince the third party to increase the share that it pays. Conversely, the third party could make its compensation policy less generous. In the discussion of the estimations, it is assumed that the proportion paid is constant, that it is just a background variable.

The *total* marginal utility of the *price* attribute is given by

$$\beta_{total\ q} = (\beta_{p2} + \beta_g \text{*gender}_q) \text{ proportion paid}_q + \beta_{p3}(\text{1-proportion paid}_q) \tag{10}$$

Table 4: Estimation of the final MNL model.

		Unrestricted card (1)		*Restricted card (2)*		*No card (3)*	
		Coeff.	t-statistic	Coeff.	t-statistic	Coeff.	t-statistic
Attributes							
price*proportion paid (generic)		-0.0064***	-8.44	-0.0064***	-8.44		
price*proportion paid by others (generic)		-0.0023***	-4.85	-0.0023***	-4.85		
price*proportion paid*gender (generic)		0.0043***	4.01	0.0043***	4.01		
Displacement time outbound trip earlier				-0.0085***	-3.72		
Displacement time outbound trip later				-0.0187***	-9.29		
Displacement time return trip earlier				-0.0118***	-6.33		
Displacement time return trip later				-0.0098***	-4.63		
Max 5 days travel				-0.2578***	-2.75		
Control variables							
Inflexible travel moment				-0.1342***	-3.99		
Journey time in	15 min or less			Reference Group		Reference Group	
minutes dummies:	16 to 30 min			0.1166	0.78	-0.7542***	-4.65
	31 to 45 min			-0.1603	-0.97	-0.8073***	-4.49
	46 to 90 min			-0.3540**	-2.02	-0.7452***	-4.02
	More than 90			-0.1733	-1.04	-0.9741***	-5.10
Car in household				0.1916*	1.82	0.0473	0.41
Frequency trip				0.0273	0.33	-0.0736	-0.77
Gender dummy (1=women)				-0.0658	-0.67	-0.0918	-0.71
Age dummies	18 or less					0.8275	1.21
	19 to 29					1.1382*	1.87
	30 to 39					1.2101**	1.99
	40 to 49					0.8267	1.36
	50 to 59					1.1639*	1.92
	60 and older					Reference Group	
ASC				-0.7514***	-3.59	-3.0454***	-4.79

Respondents 568 Choice cards per respondent 8 log-likelihood -2815.6 Adjusted Rho^2 0.5700

Note: ***, ** and *, respectively indicate significance of the coefficient at the 1%, 5% and 10% level.

The betas in this formula are the same for everyone. The coefficient *of price*proportion paid by others* from the estimation of Table 4 is the β_{p3} (β_{p3} =-0.0023). The β_{p2} is the coefficient of *price*proportion paid*. The β_g is the coefficient of *price*proportion paid*gender*. For instance, for men who receive no travel cost compensation the total marginal utility of price is equal to β_{p2}.. The resulting group specific coefficient is used in the calculation of elasticities and WTP's. On average the total marginal utility of *price* is -0.00288. This suggest that ignoring the heterogeneity caused by the compensation, as the estimation of Table 3 did, has no effect on the mean estimate of the marginal utility of price. However, ignoring the heterogeneity does cause the probabilities to be biased. When heterogeneous marginal utilities are ignored, the unobserved elements of the two card alternatives will be correlated, as they both contain the deviation from the mean marginal utility (because of the travel cost compensation) multiplied by the price. Thus controlling for travel cost compensation is especially important when doing forecasting or calculating elasticities. Furthermore, by ignoring cost compensation one ignores an important source of heterogeneity and this heterogeneity might also be of interest in itself.

Table 5 shows the average WTP's for the restrictions. A Willingness-to-Pay (WTP) is calculated by dividing the coefficient of a (restriction) attribute by the (group average) marginal utility of the *price* attribute. A WTP measures how much of a *price* increase would give the same utility as a one unit increase in the attribute, and thus what *price* decrease the average respondent requires to accept a one unit worsening in that attribute and being equally well off as before.

The fully compensated are willing to spend much more for reductions in the restrictions than those who are not fully compensated. Women are willing to spend substantially more than men. Men will on average accept a €2.92 per month *price* increase and women €8.19, for a one minute decrease in the displacement time later for the outbound trip. A one-minute decrease in the displacement time earlier for the return trip gives men on average the same utility as a price increase of €1.85. The value for the displacement later for the return trip for women is €4.28. The maximum 5 days of travel by season card is valued on average as much as a *price* increase of €40.34 by men and €113.03 by women. This is equal to a displacement time earlier and later for the outbound trip of 30 and 14 minutes.

Table 5: Willingness-to-Pay for reductions in the restrictions for the final MNL model.

Variable	*Coeff. / average total combined marginal utility of price*			*For the fully compensated*	*For those who receive no cost compensation*
	Both genders	Men	Women		
Displacement time outbound trip earlier	€ 1.85	€ 1.33	€ 3.73	€ 3.70	€ 1.68
Displacement time outbound trip later	€ 4.06	€ 2.92	€ 8.19	€ 8.13	€ 3.70
Displacement time return trip earlier	€ 2.58	€ 1.85	€ 5.20	€ 5.13	€ 2.34
Displacement time return trip later	€ 2.12	€ 1.53	€ 4.28	€ 4.26	€ 1.94
Max 5 days travel	€ 56.06	€ 40.34	€ 113.03	€ 112.09	€ 74.26

Table 6: Aggregate price elasticities for the final MNL model.

	Unrestricted season card			*Restricted season card*		
	Combined	Men	Women	Combined	Men	Women
For the whole group	-0.132	-0.164	-0.088	-0.369	-0.427	-0.279
For the fully compensated	-0.091	-0.098	-0.082	-0.292	-0.304	-0.275
For those who receive no travel cost compensation	-0.216	-0.296	-0.058	-0.492	-0.613	-0.210

The price elasticities of the *unrestricted* and *restricted card* are differentiated in Table 6 by the "proportion paid" of the season card's price and gender. The choice situation specific elasticities are calculated with (3). After the calculation of the micro elasticities, the elasticities are aggregated by calculating the choice probability weighted average.

The price elasticities are rather low (in absolute sense). Especially, the price elasticities for the *unrestricted card* are very small. The elasticities are in fact so low that it is suspicious. Women react more inelastically to price changes than men. Surprising is that the women who currently are fully compensated have a larger elasticity (in absolute sense) to total price than the women who pay the entire price themselves (as they receive no compensation). This is a peculiar result, as one would expect that the larger share a person has to pay, the more price-sensitive she is.

The elasticities for the *restricted card* are larger in absolute sense than for the *unrestricted card*. This result is because the choice probabilities for the *restricted card* are much lower than for the *unrestricted card*, and ceteris paribus the higher the probability the smaller the absolute size of a MNL elasticity. This is also visible in the MNL elasticity formula (3). See also Figure 1 for the distribution of the choice frequencies.

The responses of the respondent seem very price inelastic. The MNL estimations show that there is a substantial difference in the price sensitivity depending on what share a respondent pays of the card's price.

6. The nested logit estimation

The nested logit estimation controls for the correlated unobserved utilities of the two *season card* alternatives. The two *season card* alternatives are put in the "buy a season card" nest and the third (*no card*) alternative sits alone in its degenerate "do not buy a card" nest. This nest structure is also depicted in the nest tree of Figure A2 in the appendix. Adding control variables in estimation proved more difficult with nested logit than with MNL. When the *inflexible travel time* variable or the *journey length* dummies are added, the estimation does not converge. Journey length in minutes and its squared form are added to the estimation, allowing at least some control for non-linear effects.

Table 7**:** The nested logit model.

	Unrestricted card (1)		*Restricted card (2)*		*No card (3)*	
	Coeff.	t-statistic	Coeff.	t-statistic	Coeff.	t-statistic
Attributes						
Price * proportion paid (generic)	-0.0273***	-9.73	-0.0273***	-9.73		
Price * proportion paid by others (generic)	-0.0089***	-6.59	-0.0089***	-6.59		
Price * proportion paid*gender dummy (generic)	0.0137***	3.78	0.0137***	3.78		
Displacement time outbound trip earlier			-0.0089***	-3.82		
Displacement time outbound trip later			-0.0183***	-9.01		
Displacement time return trip earlier			-0.0112***	-5.84		
Displacement time return trip later			-0.0092***	-4.31		
Max 5 days travel			-0.2840***	-2.94		
Control variables						
Journey time in minutes			-0.0306***	-5.27	-0.0236***	-3.84
(Journey time in minutes)^2			0.0002***	4.82	0.0002***	3.45
Car in household			0.3086***	2.84	0.0066	0.06
Frequency trip			-0.1114	-1.29	-0.0856	-0.92
Gender dummy (1=women)			0.0741	0.68	-0.1180	-1.02
ASC			-0.6697***	-2.94	-1.9280***	-8.97
Nest level scale parameters						
Nest	Coeff.	t-statistic (against H0: scale parameter =1)				
Buy a season card	0.1710***	29.06				
Do not buy a season card	1.0000	Fixed normalised parameter				
Respondents 568	Choice cards per respondent 8		log-likelihood -2799.2		Adjusted Rho^2 0.5649	

Note: ***, **, and * respectively indicate significance of the coefficient at the 1%, 5% and 10% level

The scale parameters on the alternative level and for the degenerate *do not buy a season card* nest are normalized to one. The scale parameter for the "buy a season card" nest is very low with 0.17 and is significantly different from one and zero. This shows that the IID assumption of MNL is violated. Following Hensher, Rose and Greene (2005), the correlation between the utility functions of two alternatives is given by $\text{corr}(V_j\text{-}V_i)=1-(\lambda_l)^2$, where the λ_l is the nest level scale parameter. The correlation of the utility functions of the two season card alternatives is therefore $1-(0.17)^2=0.97$. This is a very high correlation. Furthermore, the log-likelihood of the nested logit estimation is also much higher than of the final MNL model. The nested structure is clearly an improvement to the MNL estimation.

All the coefficients of the attributes are of the expected sign, and significant at the one percent level. The control variables have a substantial effect in the estimation. The utilities of owning a *restricted card* and the *no card* alternative again decrease with *journey length*. The longer the most frequent trip takes, the less the decreasing effect of an extra minute is. This is shown by the small though significant positive coefficient of the squared version (the net effect remains negative though in the sample). The longer the *journey length* of the most frequent trip, the more likely it is that the respondent prefers the *unrestricted card*. This makes sense, since it is more difficult to avoid a certain travel window when the trip takes longer. Furthermore, for the longer trips fewer alternative modes are available. Thus the longer the most frequent trip the less attractive the *no card* alternative. The car dummy has a positive effect on the utility of the *restricted card*, though it has no effect on the third *no card* alternative.

Persons who receive no cost compensation are again substantially more price sensitive. The total *price* coefficient is calculated by the same equation (10) as with MNL and is on average -0.0118. This is more than four times the value from the final MNL model, whereas the coefficients of the restriction are almost exactly the same.

Table 8**:** WTP's for the nested logit model.

Variable	*Coeff. / average total combined marginal utility of price*			*For the fully compensated*	*For those who receive no cost compensation*
	Both genders	Men	Women		
Displacement time outbound trip earlier	€ 0.76	€ 0.68	€ 0.92	€ 1.01	€ 0.39
Displacement time outbound trip later	€ 1.56	€ 1.39	€ 1.90	€ 2.08	€ 0.80
Displacement time return trip earlier	€ 0.94	€ 0.84	€ 1.15	€ 1.28	€ 0.49
Displacement time return trip later	€ 0.79	€ 0.70	€ 0.95	€ 1.05	€ 0.40
Max 5 days travel	€ 24.22	€ 21.56	€ 29.38	€ 32.36	€ 12.37

Table 8 depicts the WTP's for the nested logit estimation. The same pattern as with MNL emerges for the valuations of the displacement time attributes. Respondent are on average willing to pay most for reductions in the displacement time later for the outbound trip. Women again have on average substantially higher WTP's. The WTP's are much lower with nested logit than with MNL, because the *price* coefficients are much more negative with nested logit. The coefficients for the restrictions are almost exactly the same with nested logit as with MNL. Thus, if the correlation between the utilities of two card alternatives is ignored, this results in an overestimation of the WTP's for our data. Note that the coefficients of the displacement time variable are very similar between nested logit and MNL. This indicates that the largest problem of the correlated unobserved elements was for the price variables.

Respondents are willing to suffer 32 and 15 minutes of extra displacement time later and earlier for the outbound trip for a lifting of the travel frequency restriction. Men are willing to accept a *price* increase of €21.56 and women of €29.38.

The choice situation specific alternative choice probabilities elasticities of Table 9 are calculated with (4), after which they are aggregated by calculating the choice probability weighted average. The elasticities are with nested logit considerably higher than with MNL. Women show elastic responses to *price* changes in the *restricted card*. Reassuring is that we no longer see the strange result that women who are fully compensated are more sensitive to *price* changes than women that receive no compensation, as was found in the MNL estimation. The result is now that the larger share a women pays of the price, the more *price* sensitive she is.

The responses to price changes of the *unrestricted card* are again much more inelastic than for the restricted season card. The price elasticities are larger because the relative size of the price coefficient with nested logit is bigger in absolute sense than with MNL. Again there is a large difference in the elasticities for the fully compensated and not compensated, hence the response to price changes are very different for the two groups. This shows again that in doing forecasting it is important to control for travel cost compensation, as otherwise the predicted changes in the probabilities will be incorrect.

Table 9: Aggregate price elasticities for the nested logit estimation.

Group	*Unrestricted season card*			*Restricted season card*		
	Combined	Men	Women	Combined	Men	Women
For the whole group	-0.355	-0.428	-0.254	-1.525	-1.724	-1.206
For the fully compensated	-0.215	-0.230	-0.196	-1.118	-1.182	-1.036
For those who receive no travel cost compensation	-0.686	-0.853	-0.352	-2.154	-2.439	-1.384

The nested logit section showed that the unobserved utilities of the two season card alternatives are correlated. However, the calculation of the choice probabilities by MNL uses the assumption that these unobserved elements are uncorrelated. The WTP's calculated from the nested logit output are substantially smaller and the price elasticities are higher.

7. Mixed logit estimation

Nested logit only relaxes the IID assumption of the MNL to some extent and it can not control for unobserved heterogeneity in the marginal utilities. Mixed logit, allows for more freedom. It seems likely that the *price* coefficients differ over the respondents for unobserved reasons. Bhat (1998) notes that not controlling for (unobserved) response heterogeneity, can lead to biased estimates of the elasticities and WTP's.

Furthermore, mixed logit allows us to take into account that the experiment has eight choice situations per respondent. MNL and nested logit assume that the unobserved elements of an alternative over the choice situations for the same person are uncorrelated and therefore that the unobserved elements are unrelated for the same person from one choice situation to the next. This seems an implausible assumption. As Train (2003) states, ignoring the repeated choices causes the unobserved element to be correlated over choice situations, and this violates the IID assumption.

This misrepresentation of the structure of the unobserved elements (by ignoring the repeated choices) can cause the standard errors of the coefficients to be incorrect. For instance, because forcing a structure that assumes that the (random element of) a marginal utility are different for an individual from one choice situation to the next produces extra noise in the estimation. However, this should not affect the mean parameter estimates. In an estimation not tabulated in this paper we re-estimated our mixed logit model while ignoring that the data is repeated choice; hence, giving the same individual different draws for different choice situations. The resulting coefficients were indeed more or less the same. However, the standard errors were different and on the whole larger. Furthermore, the log-likelihood for this second mixed logit estimation was almost 200 lower than for the panel mixed logit, while having the same number of coefficients. The panel version of mixed logit seems therefore more efficient, in that the standard errors are smaller.

With mixed logit it is possible to control for unobserved heterogeneity in the marginal utilities (i.e. response heterogeneity). By making the ASC of the *no card* alternative random, it is possible to control for unobserved differences in the utility of owning a season card (i.e. preference heterogeneity), as the ASC_3 is defined as the negative of this utility. Train (2003) notes that by giving a constant of one or more alternatives a random element it is possible to control for a nest structure. In this case, we can thus control for the nest structure of the two card alternatives by giving the ASC of the third (*no card*) alternative a random element.

In a footnote Revelt and Train (1998) note that there is a difference in what type of correlation pattern nested logit and panel mixed logit control for. Nested logit assumes that the correlated unobserved elements for a person over the choice situations are independent. Conversely, the *panel* mixed logit assumes that these correlated elements (i.e. the random element of ASC_3) are the same in all choice situations of an individual. The ASC_3 measures the minus of the utility of owning a card, which should at least be very similar, if not precisely the same, over the eight choice situations per person. Hence, the *panel* mixed logit representation of the correlation pattern seems the best choice for this experiment. Note that the random ASC causes the model to be heteroscedastic in the unobserved effects over the respondents, but not over the choice situations faced by an individual.

The marginal utilities are for lognormal and triangle distributions given by

- lognormal; $\beta_{kq} = \pm\exp(\beta_k) \; * \; \exp(\beta_{k\_sd} * N_{kq}) \; * \; \exp(v_k^T z_q),$ (11)
- triangle; $\beta_{kq} = \beta_k + \beta_{k\_sd} * T_{kq} + v_k^T z_q.$ (12)

Here N_{kq} is a normally distributed (quasi-)random variable with a zero mean and a standard deviation of one. It has the same value for individual q in all choice situations. The T_{kq} is a (quasi-)random variable with a triangle distribution, with $-1 \leq T_{kq} \leq 1$ and a zero mean. The z_q contains the interaction variables and vector $\boldsymbol{v}_k$ their effects on the marginal utility of k. The sign before the exponential in equation (11) is determined by the predetermined sign of the marginal utility. If the random parameter of an attribute must be negative, the outcome of (11) is multiplied by minus one. For our final mixed logit we used 2500 Halton draws and unconditional parameters. We used a panel version of mixed logit; hence, the 2500 were the same for individual q over the eight choice situations.

The presentation of the mixed logit needs some explanation. The “Fixed parts of the random parameters” section in Table 10 depicts the fixed parts of the marginal utilities. The following section shows the coefficients for the effect of the random elements (β_{k_sd}). The “Observed heterogeneity in marginal utility of price” gives the coefficients (v_k) for the interacted variables. The estimation of Table 10 tests whether the coefficient of *price* and the ASC_3 differ for observed and unobserved reasons.

The random element of the marginal utility of *price* has a lognormal distribution. Before the estimation, the *price* attribute was multiplied by minus one. The random element of ASC_3 has a triangular distribution. Interpreting the coefficients of the lognormal distributed random parameters is difficult, as the coefficients are inside an exponentional. An easy way to interpret the coefficients of the background variables (multiplied by the background variable) for log-normally distributed marginal utilities is that they scale the (absolute) size of the marginal utilities. Hence, their effect is not subtracted from the marginal utility, as is usually done for the effect of background variables with the other types of distribution shapes of the random element. A positive (negative) coefficient for the observed heterogeneity means that the larger the background variable the larger (smaller) the absolute size of the marginal utility.

Table 10: Random effects of price of the season card and owning a season card.

	Unrestricted card (1)		*Restricted card (2)*		*No card (3)*	
	Coeff.	t-statistic	Coeff.	t-statistic	Coeff.	t-statistic
Fixed parts of the random parameters						
Price	-6.1077#	-38.7	-6.1077#	-38.7		
ASC_3					-3.3168***	-6.25
Parameters of the random elements						
Price (lognormal)	1.1681***	12.8	1.1681***	12.8		
ASC_3 (triangular)					9.1772***	12.2
Observed heterogeneity in marginal utility of price						
Proportion paid*price	0.9648***	9.95	0.9648***	9.95		
Gender (female=1) *Price	-0.4455***	-4.00	-0.4455***	-4.00		
Car dummy*Price	1.4802***	16.69	1.4802***	16.69		
Attributes						
Displacement time outbound trip earlier			-0.0087***	4.12		
Displacement time outbound trip later			-0.0194***	9.24		
Displacement time return trip earlier			-0.0107***	5.67		
Displacement time return trip later			-0.0113***	5.60		
Max 5 days travel			-0.2950***	3.36		
Control variables						
Journey length in minutes			-0.0297***	-6.66	-0.1127***	-10.1
(Journey length in minutes)^2			0.0002***	6.26	0.0008***	8.60
Car in household			-0.1727*	-1.83	-2.9765***	-9.88
Frequency trip			0.1042	1.10	-0.5923***	-3.97
Gender dummy (female=1)			-0.1267	-1.59	1.2903***	4.33
ASC			-0.3410*	-1.90		
Respondents 568	Choice cards per respondent 8		log-likelihood -2536.1		Adjusted Rho^2 0.5132	

Note: ***, ** and *, respectively indicate significance of the coefficient at the 1%, 5% and 10% level.
As the only reasonable H0 of a zero fixed part of this marginal utility means that this coefficient should be -∞ (as Exp(-∞)=0), there is no (valid) t-statistic (Bhat, 1998). The reported t-statistic is against zero and only shows that the standard error is much smaller than the coefficient.

The log-likelihood of the mixed logit is much lower than the one of the nested logit and a likelihood ratio test reject the nested logit in favour of the mixed logit at the one percent level. To identify observable differences in *price* sensitivity, the *price* variable is interacted with the proportion paid, gender and car dummies. The coefficients of these interactions are all significant at the one percent level. The fact that the coefficient of *price* interacted with *proportion paid* is positive makes clear that the larger the proportion of the price a respondent currently pays, the more *price* sensitive she is. Women are again less price sensitive, as for women the marginal utility is multiplied by exp(-0.45). Interesting is that car ownership of the respondent's household now does have a significant effect on the marginal utility of the *price* attribute. This compares with the previous estimations which found no such effect. Other control variables had no differentiating effect on the marginal utility of *price* or the restrictions.

The ASC_3 and *price* variable have highly significant coefficients the random elements. This shows that both differ over the respondents for unobserved reasons. The ASC_3 is on average very negative. This indicates that on average there is a strong preference for owning a season card. The coefficient of the random element of the ASC_3 is in absolute terms almost three times the size of the fixed part. This ASC is meant to measure the minus of the utility of owning a season card. This shows that the spread in this unobserved utility is substantial.

The coefficients of the restriction attributes are, as expected, negative and highly significant. The coefficients of the restrictions are roughly the same as in the MNL en nested logit estimation. A noticeable difference is that the ordering of relative sizes is slightly different. Now the coefficient for *Displacement time return trip* ***later*** is slightly larger than the one of *Displacement time return trip* ***earlier***, whereas before it was the other way around. None of the restriction attributes are found to have random components. This mirrors the finding of the MNL estimations, where the coefficients of the restrictions did not differ for observed reasons.

The journey length variable and its squared form have very significant effects on the utilities of the *restricted card* and *no card* alternatives. The longer the journey length is, the lower the utilities of the second and third alternatives. The minimum of the quadratic *journey length* effect function lies for the *unrestricted card* around 149 minutes and for *no card* alternative around 141 minutes. It should be noted that the maximum *journey length in* the sample is 150 minutes and that only two respondents had a value of more than 140 minutes. It seems hence seems safe to state that the longer the *journey length,* the more likely one is to choose the *unrestricted card* and that the effect of extra *journey length* decreases, the longer the trip was to start with. The car dummy has negative effects on the utilities of the second and third alternatives. The *frequency of rail travel* and *gender* variables now have, different from the previous estimations, significant effects on the utility of the *no card* alternative. The more often a respondent travels by rail, the less likely she is to stop owning a card.

Interpreting the coefficients from logit estimation, and especially a mixed logit with lognormal coefficients, is difficult. The results are best interpreted by calculating elasticities and Willingness-to-Pay. The *choice situation specific* elasticities are determined by (8). This equation has, as was stated before, two parts that are in open-form integrals (the first for the derivative of the probability to price and the second for the choice probability itself) (Train, 2003). Therefore, the elasticities are approximated by a second simulation using 100 Halton draws. With the draws, expected values for each choice situation are calculated for the derivative and the choice probability, and these are used to calculate the simulated *choice situation specific* elasticities.

As is visible in (8) the derivative depends on the realisation of the (random elements of the) marginal utility of *price* and the ASC of the *no card* alternative. For *price* the marginal utility is given by a rewritten version of (11), which is given in (13). Here N_{pq} is a quasi-random variable, the β_p the fixed part of the marginal utility, β_{p_sd} the coefficient of the random element and the v's give the coefficients of the interactions.

$$\beta_{price\ q} = -\exp(\beta_p) \ * \ \exp(\beta_{p\_sd} * N_{pq}) \ * \ Exp(v_{prop} * proportionpaid_q + v_g * gender_q + v_{car} * car\ dummy_q). \qquad (13)$$

Table A.3 in the appendix gives the descriptive statistics for the expected values of the marginal utilities, based on the second simulation. The average marginal utility of *price* from (13) is -0.0167, which is somewhat larger than with nested logit. Conversely, the coefficients of the restrictions are of comparable sizes in the two estimations.

The micro elasticities, as simulated by (8), were aggregated by calculating the choice probability average[3]. Tables 11 and 12 depict the aggregate elasticities for the *unrestricted* and *restricted card*. The elasticities are differentiated by proportion paid by the respondent, car ownership of the households of the respondents and gender.

Table 11: Aggregate elasticities for the *unrestricted season card*.

Group	*Average*	*A car in the household*			*No car in the household*		
		Both genders	Men	Women	Both genders	Men	Women
All respondents	-0.431	-0.544	-0.668	-0.377	-0.173	-0.223	-0.108
For the fully compensated	-0.173	-0.437	-0.546	-0.299	-0.113	-0.152	-0.069
For those who receive no travel cost compensation	-0.544	-0.713	-0.796	-0.550	-0.335	-0.359	-0.271

Table 12: Aggregate elasticities for the restricted season card.

Group	*Average*	*A car in the household*			*No car in the household*		
		Both genders	Men	Women	Both genders	Men	Women
All respondents	-1.624	-1.941	-2.086	-1.651	-0.725	-0.826	-0.541
For the fully compensated	-1.476	-1.775	-1.921	-1.496	-0.529	-0.647	-0.358
For those who receive no travel cost compensation	-1.861	-2.187	-2.282	-1.949	-1.033	-1.053	-0.965

For the *restricted card* alternative, the responses are highly elastic to the *price* attribute. Conversely, the demand for the *unrestricted card* is on the whole price inelastic. The restricted card must offer a large price saving for it to be competitive.

Car availability has a large effect on the price sensitivities. Respondents with one or more cars in the household react elastically to price changes, whereas the respondents without a car react very inelastically. This is logical as in the Netherlands for inter-city transport the car is the main alternative to the train. The fully compensated are again far less price sensitive than the respondents who receive no cost compensation.

The elasticities are somewhat larger than those of the nested logit model and much larger than those of the MNL. This suggests that ignoring the heterogeneity in the price sensitivity and the correlation between the unobserved elements causes an underestimation of the average price sensitivity. This is a comparable result to the findings of Bhat (1998), who found for his data that the elasticities with mixed logit are higher than with MNL.

The elasticities found here are of course not comparable to those found in other situations, as currently the *restricted season card* does not exist. For the purpose of comparison we therefore deleted the second *restricted card* alternative in a second calculation of the elasticities, using the coefficients of the same MNL, nested logit and

[3] The second simulation was performed in Gauss 6.0 and the Halton draws were based on the primes 2 and 3. This simulation by 100 draws was remarkably stable. When we ran the same program using the primes 3 & 2, 5 & 7, 5 & 13, 7 & 11 and 11 & 13 the resulting (differentiated) aggregates only differed from each other by a few thousands.

mixed logit estimations. Following, this we re-calculated the aggregate price elasticities for the (*unrestricted) season card*. The responses in the SP study had a very strong nested structure, because the *restricted card* is so similar in unobserved characteristic to the *unrestricted card*. Consequently, the probability from the deleted alternative is not shared proportionally over the two remaining alternatives, but goes predominantly to the first *season card* alternative. Hence, as is also visible in Table 13, the (absolute) price elasticities are now much smaller. The aggregate elasticity (in the *average* column) in Table 11 is 7.4 times the size of same elasticity in Table 13.

The demand is even almost perfectly inelastic. This result might seem surprising. However, the result is rather plausible observing that the owners of the season card predominantly are commuters and business travellers. Furthermore, a very large share of the respondents is fully compensated and of course travel cost compensation also lowers the price sensitivity. The table, hence, shows that the demand for season cards is actually very inelastic, even though the *alternative choice probability* elasticities are much larger in absolute sense. Note though that even these elasticities are only representative for the current cardholders and not for the whole population of potential cardholders. Since, the used experiment only included current cardholders.

This table also clearly shows that the IID assumption is violated. The MNL elasticities are now after the deletion higher than the nested logit elasticities, whereas, before they were much smaller. With MNL by assumption the relative size of the probabilities of the two remaining alternatives stays the same, as $P_{card} / P_{no\ card} = \exp(V_{card} - V_{no\ card})$. Consequently, the probability of the deleted *restricted card* alternative is distributed proportionally over the two remaining alternatives. In really the fast majority probability goes to the *unrestricted season card*, because of the strong nested structure. Hence, because of the IID assumption, the increase in the probability of the *unrestricted card* following the deletion with MNL is much lower than with nested logit. This in turn causes the recalculated price elasticities from MNL to be larger than the recalculated nested and mixed logit elasticities.

Table 13: Aggregated elasticities for the *unrestricted card* with the restricted card alternative deleted

	MNL	*Nested Logit*	*Mixed logit*
All respondents	-0.0723	-0.0517	-0.0585
For the fully compensated	-0.0652	-0.0473	-0.0475
For those who receive no travel cost compensation	-0.1124	-0.0620	-0.0817

Table 14 depicts the average WTP's. The WTP were simulated by the same draws as the elasticities[4]. The average WTP's for the five restrictions are calculated by dividing the relevant coefficient by the (expected) marginal utility of *price* for each individual, and then calculating the average. The WTP's for the restrictions have the same pattern of relative sizes as with the nested logit and MNL, except that now the WTP's for the *Displacement time return trip* ***earlier*** are slightly smaller than those of the *Displacement time return trip* ***earlier***. To take away the 5 day per week maximum of travel days the respondents are on average willing to spend more than 32 euros. This has the same value for the average respondent as an increase in the displacement time earlier and later for the outbound trip of 34 and 15 minutes. The WTP's calculated from this mixed logit

[4] Similar to the simulation of the elasticities, the simulated WTP's were very stable in regard to the choice of primes on which the Halton draws are based, with only differences of a few thousands of a Euro of the average values over the different sets of draws.

are smaller than those from MNL. They are, however, larger than those of the nested logit, even though the average marginal utility of *price* is higher with mixed logit and the coefficients of the restrictions from the two estimations almost exactly the same. This is caused by the heterogeneity in the marginal utility from the mixed logit. There are some cases with simulated marginal utilities that are very close to zero, and this has an increasing effect on the average WTP.

Table 14: WTP's for the travel restrictions for the mixed logit estimation.

Variable	*Average*			*For the fully compensated*	*For those who receive no compensation*
	Both genders	Men	Women		
Displacement time outbound trip earlier	€ 0.95	€ 0.74	€ 1.25	€ 0.40	€ 1.09
Displacement time outbound trip later	€ 2.13	€ 1.65	€ 2.80	€ 0.90	€ 2.44
Displacement time return trip earlier	€ 1.17	€ 0.91	€ 1.54	€ 0.49	€ 1.34
Displacement time return trip later	€ 1.24	€ 0.96	€ 1.63	€ 0.52	€ 1.42
Max 5 days travel	€ 32.31	€ 25.16	€ 42.53	€ 13.63	€ 37.03

Mixed logit can control for unobserved heterogeneity, whereas nested logit and MNL can not allow for this. The marginal utility of the *price* of the season card differs over the respondents for unobserved reasons and the ASC_3 has a random element to control for unobserved heterogeneous utility of owning a season card. The price elasticities from mixed logit are much larger than from MNL. This seems a plausible finding, as the elasticities from MNL were surprisingly small. The elasticities found by mixed logit are also larger (in absolute sense) than those from nested logit. This suggests that ignoring the response heterogeneity may cause biased estimations of the price elasticities.

8. Conclusions

This paper studies a Stated Preference experiment conducted among current Dutch railways season cardholders. The paper uses multinomial logit (MNL), nested logit and mixed logit to analyse the responses of 568 cardholders to eight choice cards. The respondents chose between (1) an *unrestricted season card*, (2) a cheaper season card with peak travel and travel frequency restrictions and (3) the *no card* alternative.

The analysis showed that the assumptions behind the MNL method are violated by the structure of the experiment. The two card alternatives are perceived as very similar by the respondents and their unobserved utilities are highly correlated, while the alternative *no card* is rather different. The respondents show heterogeneous responses to price of the season card: different persons have very different marginal utilities for *price*. The mixed logit specification appears to provide the most satisfactory results, as it controls for the unobserved response heterogeneity, the fact that the SP experiment had repeated choices and the correlated unobserved elements.

There are large differences between the price elasticities of the *restricted* and *unrestricted card*. The demand for the *restricted season card* is very price elastic, while the (absolute) price elasticity for the *unrestricted card* is generally low. The elasticities for the price obtained with the MNL and nested logit are smaller in absolute sense than those obtained with mixed logit. The estimated Willingness-to-Pay for the reductions in the restrictions are much lower MNL than with mixed logit. The price elasticities for *unrestricted card* when we recalculated them, after deleting the *restricted card* alternative, are very close to zero. This suggests that the demand for season cards (in the current situation with only one type of season card available) is very price inelastic.

Our findings on the effect of unobserved heterogeneity on the performance of MNL are comparable to those of Bhat (1998; 2000a) and in contradiction to the theoretical paper of Horowitz (1980). An interesting question for further research is under what circumstances the heterogeneity leads to biased estimates of MNL for the elasticities and relative values of the coefficients (i.e. WTP's).

The proportion that respondents pay of the price of the season card has, as expected, a large influence on their price sensitivities. Respondents who pay nothing or a small share themselves of the price have much lower (absolute) price elasticities. This is obvious, but important, because a very large share of (Dutch) travellers get their travel costs entirely of partly compensated.

It is important to control for this cause of heterogeneity in the marginal utility of price when doing forecasting or calculate elasticities. Without this control the choice probabilities might be incorrect (as it is a form of non-IID unobserved elements), and thus the elasticities and forecasts will be inaccurate. The best control seems interacting a background variable on the travel cost compensation with the price, as the used survey enabled us to do. However, if there is no data on the travel cost compensation, it is of course also possible to include this heterogeneity in the unobserved heterogeneity of the marginal utility with a mixed logit estimation.

Acknowledgements

The authors are grateful for the support from *NS* (Dutch Railways) in the carrying out of this research. We are especially thankful for the support of Freek Hofker and Theo van der Star from the *NS*. This work uses data from an SP experiment that was designed and carried out by Steer Davies Gleave. Their efforts and their comments on an earlier version of this paper are gratefully acknowledged. This paper benefited greatly from the comments of three anonymous referees. The support and comments on an earlier version of this paper of Piet Rietveld are also gratefully acknowledged. We are also grateful for the helpful comments from the participants of the Kuhmo / Nectar Conference 2007 on the 13th of July 2007. This paper is part of the project *Betrouwbaarheid van transportketens*, which is made possible with support of Transumo. Transumo (TRANsition SUstainable MObility) is a Dutch platform for companies, governments and knowledge institutes that cooperate in the development of knowledge with regard to sustainable mobility. The opinions and any remaining erros in this paper are purely our own responsibility.

References

Bhat, C. R. (1998) "Accommodating Variations in Responsiveness to Level-of-Service Variables in Travel Mode Choice Models", *Transportation Research Part A* 32: 455-507.

Bhat, C. R. (2000a) "Incorporating Observed and Unobserved Heterogeneity in Urban Work Travel Mode Choice Modeling", *Transportation Science* 34(2): 228-239.

Bhat, C. R. (2000b) "Flexible Model Structures for Discrete Choice Analysis", in: Hensher, D.A. and K. J. Button (Eds.) Handbook of Transport Modelling, Elsevier Science, Oxford.

Greene, W.H. (2002) *Nlogit version 3.0 Reference guide,* Econometric software inc., New York.

Hensher, D. A., Rose, J. M., and Greene, W. H. (2005) *Applied Choice Analysis: A Primer*, Cambridge University Press, Cambridge.

Horowitz, J. (1980) "The Accuracy of the Multinomial Logit Model as an Approximation to the Multinomial Probit Model of Travel Demand", *Transportation Research Part B* 14: 331-342.

Koppelman, F. S. and Sethi, V. (2000) "Closed form Discrete Choice Models", in: Hensher, D. A. and K. J. Button (Eds.) *Handbook of Transport Modelling*, Elsevier Science, Oxford.

Louviere, J. J., Hensher, D. A., and Swait, J. D. (2000) *Stated Choice Methods: Analysis and Applications*, Cambridge University Press, New York.

Revelt, D. and Train, K. (1998) "Mixed logit with Repeated Choices: Households' Choices of Appliance Efficiency Level", *The Review of Economics and Statistics* 80(4): 647-657.

Steer Davies Gleave. (2006a) *NS Tariff Structure Review: Final Report (version of Thursday, 30 November 2006),* Steer Davies Gleave, London.

Steer Davies Gleave. (2006b) *NS Tariff Structure Review: Summary of Stated Preference Research (version of November 2006),* Steer Davies Gleave, London.

Steer Davies Gleave. (2007) *NS Tariff Structure Review Stated Preference Survey Dataset (version of 8 march 2007),* Steer Davies Gleave, London.

Train, K. E. (1998) "Recreation Demand Models with Taste Differences over People" *Land Economics* 74 (2): 230-239.

Train, K. E. (2003) *Discrete Choice Methods with Simulation*, Cambridge University Press, Cambridge.

Appendix

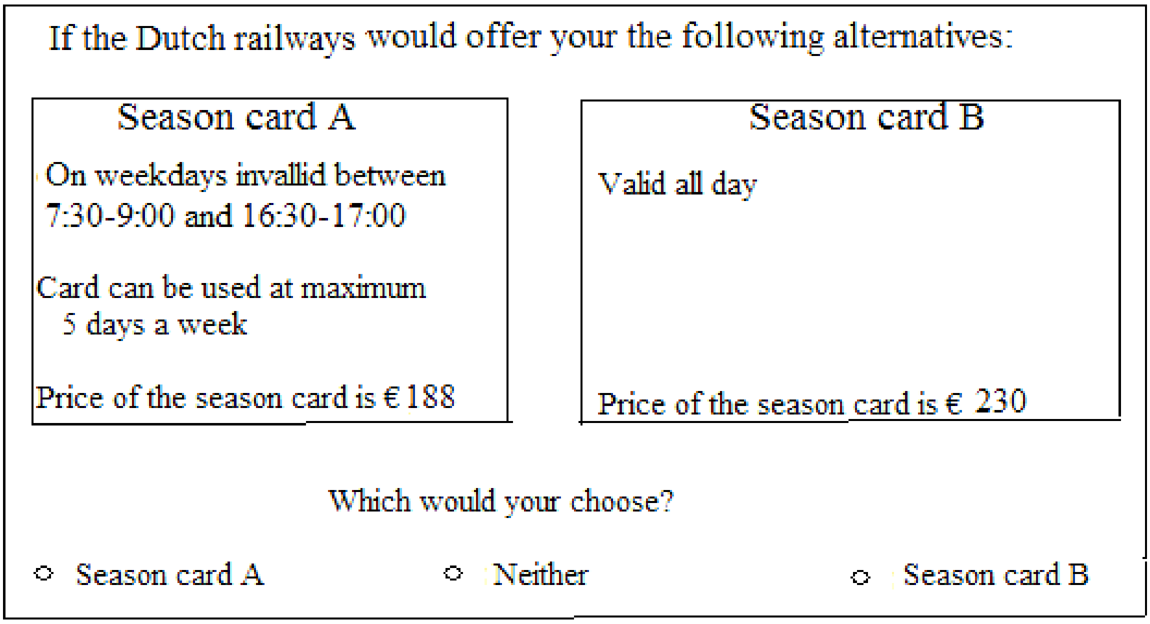

Figure A.1: Translated example of a season card SP choice card.
Note: The original choice cards were in Dutch, this version was created by the authors. The figure is based on Steer Davies Gleave (2006b, pp 7, fig. 3.1).

Table A.1: Estimation with control for who pays the season card.

		Unrestricted card (1)		*Restricted card (2)*		*No card (3)*	
		Coeff.	t-statistic	Coeff.	t-statistic	Coeff.	t-statistic
Attributes							
Price * proportion paid (generic)		-0.0042^{***}	-6.82	-0.0042^{***}	-6.82		
Price * proportion paid by others (generic)		-0.0018^{***}	-3.62	-0.0018^{***}	-3.62		
Displacement time outbound trip earlier				-0.0085^{***}	-3.71		
Displacement time outbound trip later				-0.0187^{***}	-9.31		
Displacement time return trip earlier				-0.0119^{***}	-6.35		
Displacement time return trip later				-0.0097^{***}	-4.60		
Max 5 days travel				-0.2572^{***}	-2.75		
Control variables							
Inflexible travel moment				-0.1323^{***}	-3.94		
Journey time in minutes dummies:	15 min or less			0.1271	0.85	-0.7136^{***}	-4.44
	16 to 30 min			-0.1342	-0.82	-0.7435^{***}	-4.19
	31 to 45 min			-0.3339^{*}	-1.91	-0.6394^{***}	-3.46
	40 to 90			-0.1273	-0.77	-0.7721^{***}	-4.09
	More than 90			0.1876^{*}	1.78	-0.0019	-0.02
Car in household				0.0162	0.20	-0.1118	-1.21
Frequency trip				0.1271	0.85	-0.7136^{***}	-4.44
ASC				-0.7564^{***}	-3.71	-1.8620^{***}	-9.32
Respondents 568	Choice cards per respondent 8		log-likelihood -2833.2		Adjusted Rho^2 0.5721		

Note: ***, **, and *, respectively indicate significance of the coefficient at the 1%, 5% and 10% level.

Table A.2: Final MNL model without gender effects.

		Unrestricted card (1)		*Restricted card (2)*		*No card (3)*	
		Coeff.	t-statistic	Coeff.	Coeff.	t-statistic	Coeff
Attributes							
price*proportion paid (generic)		-0.0043***	-7.13	-0.0043***	7.13		
price*proportion paid by others (generic)		-0.0017***	-3.60	-0.0017***	3.60		
Displacement time outbound trip earlier				-0.0085***	-3.71		
Displacement time outbound trip later				-0.0187***	-9.29		
Displacement time return trip earlier				-0.0118***	-6.33		
Displacement time return trip later				-0.0098***	-4.63		
Max 5 days travel				-0.2573***	-2.75		
Control variables							
Inflexible travel moment				-0.1335***	-3.98		
Journey time in minutes dummies:	15 min or less			Reference group		Reference group	
	16 to 30 min			0.1288	0.86	-0.7207	-4.46
	31 to 45 min			-0.1324	-0.81	-0.7427	-4.16
	46 to 90 min			-0.3309*	-1.89	-0.6577	-3.54
	More than 90			-0.1254	-0.76	-0.7975	-4.23
Car in household				0.1881*	1.79	0.0079	0.07
Frequency trip				0.0159	0.20	-0.1175	-1.25
Age dummies	18 or less					0.6071	0.89
	19 to 29					0.9765	1.61
	30 to 39					1.0895*	1.81
	40 tp 49					0.7803	1.29
	50 to 59					1.1483*	1.91
	60 and older					Reference group	
ASC				-0.7540***	-3.69	-2.8178***	-4.47
Respondents 568		Choice cards per respondent 8		log-likelihood -2827.1		Adjusted Rho^2 0.5721	

Note: ***, ** and *, respectively indicate significance of the coefficient at the 1%, 5% and 10% level.

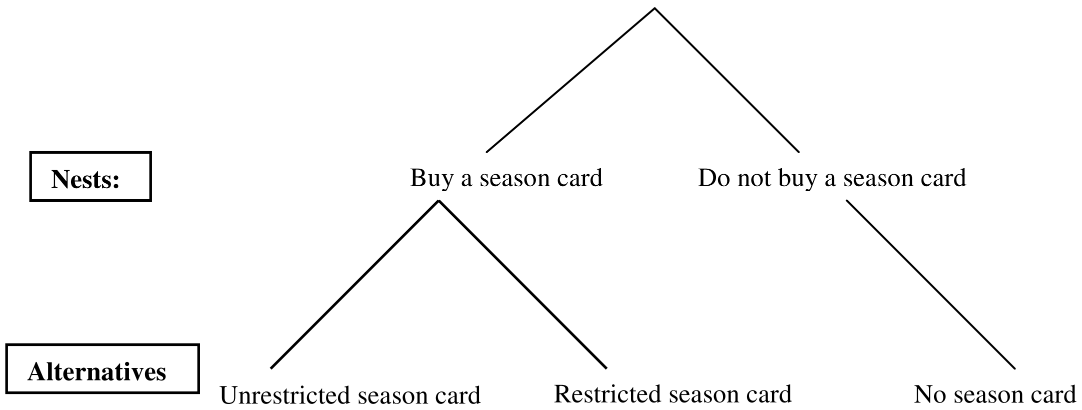

Figure A.2: The nest tree of the alternatives

Table A.3: Descriptive statistics of the expected mixed logit marginal utilities from Table 10.

Coefficient	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
Total marginal utility of price	-0.0166	0.0173	-0.0487	-0.0021
ASC_3 of the third alternative	-3.3205	0.5950	-5.4091	-1.2363
ASC_3 plus the effect of the control variables	-8.5267	1.9642	-12.4807	-2.5245