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Mixed Logit Estimation of the Value of Travel Time[†]

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Abstract

In this paper we use mixed logit specifications to allow parameters to vary in the population when estimating the value of time for long-distance car travel. Our main conclusion is that the estimated value of time is very sensitive to how the model is specified: we find that it is significantly lower when the coefficients are assumed to be normally distributed in the population, as compared to the traditional case when they are treated as fixed. In our most richly parameterised model, we find a median value of time of 57 SEK per hour, with the major part of the mass of the value of time distribution closely centred around the median value. The corresponding figure when the parameters are treated as fixed is 89 SEK per hour. Furthermore, our finding that the ratio of coefficients in a mixed logit specification differ significantly from the ones in a traditional logit specification is contrary to the results obtained by Brownstone & Train (1996) and Train (1997). Whether the ratios will differ or not depends on the model and the data generating process at hand.

Keywords: Mixed Logit, Simulation Estimation, Value of Time

JEL Classification: C15, C25, R41

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1. Introduction

When investigating consumers' choices between different transportation alternatives the value of time is a central concept. The value of time is calculated as a trade-off ratio between the in-vehicle time coefficient and the cost coefficient. Usually one trade-off is used for a specific segment. A common segmentation is trip purpose, especially private trips and business trips. However, sometimes the segmentation is extended to account for income levels, trip length etc. Such an approach was also used in the analysis of the Swedish Value of Time study 1994/95. It may still be of interest to account for the distribution of the value of time, especially in forecasting. One way to account for the distribution is to specify a model with regressors that capture the influence of different socio-economic variables and then apply this on the actual sample (or a more representative sample) all resulting in a sample specific distribution of the value of time (see Lindqvist Dillén & Algiers (1998)). Such a distribution gives us a picture of the relative importance of the systematic variation in data.

However, the mentioned study, as well as most earlier ones that have estimated the value of travel time, have adopted the multinomial logit model. Some disadvantages with the multinomial logit approach is that one has to assume (i) that the coefficients are fixed in the population, (ii) that the IIA-assumption holds (implying that the odds ratio between two alternatives does not change by the inclusion (or exclusion) of any other alternative), and (iii) that repeated choices made by a respondent are independent. In this study we will, using stated preference data, adopt a mixed logit approach (also called random parameters logit or random coefficients logit) to allow parameters to vary in the population when estimating the value of time for long-distance car travel. By using a mixed logit approach, we do not have to assume that (i)-(iii) are fulfilled. Of particular interest in this study is to estimate distribution parameters of the coefficients and to investigate how the value of travel time is affected by allowing the parameters to vary in the population.

Our main conclusion is that the estimated value of time is very sensitive to how the model is specified: we find that it is significantly lower when the coefficients are assumed to be normally distributed in the population, as compared to the traditional case when they are treated as fixed. We also get significantly better model specifications (better fit to the data) when we allow the parameters to vary in the population. The finding that the ratio of coefficients in a mixed logit

specification differ significantly from the ones in a traditional logit specification is contrary to the results obtained by Brownstone & Train (1996) and Train (1997). Our conclusion is that whether the ratios will differ or not depends on the model and the data generating process at hand. Finally, when we allowed the parameters to vary log-normally in the population, we found that the models did not converge unless we constrained the dispersion parameter of the log-normal distribution. This pattern was also observed by Brownstone & Train (1996), and their solution was to constrain the dispersion parameter to be 0.8326. We also tried that solution but found, when we tested different restrictions on the dispersion parameter to investigate how the estimated value of time was affected, that it was very sensitive to the imposed restriction.

The paper is organised as follows: section 2 discusses the theoretical model, section 3 discusses the econometric method, section 4 describes the data, section 5 presents the results, and section 6 concludes.

2. Theoretical Framework

Linear random utility models are widely used when dealing with the value of time estimated on revealed preference data. One reason for this is that the correlation between first and second order terms (including higher order terms) can be quite high and make it impossible to estimate separate coefficients. Linearity is though a strong assumption in estimation of the value of time and may hence be inadequate. As we deal with stated preference data which, in contrast to revealed preference data, is based upon a less correlated design, a non-linear functional form will be developed and analysed. In our theoretical model, we will follow the standard set-up used in the literature (see, e.g., Train & McFadden (1978) and Hultkrantz & Mortazavi (1998)).

Assume that the utility function for an individual i is defined by $U_i(G, L, S)$, where G is private consumption, L is leisure, and S is socio-economic status of the individual. We let the individual maximise utility subject to money and time constraints:

$$\begin{aligned} & \max U_i(G, L, S) \\ & \text{s.t.} \\ & G + c_{ij} = E + wW \\ & L = T - W - t_{ij} \\ & j \hat{=} M \end{aligned}$$

G - consumption

S - socio-economic status
 c_j - travel cost for alternative j
 w - wage rate, given
 W - number of hours worked
 E - exogenous income, given
 L - leisure
 t_j - in-vehicle time for alternative j
 T - total amount of time, given

In words, the first constraint implies that the expenditure on consumption, G , and travel cost, c_j , is equal to labour income, wW , and exogenous income, E . The next constraint state that time spent on leisure, L , is equal to the total amount of time given, T , minus time working, W , and time travelling, t_j . There are M travel alternatives. The individual chooses the travel alternative, and hence c_j and t_j , and the number of hours worked so as to maximise utility $U_i(G, L, S)$ subject to the identities.

Inserting the first order conditions from the maximisation problem as well as the optimal working time, $W^* = f(c_j, t_j, w, E, T)$, into the direct utility function, $U_i(G, L, S)$, yields the following indirect utility function:

$$V_{ij}(c_j, t_j) = U_{ij}(E + wf(c_j, t_j, w, E, T) - c_j, T - f(c_j, t_j, w, E, T) - t_j, S)$$

Let us approximate V_{ij} with a second order Taylor expansion around the reference states c_0 , t_0 and s_{0x} (which is a socio-economic vector including K characteristics, where $x = (1, \dots, K)$) for travel alternative $j \neq 0$ and individual i :

$$\begin{aligned}
 V_{ij}(c_j, t_j) = & (c_0, t_0) + \left[(c_i - c_0) \frac{dV}{dc} + (t_i - t_0) \frac{dV}{dt} + \sum_{x=1}^N (s_{jx} - s_{0x}) \frac{dV}{ds_x} \right] + \\
 & \frac{1}{2} \left[\left[(c_i - c_0)^2 \frac{d^2V}{dc^2} + (t_i - t_0)^2 \frac{d^2V}{dt^2} + \sum_{x=1}^N (s_{jx} - s_{0x})^2 \frac{d^2V}{ds_x^2} + \right. \right. \\
 & \left. \left[(c_i - c_0)(t_i - t_0) \frac{d^2V}{dc dt} + \sum_{x=1}^N (c_i - c_0)(s_{jx} - s_{0x}) \frac{d^2V}{dc ds_x} + \sum_{x=1}^N (t_i - t_0)(s_{jx} - s_{0x}) \frac{d^2V}{dt ds_x} + \right. \right. \\
 & \left. \left. \sum_{\substack{x=1 \\ x \neq z}}^N \sum_{z=1}^N (s_{jx} - s_{0x})(s_{jz} - s_{0z}) \frac{d^2V}{ds_x ds_z} \right] \right]
 \end{aligned}$$

When a Taylor expansion to order n is assumed to be sufficiently accurate, then the rest term is close to zero, why this term is left out. The last equation will form the basis for our empirical investigation. Since factors that are constant over alternatives cancel out in the probability expression, we can only identify socio-economic variables when these are interacted with the cost and/or time variable. Before turning to the actual results we will next discuss the econometric method to be used.

3. Econometric Method

In this paper we make use of panel data (repeated choices in a stated preference study) with the decision-makers facing two alternatives in each choice situation.¹ A main purpose with the paper is to estimate distribution parameters for coefficients in a value of time study. To achieve this goal we will adopt the mixed logit procedure described in Revelt & Train (1997) and Train (1997).

The fixed coefficient assumption is the traditional one in value of time studies. If we have panel data, the utility functions typically take the form

$$U_{ijt} = \mathbf{b}'x_{ijt} + \mathbf{e}_{ijt}$$

where $i = 1, \dots, n$ denotes individual i , $j = 1, \dots, c$ denotes choice alternative j , $t = 1, \dots, T$ denotes time period (or choice situation) t , and \mathbf{e}_{ijt} is the stochastic part of the utility function.

To give an example by means of a parsimonious value of time model, the deterministic part of the utility function would take the form $\mathbf{b}'x_{ijt} = \mathbf{b}_1 \text{cost}_{ijt} + \mathbf{b}_2 \text{time}_{ijt}$.

The common estimation methods in many earlier value of time studies with panel data (at least with stated preference data) have been bivariate probit and/or bivariate logit. This means that the likely correlation induced between the choices made by each individual has not been dealt with appropriately.

¹ "Panel data" can be thought of as either revealed preference data where we observe each individual during two or more time periods or as stated preference data where each individual faces repeated choices.

The most common estimation method with multiple alternatives is the multinomial logit (MNL) method as developed and described by McFadden (1973, 1978). A disadvantage with the MNL model is that it relies on the IIA property, implying that the odds ratio between two alternatives does not change by the inclusion (or exclusion) of any other alternative. The IIA property follows from the assumption that the extreme value distributed residuals are independent over utilities. An obvious (theoretical) way to handle the IIA property is to allow the unobserved part of the utility function to be correlated over alternatives by means of a multinomial probit model or a mixed logit model. This approach has, however, been less obvious in empirical applications since multiple integrals then have to be evaluated. The improvements in computer speed and in our understanding of the use of simulation techniques in estimation have however made other approaches than the traditional one as viable alternatives.

In this paper we want to relax the assumption that the coefficients are the same for all individuals. We will call the models within this approach mixed logit models.² Estimating distribution parameters for coefficients that vary randomly in the population requires more demanding estimation techniques than in the traditional model with fixed coefficients. With panel data, the utility functions take the form

$$U_{ijt} = \mathbf{b}_i' \mathbf{x}_{ijt} + \mathbf{e}_{ijt}$$

where \mathbf{b}_i is unobserved for each i ; otherwise with the same notation as above. This set-up allows us, for example, to let the coefficient for the cost and/or time variable in a value of time study to vary over individuals (following, e.g., a normal or a lognormal distribution).

For a general characterisation in a cross-sectional setting, let \mathbf{b}_i vary in the population with density $f(\mathbf{b}_i|\mathbf{q})$, where \mathbf{q} are the true parameters of the distribution. Furthermore, assume that \mathbf{e}_{ij} are iid extreme value distributed. If we knew the value of \mathbf{b}_i , the conditional probability that person i chooses alternative j is standard logit:

² Several names have been used in the literature: random coefficient logit, random parameters logit, mixed multinomial logit, error components logit, probit with a logit kernel, and mixed logit. These names label the same underlying model. We stick, as mentioned, with the name ‘mixed logit’.

$$L_{ij}(\mathbf{b}_i) = \frac{e^{\mathbf{b}_i' \mathbf{x}_{ij}}}{\sum_j e^{\mathbf{b}_i' \mathbf{x}_{ij}}} \quad (1)$$

We do not, however, know the persons' individual tastes. Therefore, we need to calculate the unconditional probability, which is obtained by integrating (1) over all possible values of \mathbf{b}_i :

$$L_{ij}(\mathbf{q}) = \int L_{ij}(\mathbf{b}_i) f(\mathbf{b}_i | \mathbf{q}) d\mathbf{b}_i = \int \frac{e^{\mathbf{b}_i' \mathbf{x}_{ij}}}{\sum_j e^{\mathbf{b}_i' \mathbf{x}_{ij}}} f(\mathbf{b}_i | \mathbf{q}) d\mathbf{b}_i \quad (2)$$

One study using two alternatives and cross-sectional data is conducted by Ben-Akiva, Bolduc & Bradley (1993). They allow the value of time parameter to follow a lognormal distribution³, and use a Gaussian quadrature to evaluate the integral.⁴ However, using quadratures becomes less attractive the larger the dimension of the integrals we have to evaluate (see, e.g., Press et al. (1992)). Since, in the model described in equations (1) and (2), the dimension of the integrals to be evaluated increases with the number of coefficients that are allowed to vary in the population, approaches using Gaussian quadrature to evaluate integrals must be considered being of limited value. A more fruitful approach is then to use simulation methods. Brownstone & Train (1996) and Brownstone, Bunch & Train (1997) have considered this, in a cross-sectional setting, through a mixed logit specification. The model specification in these two papers is identical.

Brownstone & Train (1996) and Brownstone, Bunch & Train (1997) assume that $\mathbf{b}_i' \mathbf{x}_{ij} = (\mathbf{b} + \mathbf{h}_i)' \mathbf{x}_{ij} = \mathbf{b}' \mathbf{x}_{ij} + \mathbf{h}_i' \mathbf{x}_{ij}$, where \mathbf{b} is the population mean and \mathbf{h}_i is the stochastic deviation which represents the individual's tastes relative to the average tastes in the population. This means that the utility function takes the form $U_{ij} = \mathbf{b}' \mathbf{x}_{ij} + \mathbf{h}_i' \mathbf{x}_{ij} + \mathbf{e}_{ij}$, where $\mathbf{h}_i' \mathbf{x}_{ij}$ are error components that induce heteroskedasticity and correlation over alternatives in the unobserved portion of the utility. This means that an important implication of the mixed logit specification is that we do not have to assume that the IIA property holds. Let $g(\mathbf{h}_i | \mathbf{q})$ denote the density for \mathbf{h}_i . Then different patterns of correlation, and hence different substitution patterns, can be

³ Ben-Akiva et al. rewrite their basic model to obtain a model in which one of the parameters is interpreted as a value of time parameter. The other parameters in their model have degenerate distributions.

⁴ More specifically, they use a Gauss-Hermite quadrature. Several different Gaussian quadratures exist (see, e.g., Press et al. (1992)).

obtained through different specifications of $g(\cdot)$ and x_{ij} . For some further results for the mixed logit model, see below.

The version of the mixed logit model described here is not designed for panel data. Revelt & Train (1997) and Train (1997) have, however, provided such an extension. Next we turn to these models.

The basic set-up in Revelt & Train (1997) and Train (1997) is the same as the one outlined above. The major difference is that a subscript t enters into equations (1) and (2) and into the utility function, which now takes the form $U_{ijt} = \mathbf{b}'x_{ijt} + \mathbf{h}_i'x_{ijt} + \mathbf{e}_{ijt}$. However, since we have panel data, we need an expression for the probability to observe each sampled person's sequence of observed choices. Conditional on \mathbf{h}_i , the probability of i 's observed sequence of choices is the product of standard logits:

$$S_i(\mathbf{h}_i) = \prod_t L_{ij(i,t)}(\mathbf{h}_i)$$

where $j(i,t)$ denotes the alternative that person i chooses in period t .

The unconditional probability for the sequence of choices is then:

$$S_i(\mathbf{q}) = \int S_i(\mathbf{h}_i) f(\mathbf{h}_i|\mathbf{q}) d\mathbf{h}_i = \int \prod_t L_{ij(i,t)}(\mathbf{h}_i) f(\mathbf{h}_i|\mathbf{q}) d\mathbf{h}_i \quad (3)$$

Since the integral in (3) cannot be evaluated analytically, exact maximum likelihood estimation is not possible. Instead the probability is approximated through simulation. Maximisation is then conducted on the simulated log-likelihood function.⁵ The algorithm we use to obtain the

⁵ The mixed logit approach as described here has been used in some applications. Examples include Brownstone & Train (1996) (households' choices among gas, methanol, electric, and CNG vehicles; stated preference data), Brownstone, Bunch & Train (1997) (households' choices among gas, methanol, electric, and CNG vehicles; stated and revealed preference data), Revelt & Train (1997) (households' choices of appliance efficiency level; stated preference data), and Train (1997) (anglers' choice of fishing site; revealed preference data). As far as we know, no study estimating value of travel time has so far employed a mixed logit specification in the general way described here.

simulated maximum likelihood results can somewhat heuristically be described as follows (for further details see, e.g., Brownstone & Train (1996) and Revelt & Train (1997))⁶:

- i) Set starting values for the distribution of the coefficient of interest, say \mathbf{b} , i.e. in case of a normally distributed coefficient, the mean and the variance, say b and \mathbf{h} .
- ii) Draw a random individually specific coefficient \mathbf{b}_i from this distribution for each person. This coefficient is kept constant for the individual through all of his/her responses. The random coefficients are, still assuming normally distributed coefficients, distributed as $\beta \sim \text{NID}(b, \mathbf{h})$
- iii) Use data and the obtained random coefficients to evaluate the likelihood function in a standard fashion, i.e. treating the random coefficients as if they were fixed.
- iv) Repeat steps ii) and iii) r times, thus obtaining r values for the likelihood function ℓ_i .

v) Compute the average $\frac{\sum_{i=1}^r \ell_i}{r}$, which is our simulated value for the likelihood.

vi) Change b and \mathbf{h} and repeat steps ii) - v) until we have found a maximum. The values of b and \mathbf{h} are then our simulated maximum likelihood estimates.

Compared to the panel data model with degenerate distributions for the coefficients, the specification in (3) has (at least) two advantages: it does not exhibit the restrictive IIA property and it accounts explicitly for correlations in unobserved utility over time or over repeated choices by each individual.

An alternative to the mixed logit model described above is the multinomial probit model, which might allow for correlations over alternatives and time (or repeated choices). There are however

⁶ The estimation method proposed and used for mixed logit models in earlier studies is the maximum simulated likelihood (MSL). According to Stern (1997), the MSL is one of four existing simulation based estimation methods. The other three are the method of simulated moments (MSM), the method of simulated scores (MSS), and the Monte Carlo Markov Chain (MCMC) method (where one of the most known MCMC methods is Gibbs sampling). The most common methods are MSL and MSM, with some advantages for MSL (see Börsch-Supan & Hajivassiliou (1993) and Hajivassiliou, McFadden & Ruud (1996)). According to Stern, MSS is the least developed of the four, but it holds some significant promise. There are mixed evidence regarding the properties of Gibbs sampling methods (see Stern (1997)). It is left for future research to decide if any of the less developed methods is to be preferred over

some results in the literature indicating that the mixed logit model might be preferable in situations where the aim is to estimate distribution coefficients for parameters in a model. These and other results will be discussed in the rest of this section.

McFadden & Train (1996) establish, among other results, the following:⁷ (1) Under mild regularity conditions, any discrete choice model derived from random utility maximisation has choice probabilities that can be approximated as closely as one pleases by a mixed logit model, (2) A mixed logit model with normally distributed coefficients can approximate a multinomial probit model as closely as one pleases, and (3) Non-parametric estimation of a random utility model for choice can be approached by successive approximations by mixed logit models with finite mixing distributions; e.g., latent class models. From an economic point of view, result (1) is interesting since we often want to put a utility maximising perspective on the problem at hand. Furthermore, if we want to make welfare analysis (e.g., calculate willingness to pay), it is crucial that the observed choice probabilities can be motivated as the outcome of a utility maximisation problem. If not, welfare analysis cannot be conducted. Result (2) is useful since it implies that mixed logit can be used wherever multinomial probit has been suggested and/or used. Additional evidence on this point is given by Ben-Akiva & Bolduc (1996) (as reported by McFadden (1996)) and by Brownstone and Train (1996). Ben-Akiva & Bolduc (1996) find in Monte Carlo experiments that the mixed logit model gives approximation to multinomial probit probabilities that are comparable to the Geweke-Hajivassiliou-Keane simulator. Brownstone and Train (1996) find in an application that the mixed logit model can approximate multinomial probit probabilities more accurately than a direct Geweke-Hajivassiliou-Keane simulator, when both are constrained to use the same amount of computer time.

Advantages with the mixed logit specification does then include:

- i) The model does not exhibit the IIA property.
- ii) The model accounts for potential correlation over repeated choices made by each individual.
- iii) The model can be derived from utility maximising behaviour.
- iv) The model can, as closely as one wishes, approximate multinomial probit models.
- v) Unlike pure probits, mixed logits can represent situations where the coefficients follow other distributions than the normal. Furthermore, as results in Revelt & Train (1996) and

the MSL method. For introductory and survey literature on simulation estimation, see Hajivassiliou & Ruud (1994), McFadden & Ruud (1994), Gouriéroux & Monfort (1996), and Stern (1997).

⁷ These results are obtained from McFadden (1996).

Brownstone and Train (1996) show, when using the estimates for forecasting one may obtain counter-intuitive and unrealistic results by imposing a normal distribution on some coefficients. By their very nature, pure probits are sensitive to this problem. For further discussion on this topic, see, e.g., Brownstone and Train (1996, p. 12f).

- vi) If the dimension of the mixing distribution is less than the number of alternatives, the mixed logit might have an advantage over the multinomial probit model simply because the simulation is over fewer dimensions.

4. Data

The data used in this study is part of the 1994 Swedish Value of Time study. When this study was initiated, it was decided to concentrate on regional and long distance trips, since they would be the most important trip types in the evaluation work, and since some information already existed for local trips. Information was collected for private as well as for business trips for six different modes; car, air, long distance train, regional train, long distance bus and regional bus.

The study was based on stated preference data and was ambitiously prepared. The main study was preceded by several pilot studies and international expertise was involved in the work.

The study was designed as a telephone survey, in which socio-economic information of the respondent and her household, information related to business trips and responses to stated preference experiments was collected.

The principle for the fieldwork was first to contact a person during a trip, in order to give the stated preference experiment a realistic context, and then to make the interview by telephone on the agreed day. However, for the car mode, which is the mode we focus on in this paper, this meant that license plate numbers were noted at selected road sections, and then the car owners were contacted and asked for the person who drove the car at the specific time and location.

The sample size (comprising private values for private and business trips) contained about 850 car interviews. The response rate for the car interviews was about 65 percent.

The stated preference experiment was designed so that the respondent was presented one base alternative and a change from this alternative. This had the advantage that the design did not contain dominant alternatives, which could make the respondents annoyed if included and could cause estimation problems if excluded. A drawback might however be that it makes it easier for the respondents to escape to a “no change” choice. To reduce this problem, the reported data on actual time and cost was randomly multiplied by 0.9 or 1.1, so that the base alternative would not appear to be exactly the same. The base alternative was also referred to as the “C” alternative, which was to be compared to A, B, D, E etc.

To give information on the value of time losses as well as time savings, changes representing gains and losses were presented equally often (four times each in each game). The first choices were randomly gains or losses, to avoid bias depending on the initial question.

In this study we restrict the analysis to one of the segments that we dealt with in 1994/95, namely private car trips over 50 kilometres. Furthermore, we only use those individuals who have eight fulfilled choices, leaving us with a sample of 2024 observations.

5. Results

Brownstone & Train (1996) and Train (1997) find that ratios of their estimated coefficients in a mixed logit specification are similar to those estimated in a traditional logit specification. Brownstone & Train (1996) then conclude that “If indeed the ratios of coefficients are adequately captured by a standard logit model, ... , then the extra difficulty of estimating a mixed logit or a probit need not be incurred when the goal is simply estimation of willingness to pay, without using the model for forecasting.”. Since our goal is “simply to estimate willingness to pay”, we will start out by investigating if the ratios of coefficients (i.e. the value of time) are unaffected by the model specification also in our case. In doing this, we estimate a parsimonious model in which we only have cost (COST), in-vehicle time (TIME), and an alternative-specific constant for the base alternative which we will refer to as an inertia coefficient (INERTIA) as explanatory variables. Using the data described in the former section, we have estimated all eight possible combinations of normal and fixed parameters for the three coefficients mentioned above. The estimation was carried out on the entire sample as well as the sub-samples where individuals were offered only a shorter in-vehicle time at a higher cost (the willingness to pay,

WTP, sample) and where they were offered only a longer in-vehicle time at a discount (the willingness to accept, WTA, sample). The computed values of time for all of these models are given in Table 1⁸, whereas the corresponding log-likelihood values are given in Table 2. The entire estimation output is included as Appendix A. In all estimations we used 1000 replications (i.e., $r = 1000$) to calculate the simulated likelihood function.⁹

Table 1. Value of time (SEK/h).

Model	WTA	WTP	Pooled	CTI
1	117.04 (9.00)	102.19 (12.00)	92.41 (6.00)	FFF
2	137.94 (12.60)	93.33 (12.00)	85.25 (6.60)	FNF
3	112.53 (10.20)	87.67 (10.20)	91.81 (4.80)	FFN
4	76.26 (17.40)	28.27 (4.80)	51.32 (5.40)	NFF
5	95.35 (13.20)	60.44 (10.80)	59.73 (5.40)	NNF
6	83.01 (12.60)	51.35 (8.40)	47.87 (4.80)	NFN
7	132.90 (12.60)	97.20 (12.00)	82.58 (6.60)	FNN
8	99.00 (14.40)	56.58 (7.20)	55.98 (4.80)	NNN

Notes: The number of each model corresponds to those of Appendix A. Values of time are given in SEK per hour. Values in parentheses are standard errors. The column CTI (**C**ost **T**ime **I**nertia) indicates which of the coefficients that have been treated as **F**ix or **N**ormally distributed.

⁸ The estimated value of time (per minute) is obtained by dividing the estimated marginal utility of time with the estimated marginal utility of cost. For the parsimonious model given here, this is simply TIME/COST. In calculating standard errors for the estimated value of time, we have used the Delta method.

⁹ All estimations have been conducted by a GAUSS program written by Kenneth Train, David Revelt, and Paul Ruud. The program is available at <http://elsa.Berkeley.EDU/~train/>

The most striking result is that the value of time appears quite sensitive to the assumptions we make on the coefficients. Adopting a standard logit model by assuming fixed coefficients (model 1) or, to put it differently, ignoring individual heterogeneity, appears to lead to systematically higher values of time. Specifically, assuming a fixed cost coefficient yields a considerably higher value of time. Looking at the log-likelihood values in Table 2, it also appears that the assumptions of fixed coefficients are by no means “innocent” ones. Comparing with the least restricted model (model 8), where all coefficients are assumed to be normally distributed, no restrictions are accepted using a likelihood ratio test. Model 5 is the model that is closest to be accepted, but only for the WTA and WTP sub-samples. For the pooled sample, none of the other models would be accepted in favour of model 8. Returning to the values of time, a rather odd feature is that the values for the pooled model do not appear to be averages of the two sub-samples. A natural suspicion is that this is due to the fact that we have imposed the restriction that the Inertia parameter should be equal for WTA and WTP observations in the pooled sample; a restriction not supported by the estimation results for the sub-samples (see Appendix A)¹⁰. This could also be an explanation as to why the restriction of a fixed inertia coefficient is rejected for the pooled sample. In order to investigate this, we have also estimated the pooled sample with separate WTA and WTP inertia-parameters. Estimating all 16 models that the additional coefficient would give rise to if treated as above, is hardly meaningful. We have therefore estimated the least (NNNN) and the most (FFFF) restricted models, as well as versions of model 5, which was the one that gave rise to the most plausible alternative specification above. The results can be seen in Table 3.

Table 2. Log-likelihood values.

	WTA	WTP	Pooled	CTI
1	-547.94	-633.54	-1191.99	FFF
2	-483.02	-522.52	-1077.16	FNF
3	-484.62	-527.51	-1169.04	FFN
4	-485.61	-560.03	-1091.14	NFF
5	-468.97	-499.96	-1031.83	NNF
6	-471.72	-515.25	-1032.24	NFN
7	-476.08	-515.95	-1024.82	FNN
8	-465.66	-494.02	- 971.52	NNN

¹⁰ This result is also in line with the findings in Lindqvist Dillén & Algers (1998).

Table 3. Separate inertia parameters.

Model CTI_{WTP}I_{WTA}	Value of Time	Log L
FFFF	107.66 (7.20)	-1186.57
NNFF	78.54 (10.20)	-1027.36
NNFN	68.86 (7.80)	-983.00
NNNF	74.65 (9.00)	-968.00
NNNN	77.62 (9.00)	-958.09

Relaxing the assumption that the inertia parameter is identical for the WTA and WTP subsamples, provides us with value of time estimates that seem more like an average of those obtained from the two samples estimated separately. Estimating both inertia parameters as normal does also cause the log likelihood to increase significantly as compared to the previous model 8 for the pooled sample. Treating either or both of the inertia parameters as fixed does however not appear to be a valid restriction, and the model with all four coefficients random and normal would hence be our preferred specification in this simple setting.

The conclusion from this exercise is hence that the value of time estimates are sensitive to the assumption that the parameters do not vary in the population. This result contradicts the results in Brownstone & Train (1996) and Train (1997), implying that whether ratios of coefficients in mixed logit specifications and standard logit specifications differ from each other or not, depends on the model and datagenerating process at hand and must hence be examined in each case.

Second order Taylor series expansion

In order to obtain a somewhat richer specification, we will now estimate an empirical model motivated by the second order Taylor series expansion of the indirect utility function given in section 2. This model will contain squares of the cost and time variables, as well as cost and time

interacted with some socio-economic variables. These are **Age**, which is a dummy variable taking the value 1 if the respondent is aged 45 or older, **Punct**, a dummy indicating if the respondent considers punctuality an important feature of the journey undertaken, **Work**, a dummy indicating if the journey was a worktrip, **Paid**, a dummy indicating if the person is gainfully employed, and finally, **Hhinc**, a variable indicating to which out of 14 household income classes the respondent belongs. If a socio-economic variable has been interacted with the cost variable (time variable), it will have a “C” (“T”) in front of it in Table 4.

Table 4. Estimating the model resulting from a second order Taylor series expansion with socio-economic interaction terms

Variable	Model 1		Model 2		Model 3	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
cost (mean)	-0.09623*	0.02380147	-0.10199*	0.01410378	-0.02889*	0.00629035
cost (sd)	0.07570*	0.01329421	0.09445*	0.01897846		
time (mean)	-0.15811*	0.02739691	-0.15119*	0.02352799	-0.06163*	0.00789074
time (sd)	0.02368	0.01598253	0.02468	0.01319905		
Cage (mean)	0.01095	0.01991367			0.01097	0.00588838
Cage (sd)	0.00127	0.00924779				
Cpunct (mean)	-0.05861	0.03832919			-0.04917*	0.02066133
Cpunct (sd)	0.02548	0.04440426				
Cwork (mean)	-0.27368*	0.07036961	-0.32663*	0.08004169	-0.08956*	0.01942279
Cwork (sd)	0.24141*	0.07015764	0.24534*	0.06540797		
Cpaid (mean)	-0.03633	0.02169053			-0.01396*	0.00583043
Cpaid (sd)	0.04017	0.02068383				
Chhinc (mean)	0.00534	0.00388423			0.00156	0.00096581
Chhinc (sd)	0.00284	0.00277444				
Tage (mean)	0.06788*	0.02028730	0.06526*	0.01978550	0.03055*	0.00695130
Tage (sd)	0.01391	0.01374937				
Tpunct (mean)	-0.02148	0.03015937			-0.02269	0.01527083
Tpunct (sd)	0.00397	0.03417271				
Twork (mean)	-0.15190*	0.05090743	-0.15276*	0.04491958	-0.05356*	0.01543473
Twork (sd)	0.12122*	0.06121859	0.09442*	0.04292405		
Tpaid (mean)	-0.06698*	0.02601288	-0.05613*	0.02390065	-0.02442*	0.00646841
Tpaid (sd)	0.09928*	0.01724521	0.08358*	0.01625255		
Thhinc (mean)	-0.00954*	0.00368550	-0.00867*	0.00327612	-0.00292*	0.00118176
Thhinc (sd)	0.00248	0.00509888				
dwta (mean)	0.39461	0.28919065	0.49318	0.28977811	0.20481	0.10756544
dwta (sd)	1.95318*	0.30595142	1.93781*	0.32722020		
dwtp (mean)	1.67058*	0.32804356	1.62451*	0.33080340	0.80177*	0.11414634
dwtp (sd)	2.58605*	0.34570052	2.50861*	0.36522659		
Log L	-915.94		-925.38		-1099.63	

Notes:

Model 1: All variables follow a normal distribution.

Model 2: Model 1 with insignificant parameters restricted to zero.

Model 3: All variables are treated as fixed (i.e., traditional logit estimation).

* indicates significance at a 5% level

Estimating the model with both quadratic and interaction terms left the former ones insignificant at all times, and therefore these terms have been omitted in the specification reported in Table

4¹¹. We have estimated three models; the two latter nested in the first. The first and most general model includes all interaction terms and treats all coefficients as random and normally distributed (Model 1). The second model restricts the insignificant parameters of the first to equal zero (Model 2). That is, in Model 2 we treat the parameters as fixed whenever the standard deviation parameter is insignificant, and as equal to zero when both the mean and the standard deviation are insignificant.

Conducting a likelihood ratio test for the restrictions of Model 2 yields a test value of 18.88 with 12 degrees of freedom, implying that we cannot reject the null hypothesis that the coefficients are jointly zero at a 5% significance level. Model 3 is the standard logit specification that treats all coefficients as fixed. Performing a likelihood ratio test between models 1 and 3 emphatically rejects the restrictions imposed. From these tests, Model 2 is the specification to be preferred.

We have also experimented with allowing the coefficients to follow a log-normal distribution.¹² However, without restricting the dispersion parameter of the log-normal distribution (\mathbf{s}_k), we have failed to get the models to converge. This pattern was also observed by Brownstone & Train (1996). Their solution was to mechanically constrain each \mathbf{s}_k to be 0.8326. We have also tried that solution and, as a sensitivity analysis, we tested different restrictions on the dispersion parameter to investigate how the estimated value of time was affected. It turned out that the value of time was quite sensitive to the imposed restriction. An illustration of this is given in Table 5 for the WTP-sample. In this example, COST and INERTIA are treated as fixed while TIME is assumed to follow a log-normal distribution, and we have constrained \mathbf{s} to be (0.4, 0.5, 0.6, 0.7, 0.8, 0.86636) respectively in six different estimations. 0.86636 is the highest value \mathbf{s} can take for the model to converge. As can be seen from the last column, the value of time is very sensitive to the imposed restriction: it decreases from 188.41 SEK/hour to 141.88 SEK/hour when \mathbf{s} is constrained to be 0.4 instead of 0.86636. When allowing COST or INERTIA or some combination of the parameters to follow a log-normal distribution, the same pattern as in Table 5 occurred. Our conjecture is hence that the log-normal distribution is problematic in the present context, and we will keep Model 2 in Table 4 as our preferred specification.

¹¹ All estimates including quadratic terms are available upon request.

¹² The k-th coefficient with a log-normal distribution is specified as $\exp(\mathbf{m}_k + \mathbf{s}_k \mathbf{u}_k)$, where \mathbf{u}_k is iid standard normal and \mathbf{m}_k and \mathbf{s}_k are parameters to be estimated.

Table 5. Effects on the value of time of constraining the dispersion parameter (\mathbf{s}) in the log-normal distribution. TIME is assumed to be log-normally distributed, while COST and INERTIA are assumed to be fixed (INERTIA-estimates not reported).

TIME (\mathbf{s})	TIME (\mathbf{m})	TIME (mean)	COST	Value of time
0.86636	-1.56494	-0.30433	-0.09691	188.41
0.8	-1.5585	-0.28982	-0.09672	179.80
0.7	-1.55822	-0.26895	-0.09591	168.26
0.6	-1.58127	-0.24628	-0.09337	158.27
0.5	-1.65153	-0.21729	-0.08725	149.43
0.4	-1.82268	-0.17505	-0.07403	141.88

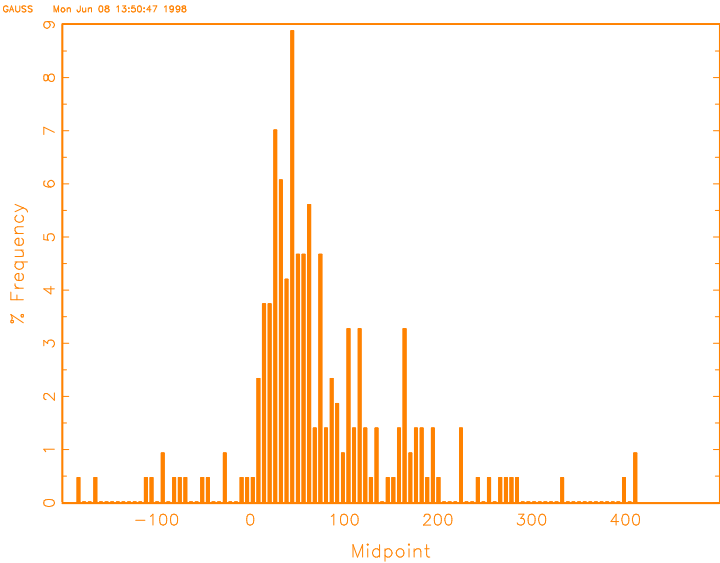
Looking a bit more closely at Model 2, it appears as if the coefficients have reasonable signs. If the journey in question is a “work-trip”, utility is affected more negatively than else by both increased cost and time, which seems plausible since if the journey is repeated on a daily basis, the cost and time associated to it should reduce utility more than if the journey was just a one time occasion. It is furthermore worth noting that the variance of C_{work} is quite large, which perhaps could be explained by the fact that several respondents may obtain tax allowances for work-trips and hence have little or no extra dis-utility from the journey being a work-trip.

Age enters just through the time interaction term and it enters with a positive sign, indicating that people aged 45 or more seem less sensitive to travel time than do younger respondents. Income, which probably is correlated with the Paid-dummy, enters significantly and negatively interacted with time, suggesting that people with higher income get relatively higher dis-utility from the time spent on their journeys.

The main source of concern in the specification obtained is the rather large variance of the cost-coefficient. Since our key variable of interest is the value of time, where the cost coefficient is included in the denominator, there is a relatively large probability of obtaining realisations of this coefficient equal to or close to zero. This poses a problem in that we are likely to obtain unrealistic values of time as a direct consequence of the empirical model if the focus is to estimate the distribution of the value of time. To alleviate this we have tried to let the cost-coefficient follow a log-normal distribution, however encountering the convergence problems mentioned earlier. The restriction of treating the cost coefficient as fixed is also emphatically rejected by a likelihood ratio test.

The values of time implied by Model 2 in Table 4 have to be simulated using the data at hand since these will involve the regressors and become individually specific, once we have allowed for higher order terms. Due to the problem with potentially extreme observations, there are two ways of attacking the problem. Either we treat the obtained averages of the estimated coefficients as fix and evaluate the value of time distribution at these points (which would be in line with earlier research, see e.g. Lindqvist Dillén & Algers (1998)), or we could use simulation techniques and assign each individual random coefficients, where the coefficients are drawn from normal distributions with distribution coefficients given by the estimation results. Even though the averages of the two methods hardly would be comparable, the much less outlier-sensitive medians would be a reasonable point of comparison. We will therefore make use of the median value of time.

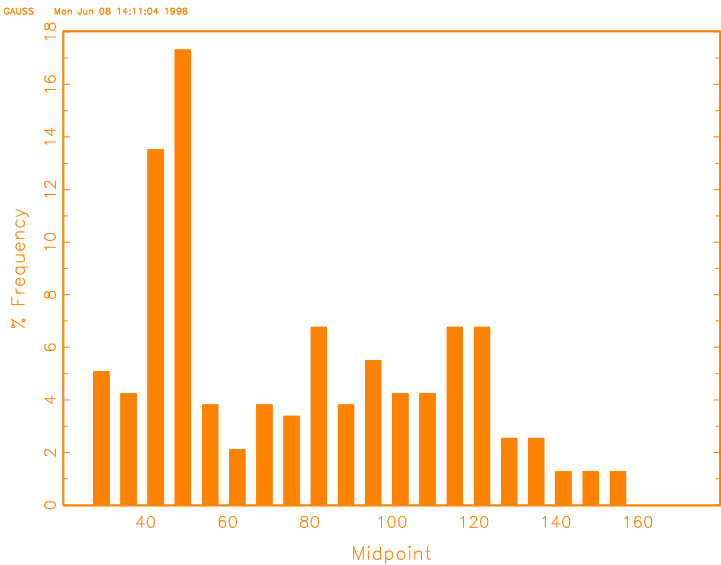
Figure 1. Value of time distribution (90% of the mass) Model 2 and value of time distribution calculated when the distribution of the parameters is taken into account (calculated through simulation).



Notes to Figure 1:
 5% in each tail has been dropped.
 Median value of time for whole distribution: 56.98
 Median value of time for distribution presented in Fig. 1: 56.28
 5th percentile value of time: -187.91
 95th percentile value of time: 417.16

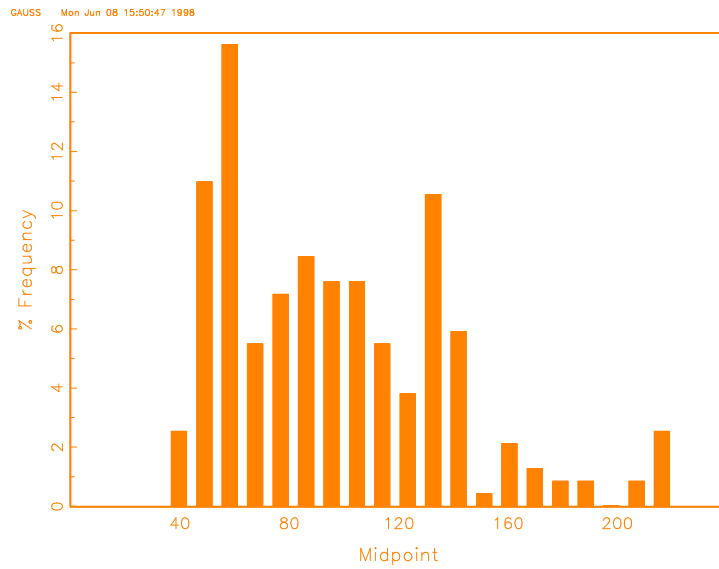
Starting with the estimates obtained in Model 2 and calculating the value of time distribution when the distribution of the parameters is taken into account, we obtain a median value of time of 56.98 (see Figure 1). From Figure 1 we can also see that the major part of the mass is in a close interval around the median value of time. If we still use Model 2, but follow earlier studies and treat all coefficients as fixed in the calculation of the value of time (i.e., ignoring the estimated standard deviations of the coefficients in Model 2), we get the distribution given in Figure 2. The median value of time increases to 74.18. This result can be compared to the distributions presented so far in the literature, where coefficients have been treated as fixed in both the estimation and in the calculation of the distribution of the value of time. That is, using the estimates obtained in Model 3, Figure 3 presents the traditional value of time distribution. In this set-up, the median value of time has increased even more (to 89.25). This pattern of a decreasing value of time when the parameters are allowed to vary in the population is in line with the pattern we observed for the parsimonious model presented in tables 1 and 3.

Figure 2. Value of time distribution
 Model 2 and value of time distribution calculated with parameters treated as fixed.



Notes to Figure 2:
 Median value of time: 74.18

Figure 3. Value of time distribution
 Model 3: Parameters treated as fixed in the estimation.



Notes to Figure 3:
 Median value of time: 89.25

6. Conclusions

In this paper we have used mixed logit specifications to allow parameters to vary in the population when estimating the value of time for long-distance car travel. Our main conclusion is that the estimated value of time is very sensitive to how the model is specified: we find that it is significantly lower when the coefficients are assumed to be normally distributed in the population, as compared to the traditional case when they are treated as fixed. In our most richly parameterised model, we find a median value of time of 57 SEK per hour, with the major part of the mass of the value of time distribution closely centred around the median value. The corresponding figure when the parameters are treated as fixed is 89 SEK per hour. Furthermore, we get significantly better model specifications (better fit to the data) when we allow the parameters to vary in the population.

Our result that the ratio of coefficients in a mixed logit specification differ significantly from the ones in a traditional logit specification is contrary to the results obtained by Brownstone & Train (1996) and Train (1997). A second conclusion from this study is hence that whether the ratios will differ or not depends on the model and the data generating process at hand.

Finally, when we allowed the parameters to vary log-normally in the population, we found that the models did not converge unless we constrained the dispersion parameter of the log-normal distribution. This pattern was also observed by Brownstone & Train (1996), and their solution was to mechanically constrain the dispersion parameter to be 0.8326. We also tried that solution but found, when we tested different restrictions on the dispersion parameter to investigate how the estimated value of time was affected, that the value of time was very sensitive to the imposed restriction. An illustration was given in the paper in which it was shown that the value of time decreased from 188.41 SEK/hour to 141.88 SEK/hour when the dispersion parameter was constrained to be 0.4 instead of 0.86636 (where 0.86636 was the highest value the dispersion parameter could take for the model under consideration to converge). A third conclusion from this paper is then that in certain contexts it might be unwise to impose restrictions on parameters in the log-normal distribution to get models to converge. Since ratios of coefficients might be very sensitive to the imposed restrictions, a good idea would be to conduct a sensitivity analysis for each unique model.

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Appendix A

Complete estimation results for the models presented in tables 1 and 2.

A1. Pooled sample

Model 1. Standard logit results.

Variable	Coefficient	Std. Error
COST	-0.02857132	0.00239913
TIME	-0.04400165	0.00266707
INERTIA	0.43500673	0.05038086
Log Likelihood	-1191.992	
Observations	2024	
Value of time*	92.41	
	(6.00)	

* SEK per hour (standard error)

Model 2. TIME normally distributed, COST and INERTIA fixed.

Variable	Coefficient	Std. Error
COST	-0.05501511	0.00452735
TIME (mean)	-0.07816269	0.00702507
TIME (sd)	0.07029758	0.00725689
INERTIA	0.55742546	0.05987251
Log Likelihood	-1077.163	
Observations	2024	
Value of time*	85.25	
	(6.60)	

* SEK per hour (standard error)

Model 3. INERTIA normally distributed, COST and TIME fixed.

Variable	Coefficient	Std. Error
COST	-0.03217808	0.00270026
TIME	-0.04923548	0.00304682
INERTIA (mean)	0.49393659	0.07320515
INERTIA (sd)	-0.76662098	0.08989499
Log Likelihood	-1169.04	
Observations	2024	
Value of time*	91.81	
	(4.80)	

* SEK per hour (standard error)

Model 4. COST normally distributed, TIME and INERTIA fixed.

Variable	Coefficient	Std. Error
COST (mean)	-0.07576494	0.00927421
COST (sd)	0.09158090	0.01034064
TIME	-0.06480919	0.00410452
INERTIA	0.58272064	0.06062562
Log Likelihood	-1091.14	
Observations	2024	
Value of time*	51.32	
	(5.40)	

* SEK per hour (standard error)

Model 5. COST and TIME normally distributed, INERTIA fixed.

Variable	Coefficient	Std. Error
COST (mean)	-0.11189049	0.01274776
COST (sd)	0.10842281	0.01377712
TIME (mean)	-0.11139466	0.00987554
TIME (sd)	0.07641951	0.00887209
INERTIA	0.70958592	0.07111969
Log Likelihood	-1031.83	
Observations	2024	
Value of time*	59.73	
	(5.40)	

* SEK per hour (standard error)

Model 6. COST and INERTIA normally distributed, TIME fixed.

Variable	Coefficient	Std. Error
COST(mean)	-0.11384950	0.01428848
COST (sd)	0.13289484	0.01473858
TIME	-0.09082613	0.00645161
INERTIA (mean)	0.84225080	0.12614201
INERTIA (sd)	1.44748837	0.14931759
Log Likelihood	-1032.23	
Observations	2024	
Value of time*	47.87	
	(4.80)	

* SEK per hour (standard error)

Model 7. TIME and INERTIA normally distributed, COST fixed.

Variable	Coefficient	Std. Error
COST	-0.07614540	0.00662259
TIME (mean)	-0.10479940	0.01049346
TIME (sd)	-0.09857771	0.00999531
INERTIA (mean)	0.78004300	0.12297355
INERTIA (sd)	1.37871864	0.14956621
Log Likelihood	-1024.82	
Observations	2024	
Value of time*	82.58	
	(6.60)	

* SEK per hour (standard error)

Model 8. COST, TIME and INERTIA normally distributed.

Variable	Coefficient	Std. Error
COST (mean)	-0.17028816	0.02017033
COST (sd)	0.14253766	0.01707413
TIME (mean)	-0.15888294	0.01526542
TIME (sd)	0.10950636	0.01269758
INERTIA (mean)	1.04151591	0.15798329
INERTIA (sd)	1.65744534	0.18695852
Log Likelihood	-971.52	
Observations	2024	
Value of time*	55.98	
	(4.80)	

* SEK per hour (standard error)

A2. WTA sample

Model 1. Standard logit results.

Variable	Coefficient	Std. Error
COST	0.03480418	0.00366443
TIME	0.06788942	0.00664065
INERTIA	0.03412255	0.12017560
Log Likelihood	-547.94	
Observations	1012	
Value of time*	117.04	
	(9.00)	

* SEK per hour (standard error)

Model 2. TIME normally distributed, COST and INERTIA fixed.

Variable	Coefficient	Std. Error
COST	-0.09194979	0.01130053
TIME (mean)	-0.21139545	0.02551612
TIME (sd)	0.12718125	0.01687183
INERTIA	-0.82132800	0.22385750
Log Likelihood	-483.02	
Observations	1012	
Value of time*	137.94	
	(12.60)	

* SEK per hour (standard error)

Model 3. INERTIA normally distributed, COST and TIME fixed.

Variable	Coefficient	Std. Error
COST	-0.05940237	0.00706989
TIME	-0.11140799	0.01325713
INERTIA (mean)	0.04103386	0.27101912
INERTIA (sd)	-2.29804516	0.27096060
Log Likelihood	-484.62	
Observations	1012	
Value of time*	112.53	
	(10.20)	

* SEK per hour (standard error)

Model 4. COST normally distributed, TIME and INERTIA fixed.

Variable	Coefficient	Std. Error
COST (mean)	-0.09549830	0.01997407
COST (sd)	0.18550966	0.02718516
TIME	-0.12137828	0.01442329
INERTIA	0.10561015	0.21371861
Log Likelihood	-485.62	
Observations	1012	
Value of time*	76.26	
	(17.40)	

* SEK per hour (standard error)

Model 5. COST and TIME normally distributed, INERTIA fixed.

Variable	Coefficient	Std. Error
COST (mean)	-0.15304232	0.02676092
COST (sd)	0.18783736	0.03456083
TIME (mean)	-0.24320288	0.03658566
TIME (sd)	0.11899159	0.02110499
INERTIA	-0.56016455	0.29253645
Log Likelihood	-468.97	
Observations	1012	
Value of time*	95.35	
	(13.20)	

* SEK per hour (standard error)

Model 6. COST and INERTIA normally distributed, TIME fixed.

Variable	Coefficient	Std. Error
COST(mean)	-0.09945335	0.01773147
COST (sd)	0.11605056	0.02875754
TIME	-0.13758721	0.01736925
INERTIA (mean)	0.04984306	0.30172327
INERTIA (sd)	1.99539453	0.31821491
Log Likelihood	-471.72	
Observations	1012	
Value of time*	83.01	
	(12.60)	

* SEK per hour (standard error)

Model 7. TIME and INERTIA normally distributed, COST fixed.

Variable	Coefficient	Std. Error
COST	-0.07912337	0.01101260v
TIME (mean)	-0.17526329	0.02550178
TIME (sd)	-0.08449510	0.01947967
INERTIA (mean)	-0.57416166	0.2900078
INERTIA (sd)	-1.67144525	0.32508629
Log Likelihood	-476.08	
Observations	1012	
Value of time*	132.90	
	(12.60)	

* SEK per hour (standard error)

Model 8. COST, TIME and INERTIA normally distributed.

Variable	Coefficient	Std. Error
COST (mean)	-0.13028337	0.02500234
COST (sd)	0.12872039	0.04103670
TIME (mean)	-0.21498209	0.03636684
TIME (sd)	-0.09679198	0.02530494
INERTIA (mean)	-0.45525151	0.34772141
INERTIA (sd)	1.67598335	0.37530201
Log Likelihood	-465.66	
Observations	1012	
Value of time*	99.00	
	(14.40)	

* SEK per hour (standard error)

A3. WTP sample

Model 1. Standard logit results.

Variable	Coefficient	Std. Error
COST	-0.02535229	0.00352146
TIME	-0.04321327	0.00434652
INERTIA	0.56325980	0.11412749
Log Likelihood	-633.54	
Observations	1012	
Value of time*	102.19	
	(12.00)	

* SEK per hour (standard error)

Model 2. TIME normally distributed, COST and INERTIA fixed.

Variable	Coefficient	Std. Error
COST	-0.09093669	0.01161694
TIME (mean)	-0.14144647	0.01889791
TIME (sd)	0.13860639	0.01722578
INERTIA	1.23266882	0.24313172
Log Likelihood	522.52	
Observations	1012	
Value of time*	93.33	
	(12.00)	

* SEK per hour (standard error)

Model 3. INERTIA normally distributed, COST and TIME fixed.

Variable	Coefficient	Std. Error
COST	-0.06228664	0.00834668
TIME	-0.09101428	0.01124031
INERTIA (mean)	1.01065150	0.31731389
INERTIA (sd)	2.84295137	0.31791844
Log Likelihood	-527.51	
Observations	1012	
Value of time*	87.67	
	(10.20)	

* SEK per hour (standard error)

Model 4. COST normally distributed, TIME and INERTIA fixed.

Variable	Coefficient	Std. Error
COST (mean)	-0.15630464	0.02709515
COST (sd)	0.23348705	0.03977823
TIME	-0.07364639	0.00902424
INERTIA	0.04464013	0.21847392
Log Likelihood	-560.03	
Observations	1012	
Value of time*	28.27	
	(4.80)	

* SEK per hour (standard error)

Model 5. COST and TIME normally distributed, INERTIA fixed.

Variable	Coefficient	Std. Error
COST (mean)	-0.23171849	0.04764769
COST (sd)	0.19913374	0.04815863
TIME (mean)	-0.23342869	0.03543148
TIME (sd)	0.18235746	0.02806683
INERTIA	1.34670766	0.35487931
Log Likelihood	-499.96	
Observations	1012	
Value of time*	60.44	
	(10.80)	

* SEK per hour (standard error)

Model 6. COST and INERTIA normally distributed, TIME fixed.

Variable	Coefficient	Std. Error
COST(mean)	-0.13691698	0.02558714
COST (sd)	0.12013089	0.02750179
TIME	-0.11718334	0.01593822
INERTIA (mean)	0.83265093	0.39425414
INERTIA (sd)	3.19333965	0.44065746
Log Likelihood	-515.25	
Observations	1012	
Value of time*	51.35	
	(8.40)	

* SEK per hour (standard error)

Model 7. TIME and INERTIA normally distributed, COST fixed.

Variable	Coefficient	Std. Error
COST	-0.08362443	0.01132617
TIME (mean)	-0.13546708	0.01880990
TIME (sd)	0.09358154	0.01666308
INERTIA (mean)	1.36620509	0.31337889
INERTIA (sd)	2.02073803	0.36823448
Log Likelihood	-515.95	
Observations	1012	
Value of time*	97.20	
	(12.00)	

* SEK per hour (standard error)

Model 8. COST, TIME and INERTIA normally distributed.

Variable	Coefficient	Std. Error
COST (mean)	-0.23059026	0.04363866
COST (sd)	0.19880449	0.03979997
TIME (mean)	-0.21746084	0.03456401
TIME (sd)	0.14470279	0.02781579
INERTIA (mean)	1.41794733	0.40488918
INERTIA (sd)	2.10718854	0.55146506
Log Likelihood	-494.02	
Observations	1012	
Value of time*	56.58	
	(7.20)	

* SEK per hour (standard error)