Choice of Train Ticket: a Study of Dutch travellers

Vincent van den Berg[1*], Eric Kroes[1,2], Erik 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

[1] Corresponding author: Vincent van den Berg:

Tel: 0031 20 598 6049

Fax: 0031 20 444 6004,

email: vberg@feweb.vu.nl

Abstract: This paper studies the choice of type of train ticket using a Stated Preference experiment conducted among current Dutch single ticket travellers. Multinomial logit (MNL), nested logit and mixed logit models are used to analyse the choices of the respondents. The experiment has three alternatives, namely: (1) an unrestricted ticket, (2) a cheaper restricted ticket which has restrictions on travel during the peak and (3) neither the first nor the second alternative. The price elasticities for the unrestricted ticket are rather low (in absolute sense), whereas responses to changes in the price of the restricted ticket are stronger. We find that MNL, compared with mixed logit, underestimates the value of (in-vehicle) travel time and overestimates the WTP's for the travel moment restrictions. We find that travel cost compensation by the employer substantially decreases the price sensitivities of the respondents. This is an expected, but important finding, as a large share of Dutch commuters receives travel costs compensation.

***Keywords**: Train Ticket Choice, Travel Cost Compensation, Public Transport Demand, Observed and Unobserved Heterogeneity*

Introduction

An almost universal problem in the organisation of public transport is that travel demand is concentrated in the peak. Public transport operators need to provide a very large capacity to fulfil the transport demand during the peak. During off-peak hours, however, there is an excess capacity. This problem of peak concentration of travel demand has long since been recognised. For instance, Abkowitz (1981) notes the problem of *peak loading*. Spreading the demand more over the day could lower costs, because than less capacity is needed. One manner of demand spreading might be to apply different fares on different times of day.

This paper studies the price elasticities, the value of *travel time* and the value of *displacing the travel moment* to outside the peak, of Dutch *single ticket* train travellers. For this, a Stated Preference (SP) experiment on the choice between train tickets is analysed. This SP experiment was carried out by *Steer Davies Gleave*. The experiment was based on the most recent weekday trip of the respondents. Multinomial logit (MNL), nested logit and mixed logit models are used to analyse the choices of the respondents. The three types of attributes are *price*, *in-vehicle travel time* and the four *peak travel moment* restrictions.

The experiment has three alternatives, which are: (1) an *unrestricted ticket*, (2) a cheaper *restricted ticket* with *travel moment restrictions* and (3) neither the first nor the second alternative. This third *opting out* alternative we label the *no ticket* alternative. Interpreting a choice for this third alternative is rather difficult, as it is unknown what the respondent would do in this case. She could undertake the trip by car, or by bike or another form of public transport. However, she could also choose not to undertake the trip. This uncertainty in what a choice for the *no ticket* alternative entails makes it difficult to interpret the estimations.

Table 1 Who pays the price of the ticket.

	Frequency	Percentage
Respondent pays the ticket	310	66%
Someone else pays the ticket	106	22%
Ticket partly paid by respondent	19	4%
Other #	37	8%

Note: # The other category, was the rest category, and contains for instance respondents whose last trip by train was on a *free travel day* or who got the ticket with a purchase of an amusement park entry ticket.

An interesting aspect of the used survey is that it has information on whether the respondent was (partly) compensated by a third party for the price of the ticket. This enables us to control for the effect of cost compensation upon the willingness-to-pay estimates and price elasticities. This is important issue, as a large share of the Dutch travellers receive travel cost compensation (Steer Davies Gleave 2006b). Empirical studies of price sensitivities of travellers typically do not control for travel cost compensation, even though compensation is often named as a reason for why (absolute) demand elasticities are so low. Table 1 shows that 22% of the respondents in this study are fully compensated and a further 4% are partly compensated.

Bhat (1998a) notes that if there is heterogeneity in the alternative specific constants or in the marginal utilities, than ignoring this could lead to biased parameter estimates and choice probabilities.

With MNL and nested logit it is only possible to control for observed heterogeneity. For example, that different income groups have different marginal utilities of price. Consequently, also for this reason it is a big advantage that the used survey has data on travel cost compensation, as compensation is expected to have a large effect on the marginal utility of price.

Bhat (1998a) found that the WTP's for both *out-of* and *in-vehicle travel time* are with mixed logit on average slightly larger than with MNL for his dataset. He also found that the "cost" elasticity is substantially larger (in absolute sense) with mixed logit than with MNL. Bhat (2000a) found that MNL underestimates the WTP's for *out-of* and *in-vehicle travel time.* Train (1998) found for his data that the compensating variations for the attributes are slightly to substantially larger with mixed logit than with MNL. However, he also found that the compensating variations from his mixed logit with free correlation between the marginal utilities are smaller than those found by MNL and the mixed logit without correlation. He concluded 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.

However, these empirical results seem in contradiction with the results of the theoretical analysis of Horowitz (1980), who used simulated datasets. He analysed the performance of MNL when there is random heterogeneity in the marginal utilities. He found that the ratio of the two coefficients (i.e. the WTP's) estimated by MNL on the simulated datasets was for all amounts of the heterogeneity in the marginal utilities, almost identical to the design value. Consequently, he concluded that the ratio of the coefficients is unbiased when one does not control for heterogeneity in the marginal utilities.

Therefore, an important question in our paper is if the elasticities and WTP's from MNL are also different from those found by mixed logit for our dataset, as was found by other empirical studies. Furthermore, we also study what the effect is of travel cost compensation on the price sensitivity and WTP's of the respondents.

The setup of this paper is as follows. The next section describes the used SP experiment. Section 3 discusses the used utility functions. Section 4 discusses the methodology. Section 5 analyses the MNL and nested logit estimations. Section 6 discuses the mixed logit estimations. Section 7 compares our results on the effect of unobserved and observed heterogeneity on the elasticities and WTP's. Finally, Section 8 concludes.

Discussion of the Stated Preference experiment

The ticket choice experiment we use is part of a larger (SP) survey, which also studied the choice of discountcard and season card. This survey is named the *NS tariff structure review stated preference survey* and was performed by Steer Davies Gleave (2007). The survey was conducted among members of the Dutch Railways (NS) internet panel. Of the 13000 invitations sent out for the larger survey, 4571 respondents completed their experiments and questionnaires. Hence, the response rate was 35%. The main internet survey was carried out in June and July of 2006 (Steer Davies Gleave 2006a).

The respondents are Dutch railways full-fare ticket travellers, discount cardholders and (weekend) studentcard holders (Steer Davies Gleave 2006b). The discount card had, at the time of the experiment, a price of €55 and gave a 40% discount on ticket fares. However, it is only valid after 9:00 on weekdays and in weekends. The studentcard is, in principal, paid by the Dutch government. The *weekend* studentcard allows free public transport in the weekend and during holidays. The *week* studentcard does this on working days. On moments when a studentcard does not allow for free public transport, it acts (more or less) as the discountcard. An issue here is that the sample only contains current single ticket travellers and not also persons who might do so in the future (e.g. current season card holders or car users). Hence, the sample is not really representative for the entire population of potential single ticket travellers.

The full experimental design had 64 different choice cards. To limit respondent drop off and loss of concentration, each respondent was shown only eight cards. The order in which the alternatives were presented to the respondents was randomly chosen for each choice card. The eight choice cards per individual were chosen at random from the 64 cards in the design. The experiment used an orthogonal, fractional factorial design, with no correlation between any of the design variables (Steer Davies Gleave 2006b).

The respondents were asked to provide some background information, on things such as gender and age. They were also asked questions about their most recent trip. These questions concerned, for instance, the time of departure and its associated flexibility, whether it was a round trip, the price of the ticket, the purpose and length in minutes of the most recent trip, and who pays for the ticket. The purpose of the most recent train trip question had the following categories: commute, school/study, sport or event, visit to friends or family, shopping, business trip and other (rest category) (Steer Davies Gleave 2006b).

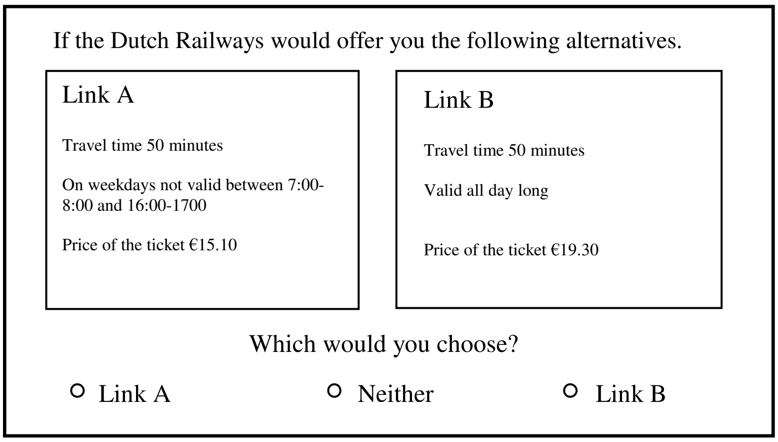
An example of the presented choice cards is given in Figure 1. The price and journey length of the last made trip questions were used to generate the attributes *ticket price* and *in-vehicle travel time*. There were four levels for the design variable *difference in price* between the *restricted* and *unrestricted ticket*. This *price difference* was split between an increase, relative to the current price, of the price of the *unrestricted ticket* and a relative price decrease for the *restricted ticket*. This split of the design variable *difference in price* was randomly generated (Steer Davies Gleave 2006b). For example, with a 40% price difference and a 1:3 split, the *unrestricted ticket* is 10% more expensive than the ticket of the most recent train trip, and the *restricted ticket* 30% cheaper.

The difference in travel time was also randomly split over the two ticket alternatives, where the *unrestricted ticket* always had the shorter *travel time*. The design variable on the d*ifference in travel time* had four values, namely 0%, 10%, 20%, and 30% of the *journey length* in minutes of the most recent train trip. The level of 0% means that the *travel time* for both ticket alternatives was the same (Steer Davies Gleave 2006b).

Travel on the *restricted ticket* was invalid during the peak hours. The restricted periods were defined by the four “restriction variables”. These four variables determine the start and end moments of the AM and PM peak travel restriction periods. During these periods, travel by the *restricted ticket* is not allowed. The start and end points of the AM and PM restricted periods varied independently from each other, around the references times of 8:00 and 17:00. Each *travel moment restriction* design variable had four levels, namely; 0, 30, 60, and 90 minutes (Steer Davies Gleave 2006b).

Of all made choices, 64% is for *the unrestricted ticket*, whereas the *restricted ticket* and *no ticket* alternatives receive 19% and 17% of the choices respectively.

Fig. 1 Example of a ticket choice SP exercise



If the Dutch Railways would offer you the following alternatives.

Link A	Link B
Travel time 50 minutes	Travel time 50 minutes
On weekdays not valid between 7:00-8:00 and 16:00-1700	Valid all day long
Price of the ticket €15.10	Price of the ticket €19.30

Which would you choose?

○ Link A ○ Neither ○ Link B

Note: the original choice cards were in Dutch, the translation is by the authors. The figure is based on Steer Davies Gleave (2006, pp 19, fig 5.1)

Utility functions for the train trip choice

This section discusses the deterministic utility functions used in our estimations. The utilities of both ticket alternatives are influenced by *ticket price* and *(in-vehicle) travel time*. It is assumed that the marginal utilities of *price* and *travel time* are the same (i.e. generic) for the two alternatives. To the utility function of the *restricted ticket* are added the peak travel moment restrictions and their marginal utilities (γ_n).

Following the work of Steer Davies Gleave (2006b) we redefine the restriction attributes before estimating. Instead of defining them relative to 8:00 and 17:00, they are rewritten relative to the moments that the respondent reported to start and finish her most recent trip. They measure in minutes how much the respondents should displace the travel moment of the most recent train trip to use the *restricted ticket*. The advantage of this *displacement time* specification is that it represents more directly what the actual impact of the restrictions is for the respondent.

An example should make this displacement *time* approach clearer. Suppose that the respondent gets on the train at 8:30 for the outbound trip, returns at 19:00 and her trip takes 30 minutes both ways. Further, suppose that the *restricted ticket* is invalid between 7:00-9:30 and 16:30-18:00. Than, if the respondent wants to travel with the *restricted ticket*, she should displace her outbound travel moment to 120 minutes earlier or to 60 minutes later. Accordingly, the displacement times earlier and later are 120 and 60 minutes. The start of the return trip needs no alteration and hence the displacement times for the return trip are zero. The displacement times *earlier* (outbound and return) are based around the current arrival times and the displacement times later on the current departure times.

The utilities of both ticket alternatives contain the utility of undertaking the most recent train trip, relative to the utility of not undertaking the trip or undertaking it by a different mode. Subtracting the utility of undertaking the trip by train from all alternatives results in the utility functions (1a-c).

$$V(1{=}\text{Unrestricted Ticket})_{qt} = \beta_{1q} * \text{Price}_{1\,qt} + \beta_{2q} * \text{In Vehicle Travel Time}_{1qt} \qquad (1a)$$

$$\begin{aligned} V(2{=}\text{Restricted Ticket})_{qt} &= \beta_{1q} * \text{Price}_{2\,qt} + \beta_{2q} * \text{In Vehicle Travel Time}_{2qt} \\ &+ \sum_{n=1}^{4} \gamma_n * \text{Displacement Time}_{n2qt} + \text{ASC\_2}_q, \end{aligned} \qquad (1b)$$

$$V(3{=}\text{No Ticket})_{qt} = \text{- utility of undertaking the trip by train}_q = \text{ASC\_3q.} \qquad (1c)$$

In these functions *q* is the indicator for the individual, *t* for the choice situation and the alternative is indicated by *i*. It is unknown what the respondent would do when choosing the third alternative. If she would go to the destination by a different mode, the utility of the third alternative is equal to the utility of undertaking the trip by a different mode minus the utility of undertaking the trip. If the respondent would not travel at all, the utility function of the third alternative is equal to minus the utility undertaking the trip. In both cases the minus of the utility of undertaking the trip by train should be negative, as otherwise the initial train trip was not rational to undertake.

The constant of the third alternative (ASC_3) should measure the sample mean preference for undertaking the trip by train. If background variables are added to the estimation, the ASC plus the mean of the background variables times their parameters measure this mean preference. The background variables measure the from this sample mean. Possible control variables are trip purpose, gender, and car ownership. Commuters are likely to have a different utility of undertaking a train trip than those who go shopping. However, the deviations from the group means of the utility of undertaking the train trip remain unobserved.

Estimation methodology

This study uses random utility maximization models. The utility function (U_{iqt}) of respondent *q* in choice situation *t* for alternative *i* is given by (2). It has two parts, a deterministic element (V_{iqt}) and a random element (ε_{it}), which is unknown to the analyst. With multinomial logit (MNL) it is only possible to estimate one common parameter for each variable. An important assumption behind alternative choice probability formula of MNL is that the unobserved elements are Independently and Identically Distributed (IID) (Train 2003).

The deterministic utility function is represented by (3). The $^{\mathbf{T}}$ in superscript indicates that the vector is transposed. The deterministic utility of alternative *i* in choice situation *t* for respondent *q*, is determined by a vector of *k* attributes ($\mathbf{x}_{iqt}$) and their parameters ($\boldsymbol{\beta}_i$). It is possible that the individual faces several choice situations, which is indicated by subscript *t*. The $\boldsymbol{\beta}_i^{\mathbf{T}}\ \mathbf{x}_{iqt}$ also contains the alternative specific constant (ASC_i). Individual characteristics ($\mathbf{z}_q$) and their vector of parameters ($\boldsymbol{\delta}_i$) can be added to V_{iqt}. People do not receive utility from these variables; they control for observable differences in the preferences. Matrix $\boldsymbol{\Psi}_i$ states the effect of the characteristics on the marginal utilities of the attributes. With this matrix we control for observable differences in the marginal utilities.

$$\mathrm{U}_{iqt} = \mathrm{V}_{iqt} + \varepsilon_{\mathrm{iqt}} \tag{2}$$

$$\mathrm{V}_{iqt} = (\boldsymbol{\beta}_i + \boldsymbol{\Psi}_i \mathbf{z}_{iq})^{\mathbf{T}} \mathbf{x}_{qt} + \boldsymbol{\delta}_i^{\mathbf{T}} \mathbf{z}_{iq} \tag{3}$$

The (direct) micro alternative choice probability elasticity for MNL is given by (4). It is the elasticity of the probability that individual *q,* in choice situation *t,* chooses alternative *i,* with respect to a change in the *k*th attribute. The choice probability of alternative *i,* is calculated by (5) for MNL. The denominator contains the sum of the exponentials of the deterministic utilities of all (three) alternatives ($\mathrm{V}_{\mathrm{jqt}}$). The probability elasticity not only depends on the marginal utility of the *k*th attribute, but also on the levels of all variables of all alternatives and their marginal utilities. Hence, the elasticities differ over the respondents and choice situations.

The data contains eight choice situations per individual; consequently, there are eight different price elasticities per respondent. To aggregate the elasticities we calculate the choice probability weighted averages of the 3776 *choice situation specific* (micro) elasticities. Alternative aggregation methods are to calculate the unweighted average or to insert the sample average values of the variables in to equation (4). Louviere, Hensher and Swait (2000) warn against using sample averages or 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 the situations (and persons) with a higher choice probability have a larger influence on total demand.

$$E^{P_{iqt}}_{x_{ikqt}} = \frac{\partial P_{iqt}}{\partial x_{ikqt}} \frac{x_{ikqt}}{P_{iqt}} = \beta_{ikq}(1 - P_{iqt})x_{ikqt} \tag{4}$$

$$P_{iqt} = \exp(V_{iqt}) \Big/ \sum\nolimits_{j=1}^{J} \exp(V_{iqt}) \;\; ; j = 1, 2, 3 \tag{5}$$

The assumption that the unobserved elements are Independently (i.e. uncorrelated) and Identically Distributed is often violated. Nested logit to some extent relaxes the assumption of no correlation between the unobserved elements. Nested logit allows for correlation between the unobserved elements of alternatives in predefined “nests” (Hensher, Rose and Greene 2005).

The three alternatives in our model are (1) the *unrestricted ticket,* (2) the cheaper *restricted ticket*, and (3) the *no ticket* alternative. The two train alternatives are very similar, as they both involve undertaking the train trip. Hence, they both produce the utility of going by train to the destination of the most recent train trip. The (group) average of this can be estimated with MNL. However, the individual deviations from this mean remain unobserved. This causes a correlation of the unobserved elements, violating the IID assumption. Consequently, the two ticket alternatives are put in the *travel by train* nest, whereas the third *no ticket* alternative is put in the degenerate *do not travel by train* nest. We normalise the scale parameters of the alternative level and of the degenerate nest to one. Note that the nest tree, as depicted in the Figure 2, has only two levels.

Under the normalisation of the alternative level scale parameters, the deterministic utility of nest *l* is $\mathrm{V}_{lqt} = \lambda_l {*} \mathrm{IV}_{lqt}$. The IV_{lqt} (“Inclusive Value” variable) is equal to the natural logarithm of the sum of the exponentials of the deterministic utilities of the alternatives in the nest (Hensher, Rose and Greene

2005). The λ_l is the scale parameter for the branch level, 1- λ_l can be used as a measure of the correlation of the unobserved elements of the alternatives in a nest. The closer λ_l is to one, the lower the correlation. If none of the nest level scale parameters are significantly lower than one, the model is best estimated by MNL (Train 2003). The (micro) elasticity under discussed normalisations and two levels to the nest tree is, following Greene (2002), given by (6).

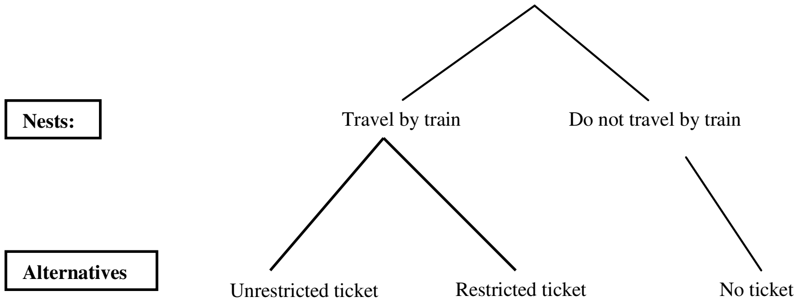


Fig. 2 The nest tree

$$E^{P_{iqt}}_{X_{ikqt}} = \lambda_l * \beta_{ikq} P_{qt}(i|l)(1-P_{qt}(l))x_{ikqt} + \beta_{ikq}(1-P_{qt}(i|l))x_{ikqt}. \tag{6}$$

Here $\mathrm{P}_{qt}(i|l)$ is the conditional choice probability of alternative *i,* conditional on its nest *l* being chosen. $\mathrm{P}_{qt}(l)$ is the choice probability of nest *l*. The unconditional choice probability of alternative *i* ($\mathrm{P}_{qt}(i)$) is the product of its conditional choice probability and the choice probability of its nest (Greene 2002). After the calculating the 3776 micro elasticities, they are aggregated by calculating the choice probability weighted average.

Nested logit only relaxes the IID assumption in a limited manner and the parameters of the variables are not allowed to vary over individuals for unobserved reasons. Mixed logit allows for unobserved heterogeneity in the marginal utilities, as the marginal utilities are influenced by a random element. It is also possible to use mixed logit as a stochastic form of the nested logit, by giving the ASC's random elements (Train 2003). ASC's with random elements also measure heterogeneous preferences for the alternatives (Bhat 1998b).

The utility function is for mixed logit given by (7). The $\mathbf{x}_{iqt}$ contains the attributes and vector $\boldsymbol{\beta}_{iq}$ the individual parameters. For each attribute the marginal utility is determined by (8). Here β_{ik} is the fixed part of the heterogeneous marginal utility, the η_{iqk} is the random individual element for attribute *k*, and β_{sd_ik} (the parameter of the standard deviation) determines the effect of the random η_{iqk} on marginal utility of attribute *k*. The η_{iqk}'s are individual specific and are the same for individual *q* in all choice situations. We hence use the panel version of mixed logit, to control for the fact that the SP dataset has repeated choices). The panel version of mixed logit was developed by Revelt and Train (1998). It is possible to measure observed differences in the marginal utilities. For this, a vector of background variables ($\mathbf{z}_q$) is multiplied by vector $\boldsymbol{\upsilon}_{ik}$, which measures the effect of these variables on marginal utility of attribute *k*. The ASC is part of $\boldsymbol{\beta}_{iq}^{\mathrm{T}}\mathbf{x}_{iqt,}$ hence it is also possible to allow for non-IID unobserved elements. An example of such non-IID unobserved elements is when the element are correlated (i.e. when the responses have a nested structure).

$$\mathrm{U}_{\mathrm{iqt}} = \beta_{iqk}^{\mathbf{T}} \, \mathrm{x}_{\mathrm{iqt}} + \varepsilon_{\mathrm{iqt}} \tag{7}$$

$$\beta_{iqk} = \beta_{ik} + \boldsymbol{\upsilon}_{ik}^{\mathbf{T}} \mathbf{z}_q + \beta_{\mathrm{sd\_ik}} * \eta_{iqk} \tag{8}$$

The unconditional choice probability is given by (9) and is a weighted by density ($\mathbf{f}(\boldsymbol{\eta}_{\mathbf{iq}})$) of the random elements average of the logit conditional probability ($\mathrm{L}_{\mathrm{iqt}}$) at all possibility values of the random elements. The formula has open-for integrals in it. Consequently, this probability can generally not be calculated directly and has to be approximated by simulation (Train 2003).

$$P_{iqt} = \int_{\boldsymbol{\beta}_{iq}} \frac{\exp\left(V_{iqt}\right)}{\sum_j \exp(V_{jqt})} \mathbf{f}(\boldsymbol{\eta}_{iq}) \, \mathbf{d}\boldsymbol{\eta}_{iq} = \int_{\boldsymbol{\beta}_{iq}} \mathrm{L}_{iqt} \mathbf{f}(\boldsymbol{\eta}_{iq}) \, \mathbf{d}\boldsymbol{\eta}_{iq} \tag{9}$$

The distributional forms of the η_{iq}'s have to be predefined. Two types of distributions of the random components are used in this paper. The first is the triangular distribution and the second the lognormal. The latter distribution has the attractive property that the marginal utility has 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] (Hensher, Rose and Greene 2005). The coefficient for the fixed part measures for the triangular distribution the average marginal utility, whereas with a lognormal it measures the mode.

For the simulation values for the random individual elements (η_{iq}'s) are drawn and then using the values of the variables, the observed choices and the distributions of the random elements, the probabilities are calculated. The simulated outcome is different for each draw. Therefore, the process is repeated for many draws and the average simulated choice probability from all the draws is used as an approximation (Hensher, Rose and Greene 2005).

A remaining question is what number of draws results in an accurate and stable estimation. Mixed logit traditionally uses pseudo-random draws. Pseudo-random draws have the disadvantage that they require many draws for accurate results. An alternative is to use Halton draws. Halton sequences are far more uniformly spread than pseudo-random draws. Consequently, the estimation is stable with fewer draws (Bhat, 2001). For this reason, this study uses Halton draws only. Note that we used LIMDEP(/NLOGIT) to estimate the models by maximum (simulated) likelihood.

Following, Train (2003) the *choice situation specific* (micro) elasticity with mixed logit is determined by equation (10). This elasticity has two parts that are in open-form integrals. One part gives the derivative to the independent variable of the choice probability and the second gives the choice probability. To approximate these parts we perform a second simulation using 250 Halton draws. Each draw results in a different derivative and probability for the same choice situation for the same person. The expected derivatives and probabilities are then used as approximations and used to calculate the micro elasticities. This second simulation was very stable. When we redid the simulation basing the Halton draws on different sets of primes, the resulting aggregate elasticities differed from each other by only a few thousands.

---

[1] It is not directly possible to estimate negative marginal utilities with this distribution. However, this is easily solved by multiplying the attribute before the estimation by minus one.

$$E_{x_{ikqt}}^{P_{iqt}} = \left[\frac{\partial P_{iqt}}{\partial x_{ikqt}} \right] \frac{x_{ikqt}}{P_{iqt}} = \left[\int_{\boldsymbol{\beta}_{iq}} \mathrm{L}_{iqt} (1 - \mathrm{L}_{iqt}) \beta_{ikq} \mathbf{f}(\boldsymbol{\eta}_{iq}) \, \mathrm{d}\boldsymbol{\eta}_{iq} \right] \frac{x_{ikqt}}{\int_{\boldsymbol{\beta}_{iq}} \mathrm{L}_{iqt} \mathbf{f}(\boldsymbol{\eta}_{iq}) \, \mathrm{d}\boldsymbol{\eta}_{iq}} \qquad (10)$$

The fixed parameter estimations

The models are estimated on the eight choices of the 472 respondents. Hence, there are 3776 observations. The experiment was based on the most recent weekday train trip of the respondents. The attributes were *ticket price*, *(in-vehicle) travel time* and the *displacement time* (peak travel restrictions) attributes. This displacement time specification comes from Steer Davies Gleave (2006b). The displacement times were created from the travel moment restrictions in the choice cards and are centred around the travel moment of the most recent trip. They reflect by how much the trip of a respondent should be sifted forward or backward in time satisfy the restrictions on the *restricted ticket* alternative. These four attributes are referred to as *displacement time outbound trip* ***earlier***, *displacement time outbound trip* ***later***, *displacement time return trip* ***earlier*** and *displacement time return trip* ***later***. Following Steer Davies Gleave (2006b), the prices of the tickets are based on a single one-way journey. For the respondents for who the experiment was on a round trip the *price* was halved.

Multinomial logit

Table 2 shows the estimation of the utility functions (1a-c) without any control variables by multinomial logit (MNL). The result is surprising. The coefficients of the *restriction* and *price* attributes are, as expected, negative and highly significant. However, the *travel time* attribute has a highly significant *positive* coefficient. This would mean that the longer the trip from A to B takes, the more utility the respondents receive. If there are two rail links between A and B and the first takes 15 minutes and the latter 2 hours, then the second should be chosen. This seems a rather implausible result.

The reason seems to be that the estimated coefficients also captures an second effect that the train alternatives become more attractive the longer the trip is. Therefore, Table 3 shows the MNL estimation with the addition to the utility function of the third *no ticket* alternative of the control variable *journey length* of the last made trip and the quadratic form of this variable. Now, the coefficient of *travel time* is of the expected negative sign, although it is insignificant.

Journey length has a significant negative effect on the utility of the *no ticket* alternative and its quadratic form has a significant positive effect. The net effect, though, remains negative in the sample. This is logical. Longer trips have higher generalised costs. Hence, the utility of the trip on which the SP assignment was based must be higher for longer trips, as otherwise the trip would not have been undertaken. Furthermore, for longer trips it is more difficult to find a different mode to travel by. Thus the larger *journey length* is, the higher the utility of undertaking the trip by train. Except for the coefficient of *displacement time return trip* ***earlier***, the coefficients of the restrictions are roughly of the same size in the two estimations. This suggests that the scale of the two estimations (i.e. the variances of the unobserved elements) are roughly the same.

The positive effect of *travel time* on the utility of undertaking a train trip was thus caused by not controlling for the effect *journey length*. Interesting is that the coefficient for the *price* attribute is also doubled by the inclusion of *journey length*. The price of rail ticket is, in the Netherlands, (partly) determined by the length in kilometres of the train journey. Hence, *journey length* in minutes is correlated with the *price* attribute. If *journey length* is not included, the result is that the *price* and *travel time* attributes are correlated with the unobserved element. This causes positive biases in the coefficients of *price* and *travel time*. Furthermore, the addition of the *journey length* variables causes the log-likelihood to almost halve. Consequently, a log-likelihood test rejects the estimation of Table 2 in favour for the estimation of Table 3 at the one pro mille level.

Table 2 Trip choice MNL estimation without control variables

	Unrestricted Ticket		Restricted Ticket		No ticket	
	Coeff	t-statistic	Coeff	t-statistic	Coeff	t-statistic
Attributes						
Price	-0.0131***	-3.00	-0.0131***	-3.00		
In-Vehicle Travel Time	*0.0066****	*8.12*	*0.0066****	*8.12*		
Displacement time outbound trip **earlier**			-0.0028***	-3.71		
Displacement time outbound trip **later**			-0.0161***	-15.98		
Displacement time return trip **earlier**			-0.0033***	-4.11		
Displacement time return trip **later**			-0.0062***	-6.89		
Alternative Specific Constant for			0.3182***	4.23	0.0203	0.42

Respondents 472 Choice cards per respondent 8 log-likelihood -6024.08

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

Table 3 Multinomial logit estimation with control of *journey length* of the last trip

	Unrestricted Ticket		Restricted Ticket		No ticket	
	Coeff	t-statistic	Coeff	t-statistic	Coeff	t-statistic
Attributes						
Price	-0.0277***	-4.15	-0.0277***	-4.15		
In-Vehicle Travel Time	-0.0006	-0.15	-0.0006	-0.15		
Displacement time outbound trip **earlier**			-0.0026**	-2.54		
Displacement time outbound trip **later**			-0.0161***	-11.52		
Displacement time return trip **earlier**			-0.0021*	-1.88		
Displacement time return trip **later**			-0.0057***	-4.74		
Control variables						
Journey length in minutes					-0.0221***	-4.85
(Journey length in minutes)^2					0.679E-05***	6.16
Alternative Specific Constant for			-0.4030***	-3.90	-0.7089***	-7.65

Respondents 472 Choice cards per respondent 8 log-likelihood -3285.32

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

Nested logit

Nevertheless, there is still the surprising result that *travel time* has no effect on utility. However, this problem disappears if the same utility function is estimated by nested logit, as in Table 4. The two ticket alternatives are put in one nest (the *travel by train* nest), as they both entail going to the same destination on the same day by train. The third alternative sits alone in its own nest. The utility of undertaking the trip by train is different for each respondent. With MNL, we can only estimate the group average of this utility. The individual deviations from the group mean remain unobserved and hence the unobserved elements are non-IID.

The scale parameters on the alternative level and for the degenerate *do not travel by train* nest are normalized to one. Thus, only the scale parameter of the *travel by train nest* is estimated. The scale parameter of the *travel by train* nest is 0.11, and is significantly lower than one and higher than zero. This shows that the data has a nested structure and the assumption of Independently and Identically Distributed (IID) unobserved elements of MNL is violated. The two ticket alternatives are perceived to be very similar by the respondents, as they both entail making a train trip to the same destination.

The nested logit gives the expected result that a longer *travel time* lowers utility. All attributes, except *displacement time early* for the return trip, have significantly negative coefficients. This could mean that the respondents do not care about the *displacement time early* for the return trip and can leave earlier in the afternoon with relative ease. Conversely, it may also be so that it is impossible for the respondents to leave earlier. In that case the displacement time earlier for the return trip does not matter to the respondent, because it is impossible to leave earlier anyway. This last reason could be the case for the commuters, since for them it is difficult to leave earlier from work. Being forced to leave later in the morning, gives the most disutility. Both ASC's are significantly negative.

Table 4 Nested logit estimation of the trip choice with control for journey length

	Unrestricted Ticket		Restricted Ticket		No ticket	
	Coeff	t-statistic	Coeff	t-statistic	Coeff	t-statistic
Attributes						
Price	-0.1267***	-6.60	-0.1267***	-6.60		
In-Vehicle Travel Time	-0.0154***	-3.34	-0.0154***	-3.34		
Displacement time outbound trip **earlier**			-0.0026**	-2.47		
Displacement time outbound trip **later**			-0.0164***	-11.44		
Displacement time return trip **earlier**			-0.0010	-0.91		
Displacement time return trip **later**			-0.0053***	-4.38		
Control variables						
Journey length in minutes					-0.0203***	-6.12
(Journey length in minutes)^2					6.3E-05***	5.76
Alternative Specific Constant for			-0.5428***	-4.82	-0.9301***	-10.05

Nest level scale parameters

Branch	coeff	t-statistic (against H0: scale-parameter =1)
Travel by train	0.1111***	-14.40
Do not travel by train	1.0000	Fixed normalised parameter

Respondents 472 Choice cards per respondent 8 log-likelihood -3271.14

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

Journey length has a negative effect on the utility of the *no ticket* alternative, and its quadratic form has a significant positive coefficient. The quadratic form is added to control for non-linear effects. The net effect of *journey length* remains negative in the sample. In fact, the effect of *journey length* becomes positive only for values above the longest possible direct train journey in the Netherlands. For 98 percent of the respondents, the function of *journey length* is increasingly negatives. The longer the trip takes, the higher the utility of undertaking the train trip relative to the utility of the *no ticket* opting out alternative.

The *price* coefficient of the MNL estimation of Table 3 is about a fifth of the coefficient from the nested logit estimation of the same model. The *travel time* coefficient with nested logit is even 25 times the coefficient found by MNL. Hence, the estimated *values of travel time* from the two estimates differ by a factor of five. Interesting is that the other coefficients and ASC's hardly differ between the estimations. This means that the WTP's of the travel moment restriction are also very different in the two specifications.

However, the *price* and *travel time* coefficients from the MNL with control for *journey length* are still much more negative than those from the MNL without this control. It is hence also necessary to control for the effect of *journey length* of the last trip. When this is not done, the *price* and *travel time* coefficients also capture the effect of *journey length*, thereby causing a missing variable bias. Conversely, on the other coefficients the effect of not including *journey length* or ignoring the non-IID unobserved elements is marginal. For these variables the only substantial effect is on the standard errors of their coefficients. Though, the effect on the coefficient of *displacement time return trip* ***earlier*** is also substantial.

Final nested logit estimation

The estimation of Table 5 adds control variables on whether the respondent travels mostly during the peak and on the purpose of the most recent train trip. The estimation also controls for travel cost compensation. This is done by adding, besides the *price* attribute alone, two *price* attribute interacted with dummies. The first interacted dummy is *respondent pays* and the second the respondent is *fully compensated.* The first dummy is one if the respondent paid the entire ticket herself. The second dummy is one if she was fully compensated.

The coefficient of the *price* attribute alone gives the *price* sensitivity of the reference group. The reference group contains the partly compensated and the rest category group. The rest group contains, for instance, respondents who got the ticket in combination with a purchase of an amusement park entry ticket. By adding the coefficient of "Price**respondent pays* dummy" to the coefficient of *price* alone, the marginal utility of *price* for the uncompensated is found. The marginal utility for the fully compensated is found by adding the coefficient of "Price**fully compensated* dummy" to the coefficient of the *price* attribute alone.

All three *price* variables have a significant effect on utility. The coefficient of "Price* *respondent pays* dummy" is negative. Hence, the respondents who pay the ticket themselves are more *price* sensitive. The marginal utility of *price* for the fully compensated is $0.171 - 0.147 = +0.024$, which is positive, though it is not significantly different from zero. Hence, for the fully compensated, *price* apparently has no effect on utility.

The coefficients of the restriction attributes, except of *Displacement time return trip* **earlier**, are significant and of the expected negative sign. Interesting is that they are of roughly the same sizes as in the previous nested logit and MNL estimations and that the same pattern of relative sizes of the restriction coefficients is visible. The *journey length* of the most recent trip has again a negative effect on the utility of the *no ticket* alternative. The *travel by train* nest scale parameter is, with 0.20, again significantly lower than one and higher than zero. However, it is larger than the nest level scale parameter found by the previous nested logit estimation. This is because the extra control variables make a part of the *correlated unobserved elements* observed.

Table 5 Final nested logit estimation.

	Unrestricted Ticket		Restricted Ticket		No ticket	
	Coeff	t-statistic	Coeff	t-statistic	Coeff	t-statistic
Attributes						
Price	-0.1474***	-4.63	-0.1474***	-4.63		
Price* *respondent pays* dummy	-0.0763**	-2.38	-0.0763**	-2.38		
Price* *fully compensated* dummy	0.1713***	4.12	0.1713***	4.12		
In Vehicle Travel Time	-0.0258***	-5.18	-0.0258***	-5.18		
Displacement time outbound trip **earlier**			-0.0038***	-3.33		
Displacement time outbound trip **later**			-0.0133***	-8.57		
Displacement time return trip **earlier**			-0.0006	-0.47		
Displacement time return trip **later**			-0.0048***	-3.60		
Control variables						
Journey length in minutes					-0.0196***	-5.88
(Journey length in minutes)^2					4.5E-05***	3.82
Travel mostly during rush hour dummy			-1.0454***	-7.58	0.4051***	3.87
Purpose of the trip dummy						
Commute			-0.4700***	-2.68	0.0216	0.14
Business trip			-1.1513***	-7.09	-0.8104***	-5.03
School			0.0807	0.39	-0.1301	-0.62
Shopping			0.9074***	4.96	-0.5489***	-2.60
Visiting			0.1305	0.76	-0.3958***	-2.08
Event			0.2491	1.27	-0.3808*	-1.74
Other			*Reference Group*		*Reference Group*	
Alternative Specific Constant for			-0.1060	-0.67	-1.0886***	-6.75

Nest level scale parameters

Branch	coeff	t-statistic (against Ho: scale -parameter =1)
Travel by train	0.2030***	-20.56
Do not travel by train	1.0000	Fixed normalised parameter

Respondents 472 Choice cards per respondent 8 log-likelihood -2988.02

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

The constant of the *restricted ticket* alternative is not different from zero, indicating that the *restricted ticket* has no inherent disutility. This is a sensible result. The two ticket alternatives both allow for a train trip to the same destination and are only different in their attributes. The constant of the *no ticket* alternative is significantly negative, indicating a positive utility of undertaking the train trip. If a respondent travels mostly during the peak, she is less likely to choose the *restricted ticket* and more likely to choose the *no ticket* alternative. Naturally, if one travels more during the peak, the *restricted ticket* is less attractive.

Purpose of the trip dummies are added to the utility function of the *restricted ticket* and *no ticket* alternatives, to differentiate the ASC's over the purposes of the last made trip. The reference group "other purpose" consists for instance of the purposes hospital/medical, holiday, going to the museum or zoo and a day out.

Commuters are less willing to accept the *restricted ticket*, whereas the *no ticket* alternative is for them not more troublesome. This is visible in Table 5, in that the commute dummy has a significant negative effect on the *restricted ticket*'s utility and no effect on the third alterative. Business travellers are less willing to deal with the restrictions or not to travel by train. For the respondents who go to school there is no difference compared with the reference group. Those who go shopping are more likely to choose the *restricted ticket*, probably because this group has more flexible travel moments. The shoppers are less willing not to travel by train. This could be because city centres are relatively difficult to reach by car, while the central train station in the Netherlands is usually near or in the centre. This could be compounded by the expensiveness of downtown parking. The respondents who went to visit friends or family or were going to an event are less willing not to travel by train. For these two last two groups there was no difference compared with the reference group in the constant of the *restricted ticket* alternative.

The other control variables in the survey had no effect in the nested logit estimations, either directly on alternative specific utilities or on the marginal utilities of the attributes. It was expected that the car dummy might influence the utility of the *no ticket* alternative, as car ownership changes the ease with which the respondent can travel by other means. It was also thought that the purpose of the trip could affect the marginal utility of *price* or *travel time*. Finally, we expected that respondents who travel during the peak have different marginal utilities of the restrictions. However, none of these hypothesized effects were supported by the estimations.

Willingness-to-pay and elasticities for the final nested logit estimation

This subsection first studies the *willingness-to-pay*'s (WTP's) for *travel time* and the travel moment restrictions. Thereafter, the price elasticities are discussed. A willingness-to-pay of an attribute measures the amount of money a person is willing to spend for a one unit change in that attribute. In the case of *travel time,* this measure is also called the value of travel time. The WTP of an attribute is calculated by dividing the relevant coefficient by the marginal utility of price. This marginal utility can be group specific or for the entire sample. The resulting numbers were multiplied by 60, to get them in a per hour format. Table 6 gives the WTP's using the final nested logit estimation. The WTP's are differentiated over cost compensation.

For the fully compensated there are no valid WTP's, as for them the marginal utility of *price* is not significantly different from zero. If one calculates the WTP's for this group one finds negative WTP's. However, as the marginal utility of *price* is not different from zero, the calculated WTP's could just as well approach minus or plus infinity. Hence, the estimated WTP's for these individuals are not useful.

The respondents who pay the entire price themselves are willing to pay less for reductions in *travel time* and the restrictions. The reference group consists of the partly compensated and the rest category group. Table 1 already showed that the uncompensated form 66% of the respondents, the fully compensated 22%, and the reference group 12%. The respondents who paid the entire ticket themselves value an hour of *travel time* by €6.92. They value an hour of earlier displacement for the outbound trip by €1.02. For an hour of *later* displacement of the outbound trip this figure is €3.58 and for *Displacement time return trip* ***later*** it is €1.30. For the partly compensated, these figures are larger as they value *ticket price* less.

The *Displacement time return trip* ***earlier*** attribute had no significant effect on utility. Hence, the WTP for this attribute is not different from zero. This could be because this restriction is no problem for the respondents, or because it is impossible to travel earlier. Being forced to travel later during the outbound trip (in the morning) appears to be the most troublesome. This is visible in that the attribute *displacement time outbound trip* ***later*** has the largest WTP of the restrictions. The *displacement time for the return trip* ***later*** has the second highest valuation, followed by the *displacement time outbound trip* ***earlier.***

Table 6 Willingness-to-pay per hour for the final nested logit estimation.

Variable	Fully compensated [*]	Fully paid by respondent	Partly compensated	All except the fully compensated
In vehicle travel time per hour	NA	€ 6.92	€ 10.50	€ 7.30
Displacement time outbound trip **earlier**	NA	€ 1.02	€ 1.55	€ 1.08
Displacement time outbound trip **later**	NA	€ 3.58	€ 5.43	€ 3.77
Displacement time return trip **earlier** [b]	NA	€ 0.16 [#]	€ 0.25 [#]	€ 0.17 [#]
Displacement time return trip **later**	NA	€ 1.30	€ 1.97	€ 1.37

Note: [*] The marginal utility of *price* for this group is not significantly different from zero. Therefore, this group does not have a valid WTP's. [#] The WTP for displacement time earlier for the return is not significantly different from zero.

Table 7 Differentiated aggregate elasticities for ticket price.

	Unrestricted ticket	Restricted ticket
For all respondents	-0.38	-0.99
For those who pay the ticket themselves	-0.60	-1.11
For those who pay nothing themselves[*]	0.03	0.16
For those who pay part of the ticket or answered other payment structure	-0.31	-0.95

Note: * For this group the price elasticities are not significantly different from zero.

The *choice situation specific* (micro) elasticities for nested logit are calculated by equation (6). These elasticities can be interpreted as the elasticity of the choice probability of alternative *i*, of individual *q*, in choice situation *t,* with respect to a change in the *k*th attribute. To aggregate the elasticities we calculate the choice probability weighted average of the micro elasticities.

Table 7 presents the aggregated elasticities for price. The elasticities are differentiated over the travel compensation groups. The aggregate elasticity for the *unrestricted ticket* are smaller in absolute sense than the one of the re*stricted ticket*. The responses for the *restricted ticket* were about unit elastic and for the *unrestricted ticket* rather inelastic. The fully compensated appear to have a positive elasticity. However, their elasticities are not significantly different from zero. On average the price elasticities are -0.38 and -0.95 for respectively the *unrestricted* and *restricted ticket.* The respondents who pay the entire price themselves react the strongest to price changes.

This section found that MNL underestimated the value of travel time, and that the assumption of Independent and Identically Distributed unobserved elements is violated. Travel cost compensation has a large effect on the *price* sensitivity. The fully compensated even seem to be completely *price* insensitive.

Mixed logit

This section discusses the mixed logit estimation. We use *unconditional* parameters, which are the same for individual *q* over all choice situations. Hence, we use the panel version of mixed logit. Nested logit relaxes the IID assumption of MNL in a limited manner. Mixed logit allows the parameters of the variables to differ for unobserved reasons. Furthermore, it can control for correlated and nonidentical unobserved elements. We use lognormal and triangular distributions for the random elements. The marginal utilities are for lognormal and triangle distributions respectively given by (11) and (12).

Here N_{kq} is a normal distributed (quasi-)random variable with a zero mean and a standard deviation of one. The T_{kq} is a triangular distributed (quasi-)random variable, with a zero mean and $-1 \leq T_{\mathrm{kq}} \leq 1$. The $\mathbf{z}_q$ are the interacted background variables and $\mathbf{v}_k$ their effects on the marginal utility of attribute k. In the lognormal distribution the effect of the fixed part, the random element and the background variables are all inside exponentionals. Consequently, the marginal utility of an attribute with a lognormal random element can never change signs. The sign of (11) is decided by the predetermined (by the analyst) sign of the marginal utility. Thus if the marginal utility is required to be negative, the outcome of (11) is multiplied by minus one.

$$\text{lognormal;} \qquad \beta_{kq} = \pm \exp(\beta_k) * \exp(\beta_{k\_sd} * N_{kq}) * \exp(\mathbf{v}_k^{\mathbf{T}}\ \mathbf{z}_q) \qquad (11)$$

$$\text{triangle;} \qquad \beta_{kq} = \beta_k + \beta_{k\_sd} * T_{kq} + \mathbf{v}_k^{\mathbf{T}}\ \mathbf{z}_q \qquad (12)$$

Table 8 gives the mixed logit estimation using the panel version of mixed logit and 2000 Halton draws. The constant of the *no ticket* alternative has a triangular random element. With this specification, we control for the unobserved utility that is shared by the *ticket* alternatives (i.e. the nested structure of the responses). The fixed part of the ASC of the *no ticket* alternative is significantly negative and the coefficient of the random element is significant and quite large. Hence, the average utility of undertaking the trip by train is positive and varies substantially for unobserved reasons.

Price and *travel time* have negative lognormal distributed parameters, with negative coefficients for the fixed parts and significant coefficients for the random elements. With a lognormal distribution, a positive (negative) coefficient for an interaction variable means that the absolute of the marginal utility of *price* increases (decreases) with this control variable. The marginal utility of *price* is differentiated by four control variables, all four of which have significant effects. Respondents who pay the entire ticket themselves are more *price* sensitive. Men are more *price* sensitive than women. The respondents with a car in the household are less *price* sensitive, than those without. This is surprising, as car availability means that the respondent has an extra alternative to the train and this reasoning would mean that price sensitivity should increase with this dummy. The result is probably because the car dummy also measures the effect of income.

Commuters are less *price* sensitive than the respondents who travelled for a different purpose. This suggests that these commuters just have to undertake the trip and that the ticket price has little effect. Conversely, commuters have a higher utility of not undertaking the train trip, suggesting that the respondent can travel not by train with ease. Presumable, if the commuting respondent would not undertake the trip by train than she would undertake the trip by other means, as the commuter has to get to work. The most likely alternative mode is the car. It is important to note that the commuters are less price sensitive, and that if they do not travel by train during the peak they will mostly travel by other modes. A policy designed to smooth out the peak by differentiating the ticket price should hence take extra notice of the commuters. During the peak a large share of the travellers are commuters. They are less price sensitive and if they do not take the train during rush hour they will probably mostly travel by car during the peak, thereby, worsening the congestion.

Table 8 The mixed logit estimation.

		Unrestricted Ticket		Restricted Ticket		No ticket	
		Coeff	t-statistic	Coeff	t-statistic	Coeff	t-statistic
Fixed part random parameters							
Price		-2.6136$^{\#}$	-7.38$^{\#}$	-2.6136$^{\#}$	-7.38$^{\#}$		
In Vehicle Travel Time		-4.5290$^{\#}$	-10.87$^{\#}$	-4.5290$^{\#}$	-10.87$^{\#}$		
ASC_3						-3.2278***	-8.11
Derived standard deviations parameters							
Price	*(lognormal)*	1.2752***	8.02	1.2752***	8.02		
In Vehicle Travel Time	*(lognormal)*	0.7490***	3.50	0.7490***	3.50		
ASC_3	*(triangular)*					5.0986***	12.42
Observed heterogeneity							
Price* *respondent pays* dummy		1.0741***	4.89	1.0741***	4.89		
Price**commuting trip* dummy		-1.6848***	-4.39	-1.6848***	-4.39		
Price* *car in household* dummy		-2.0989***	-10.38	-2.0989***	-10.38		
Price* *gender* dummy (male=1)		1.3558***	-8.03	1.3558***	-8.03		
Attributes							
Displacement time outbound trip earlier				-0.0040***	-4.30		
Displacement time outbound trip later				-0.0135***	-12.38		
Displacement time return trip earlier				-0.0013	-1.35		
Displacement time return trip later				-0.0055***	-4.81		
Control variables							
Journey length in minutes						-0.0534***	-8.18
(Journey length in minutes)^2						0.0001***	4.74
Travel mostly during rush hour dummy				-1.0522***	-9.71	0.1728	0.99
Car in household dummy				0.2100	1.58	2.6807***	8.26
Gender dummy (male=1)				0.3304***	4.11	1.4891***	8.86
Purpose of the trip dummy	Commute			-0.4129***	-3.23	1.0981***	3.92
	Business trip			-1.2387***	-10.84	-1.5828***	-5.76
	School			0.0351	0.24	-0.5198*	-1.72
	Shopping			1.0189***	7.78	-0.6968**	-2.23
	Visiting			0.0921	0.75	-0.7738**	-2.24
	Event			0.2748*	1.81	-1.3356***	-3.00
	Other			*Reference group*		*Reference group*	
Alternative Specific Constant for				0.0180	0.10		
Respondents 472		Choice cards per respondent 8		Number of Halton draws 2000		log-likelihood -2755.3	

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

$^{\#}$ As the H0 of a zero fixed part of this marginal utility means that this coefficient should be $-\infty$ ($\mathrm{Exp}(-\infty)=0$), there is no (valid) t-statistic (Bhat, 1998a). The reported t-statistic is against zero and only shows that the standard error is much smaller than the coefficient.

The coefficients for the standard deviations of the random element are significant and quite large relative to the other coefficients. This suggests that a large part of the heterogeneity in the marginal utility of price remains unobserved, even after controlling for travel cost compensation, car ownership, gender and purpose of the trip.

If we compare the mixed logit estimation with the final nested logit estimation, using a likelihood ratio test, we reject the nested logit in favour of the mixed logit at the one percent level. Furthermore, the control variables more often have significant effects in the mixed logit than in the nested logit, suggesting that the mixed logit gives a *sharper image* of the preferences. The constant of the *restricted ticket* is again insignificant. *Journey length* again has a significant quadratic effect and its net effect remains negative in the sample.

Different from the previous estimation, car ownership by the household and gender also have direct significant effects on the alternative specific utilities. Men are more likely to choose the *restricted ticket* or the *no ticket* alternatives. Presumably, for the types of travellers in the sample, the men have more flexibility in when and if to travel by train. This could be because women are more constrained by the requirements of their home life. The *car ownership* dummy has a significant positive effect on the utility of the *no ticket* alternative. A car in the household gives an alternative to travelling by train. The car dummy has no effect on the utility of the *restricted ticket*.

The effects of the purposes of the trip and the peak travel dummies with the mixed logit are broadly similar to those found by nested logit. Consequently, these results are not discussed again. The most important difference is that now commuters are significantly more willing to choose the *no ticket* alternative and that the *school* dummy now has no effect. The control variables make part of the heterogeneous preferences for the alternatives observed. The triangular random element of the ASC of the *third* alternative captures unobserved heterogeneity in the preference for undertaking the train trip.

The four travel moment restrictions again all have a significant negative effect, except for the displacement earlier for the return trip. Their coefficients from mixed logit are roughly the same as those found earlier and have the same relative sizes. None of the displacement time attributes could be estimated significantly with a random parameter or interacted with a control variable. Interactions tested were the gender dummy, commuting dummy, whether the respondent travels mostly during rush hour, and how flexible the respective travel moment is.

Willingness-to-pay and elasticities for the mixed logit estimation

Interpreting the output for a mixed logit, and especially with lognormal random parameters with interaction terms, is difficult. The results are best interpreted by calculating elasticities and WTP's. The *micro* elasticities are determined by (10). This equation has two parts that are in open-form integrals. The first part is for the derivative of the probability to price and the second for the choice probability itself). Consequently, the elasticities can hence not be calculated directly.

Therefore, the elasticities are approximated by a second simulation using 250 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 micro elasticities. In the micro elasticity equation of (10) it is visible that the derivative depends on the realisations of the random elements of the marginal utilities of the attributes and the ASC of the *no ticket* alternative. The marginal utilities of *price* and *travel time* for individual *q* are simulated respectively by (13) and (14).

$$B_{q\ \text{price}} = -\exp(-2.61 + 1.27 * N_{1q} + 1.07 * \text{respondent pays}_q - 1.68 * \text{commuting}_q - 2.10 * \text{car}_q + 1.36 * \text{gender}_q) \quad (13)$$

$$B_{q\ \text{time}} = -\exp(-4.53 + 0.\ 75 * N_{2q}) \quad (14)$$

Tables 9 and 10 respectively show the differentiated aggregate price elasticities for the *unrestricted* and *restricted ticket* alternatives. The micro elasticities were aggregated by calculating the choice probability weighted average[2]. The elasticities for the *restricted ticket* are larger in absolute sense than those of the *unrestricted ticket*. This is technically this is because the *restricted ticket* has the much lower choice probability, and ceteris paribus the lower the choice probability the larger the price elasticity. A more economical interpretation is that is that the r*estricted ticket* is a *lesser quality* substitute of the *unrestricted ticket*, and therefore has a higher price elasticity.

If the household of the respondent owns a car, the respondent has a much smaller (absolute) elasticity. This is presumably because the car dummy also measures the effect of income. The (partly) compensated react rather inelastically to price changes. Conversely, respondents who pay the entire price themselves react much stronger to price changes. Men are also more *price* sensitive than women.

Table 9 Differentiated aggregate price elasticities for the unrestricted ticket.

	all	**A car in the household**			**No car in the household**		
		Both genders	men	women	Both genders	men	women
All respondents	-0.206	-0.187	-0.326	-0.102	-0.335	-0.604	-0.254
For the respondents who pay **part or noting** of the ticket's price	-0.269	-0.250	-0.444	-0.143	-0.379	-0.708	-0.304
For the respondents that **fully** paid the ticket	-0.119	-0.107	-0.197	-0.043	-0.234	-0.473	-0.110
Car in the household	-0.056	-0.034	-0.077	-0.014	-0.110	-0.260	-0.073
No car in the household	-0.256	-0.227	-0.378	-0.127	-0.638	-0.933	-0.524

Table 10 Aggregate price elasticities for the restricted ticket.

	all	A car in the household			No car in the household		
		Both genders	men	women	Both genders	men	women
All respondents	-0.397	-0.354	-0.531	-0.209	-0.728	-1.017	-0.615
For the respondents who pay part or noting of the ticket's price	-0.437	-0.385	-0.591	-0.374	-0.885	-1.351	-0.755
For the respondents that fully paid the ticket	-0.282	-0.259	-0.374	-0.137	-0.411	-0.657	-0.241
Car in the household	-0.119	-0.068	-0.123	-0.028	-0.265	-0.462	-0.205
No car in the household	-0.397	-0.354	-0.531	-0.209	-0.728	-1.017	-0.615

In Table 11 the WTP's are shown for the whole sample and differentiated over gender and travel cost compensation. The WTP's were simulated by the same draws as the elasticities[3]. The rightmost column contains the fully and partly compensated respondents and the rest group. The rest group contains for instance those who travelled on a *free travel day*. The value of *travel time* is calculated by dividing the simulated marginal utility of *travel time* by the simulated marginal utility of *price*. For the restrictions, the individual invariant marginal utilities of the displacement times are divided by the simulated marginal utility of price.

---

[2] The second simulation was performed in Gauss 6.0. The Halton draws were based on the primes 2, 3 and 5. The simulation with 250 draws was very stable. When we ran the same code using the primes 5, 3 & 2; 5, 11 & 13; 5, 7 & 11; and 11, 13 & 17 the resulting (differentiated) aggregates only differed from each other by a few thousands.

[3] The resulting WTP's were also very stable in regard to the choice of primes on which the Halton draws are based, with only differences of a few tenths of a Euro cent between the average values from the different series of Halton draws.

The same pattern as before of relative sizes of the WTP's of the restrictions is visible. The WTP of *displacement time return trip **earlier*** is zero, as its coefficient is insignificant. Having to travel later for the morning (outbound) trip is valued the highest. The respondents are on average willing to spend €6.17 per hour of reduction in *displacement time outbound trip **later**.*

The mixed logit estimation found that the marginal utilities of *price* and *travel time* differ over the respondent for unobserved and observed reasons. The mixed logit estimation controlled for the correlated unobserved elements of the utilities of the alternatives, similarly to nested logit.

Table 11 Willingness-to-pay per hour of travel time and travel moment restrictions.

Variable	**Average**			**Ticket fully paid by the respondent**	**Ticket partly or fully paid by others**
	Both genders	men	women		
In Vehicle Travel Time	€ 6.54	€ 4.04	€ 13.58	€ 5.12	€ 13.97
Displacement time outbound trip **earlier**	€ 1.83	€ 1.13	€ 3.80	€ 1.43	€ 3.91
Displacement time outbound trip **later**	€ 6.17	€ 3.82	€ 12.82	€ 4.83	€ 13.19
Displacement time return trip **later**	€ 2.52	€ 1.56	€ 5.22	€ 1.97	€ 5.37

Comparison of the estimations

This section compares the resulting price elasticities and WTP's for the MNL estimations of Tables 2 and 3, the nested logits of Tables 4 and 5 and the mixed logit of Table 8. Table 12 gives the aggregate elasticities for the estimations. The average WTP's from the estimations are tabulated in Table 13. The aggregate price elasticity is the lowest for the MNL estimation and the highest for the final nested logit. The aggregate elasticity is lower with mixed logit than with nested logit, though it is much larger than the aggregate elasticities from the MNL's.

Bhat (1998a) found that the "cost" elasticity is larger with mixed logit than with his MNL. Bhat (1998b) also found that the elasticities were lower with his MNL than with his mixed logit which controlled for a complex pattern of correlated utilities. These results are thus similar to ours, in that the elasticities with MNL are lower than with mixed logit. We do find though that with the nested logit (which also does not control for unobserved heterogeneity) the aggregate price elasticities are higher than with mixed logit.

Bhat (1998a) found that the WTP's with MNL are somewhat larger than with mixed logit. Bhat (2000a) found that the values of *in-vehicle* and *out-of-vehicle travel time* are substantially larger with mixed logit than with MNL.

There are two distinct patterns in Table 13. The value of *travel time* increases as one moves from the most simple MNL, to the final nested logit. Note that the left most column is the most simple and the more to the right a column is, the more complex and better fitting the estimation is. There is a slight decrease in the WTP of *travel time* from the first nested logit to the mixed logit. The increase in the estimated *value of time* is the largest if we add the control for *journey length* to the MNL estimation. If *journey length* is not added this causes a missing variable bias. The second largest increase in the estimated WTP of *travel time* is when we control for the non-IID unobserved elements by nested logit.

Table 13 shows that the WTP's for the restrictions are the highest for the first MNL without control variables and the lowest for the final nested logit. The WTP's for the restrictions are larger with the mixed logit than with nested logit.

Hence, not controlling for the unobserved heterogeneity in the marginal utilities causes an underestimation of the WTP's of the restrictions. Conversely, not controlling for the correlated unobserved elements and observed heterogeneity causes an overestimation of the WTP's of the restrictions. The WTP for travel time increases as one moves from the most simple MNL to the nested logit. Not controlling for *observed* heterogeneity in the marginal utilities and non-IID unobserved elements, caused an underestimation of the value of travel time.

Table 12 Comparison of the aggregate price elasticities for the restricted ticket of all the models.

Estimation type	Aggregate price elasticities for the unrestricted ticket
MNL without control journey length (Table 2)	-0.056
MNL with control journey length (Table 3)	-0.103
Simple nested logit (Table 4)	-0.320
Final nested logit (Table 5)	-0.380
Mixed logit (Table 8)	-0.206

Table 13 Comparison of the WTP's of all the models.

average WTP's per hour	MNL without control for Journey length	MNL with control for Journey length	Simple Nested logit	Final nested logit#	Averages from mixed logit
In Vehicle Travel Time	-€ 30.23	€ 1.30*	€ 7.29	€ 7.30	€ 6.54
Displacement time outbound trip earlier	€ 12.82	€ 5.63	€ 1.23	€ 1.08	€ 1.83
Displacement time outbound trip later	€ 73.74	€ 34.87	€ 7.77	€ 3.77	€ 6.17
Displacement time return trip earlier	€ 15.11	€ 4.55	€ 0.47*	€ 0.17*	€ 0.61*
Displacement time return trip later	€ 28.40	€ 12.35	€ 2.51	€ 1.37	€ 2.52

Note: * These WTP's are not significantly different from zero. # The figures for the final nested logit are the averages ignoring the fully compensated, as these respondents do not have valid WTP's in this estimation. Hence, these figures in this column are not directly comparable with the figures in the other columns.

Our results on the effect of ignoring heterogeneity on the WTP's are thus comparable to those of earlier empirical studies. However, we should note that not controlling for observed heterogeneity and the correlation of the unobserved elements (i.e. the nested structure of the responses) causes much larger problems with the estimated WTP's and elasticities than not controlling for the unobserved heterogeneity in the marginal utilities. The effects of ignoring heterogeneity on the WTP's are different for observed and unobserved heterogeneity. Hence, there is an effect of ignoring both observed and unobserved heterogeneity. However, this effect has no clear pattern.

As discussed in the introduction, it is an interesting question what the cause is of the differences in the results of the empirical literature and the results of Horowitz (1980). In this regard the difference in the two MNL estimations, due to the effect of *journey length*, is interesting. Not including *journey length* causes underestimation of the relative sizes of the coefficients of *price* and *travel time*, because of a missing variable bias. Thus the difference in results could be caused by correlation between the unobserved elements with some of the levels of the attributes. It is interesting to note, that including the *purpose of the last made trip* dummies and controlling for travel cost compensation (see Tables 4 and 5) also has a substantial effect on the estimated WTP's. This makes it extra important to control for travel cost compensation. It is not only a source of heterogeneity in the price sensitivities, not controlling for it can also cause an underestimation of the average price sensitivity.

The different (average) WTP's and price elasticities from the MNL compared with the mixed logit could have large implications for proposed policies using the results. If the MNL estimation of Table 3 would be followed instead of the mixed logit. Than policies following this MNL estimate might invest too little in *travel time* savings, as *in-vehicle travel time* has a marginal utility of zero. A *restricted ticket* designed following this MNL might offer too much in monetary savings. The MNL also overestimates the WTP's for the restrictions. Hence, a restricted ticket designed by the MNL results might perhaps have too narrow restricted periods. A policy to increase train travel by lowering the price, might lower the price of the ticket by too large an amount.

Conclusion

This paper studies a Stated Preference experiment on the choice of train ticket, conducted among 472 current single ticket travellers in the Netherlands. We use multinomial logit (MNL), nested logit and mixed logit estimates to analyse the choices of the respondents to eight choice cards. The respondents chose between: (1) an *unrestricted ticket*, (2) a cheaper *restricted ticket* which has *travel moment restrictions,* and (3) neither the first nor the second alternative.

Both ticket alternatives entail making a train trip to the same destination and hence both produce the utility of undertaking the train trip. The choices of the respondents appear to have a very strong nested structure, thereby violating the assumption Independently and Identically Distributed unobserved elements of MNL. The marginal utilities of *travel time* and *price* are found to differ over the respondents for unobserved reasons (i.e. unobserved heterogeneity in the marginal utilities). The mixed logit method seems to most appropriate for this dataset, as it controls for unobserved heterogeneity in the marginal utilities, the panel structure of the data, and the non-IID unobserved elements.

The marginal utility of *price* also differs over car ownership, travel cost compensation, gender and the purpose of the trip. Travel cost compensation has, understandably, a large influence on the marginal utility of *price*. The respondents who paid the entire ticket themselves appear to be much more price sensitive than those who are (partly) compensated. A new pricing policy will probably, for example, have very little effect on the travel demand and behaviour of the fully compensated. This is important as a large share of Dutch travellers get their travel costs (partly) compensated. Furthermore, travel cost compensation is often named as a reason for low aggregate (absolute) price elasticities in transport. Hence, it seems very important to control for travel cost compensation in studying transport demand.

We find that not controlling for the unobserved heterogeneous marginal utilities seems to cause an overestimation of the price sensitivities, as measured by the elasticities. Conversely, not controlling for observed heterogeneity and non-IID unobserved elements seems to results in an underestimation of this elasticity. The WTP's for the travel restrictions are lower with mixed logit than with nested logit, whereas the value of travel time is higher with mixed logit. The value of time from the MNL estimate is not significantly different from zero, whereas with the mixed logit estimate the expected result is that the value of time is positive. Policies based on the MNL estimations might be very different from those based on the mixed logit. For instance, a policy might under-invest in *travel time* savings, as *in-vehicle travel time* has a marginal utility of zero in the MNL estimation.

It is a common finding in the empirical literature that estimations that control for unobserved heterogeneity find different WTP's than estimations that do not. However, this is not the case for all studies. Furthermore, of the studies that that do find differences between the WTP's from MNL and mixed logit, some find an overestimation by MNL and some other studies find an underestimation. It is an interesting question for further research to see under which circumstances the empirical reality is different from the theoretical predictions. It is noteworthy that, in this paper, the effect on the mean estimates of the WTP's of not controlling for observed heterogeneity is much larger than the effect of not controlling for unobserved heterogeneity.

Acknowledgements

The authors are grateful for the support from the NS (Dutch Railways) in the carrying out of this research and we are especially thankful for the support of Freek Hofker, Maurice Unck and Theo van der Star from the NS. The data used in this paper comes from a Stated Preference experiment that was designed and carried out by Steer Davies Gleave. Their efforts and comments to an earlier version of this paper are gratefully acknowledged. The support of Piet Rietveld is also gratefully acknowledged. This paper is part of the project Betrouwbaarheid van transportketens. The Betrouwbaarheid van transportketens project 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. Finally, the participants of the Eureka seminar (internal seminar at the VU University, Amsterdam) of 23 October 2007 and the ERSA 2008 conference in Liverpool, are thanked for their helpful comments. The opinions in this paper and any remaining errors are purely the responsibility of the authors.

References

Abkowitz MD (1981) An analysis of the commuter departure time decision. Transportation 10(3): 283-297

Bhat CR (1998a) Accommodating variations in responsiveness to level-of-service variables in travel mode choice models. Transportation Research A 32: 455–507

Bhat CR (1998b) Accommodating flexible substitution patterns in multi-dimensional choice modeling: formulation and application to travel mode and departure time choice. Transportation Research Part B: Methodological 32(7): 455-466

Bhat CR (2000a) Incorporating observed and unobserved heterogeneity in urban work travel mode choice modeling. Transportation Science 34(2): 228-239

Bhat CR (2000b) Flexible Model Structures for Discrete Choice Analysis. In: Hensher DA, Button KJ (ed) Handbook of transport modelling, Elsevier Science, Oxford

Bhat, CR (2001) Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. T*ransportation Research B* 35: 677–693

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

Hensher DA, Rose JM, Greene WH (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

Louviere JJ, Hensher DA, Swait JD (2000) Stated choice methods: analysis and applications. Cambridge University Press, New York

Revelt D, Train KE (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 KE (1998) Recreation demand Models with taste differences over people. Land Economics 74(2): 230-239

Train KE (2003) Discrete choice methods with simulation. Cambridge University Press, Cambridge

Author Biographies

Vincent van den Berg is a PhD student at the department of spatial economics of the VU University, Amsterdam. Currently his main areas of research interest are discrete choice modelling and modelling the competition between personal transport (road and rail) operators.

Eric Kroes is the Managing Director of Significance BV, Leiden. He is also an Associate Professor Transport Economics at the VU University, Amsterdam. His main areas of interest are stated preference research, discrete choice modelling, public transport and aviation studies, project appraisal, policy monitoring and evaluation.

Erik Verhoef is currently affiliated as a full professor in Spatial Economics at the VU University, and as a research fellow at the Tinbergen Institute and the Netherlands Network of Economics (NAKE). His research focuses on efficiency and equity aspects of spatial externalities and their economic regulation, in particular in transport, urban and spatial systems.