


Evidence on the distribution of values of travel time savings from a six-week diary

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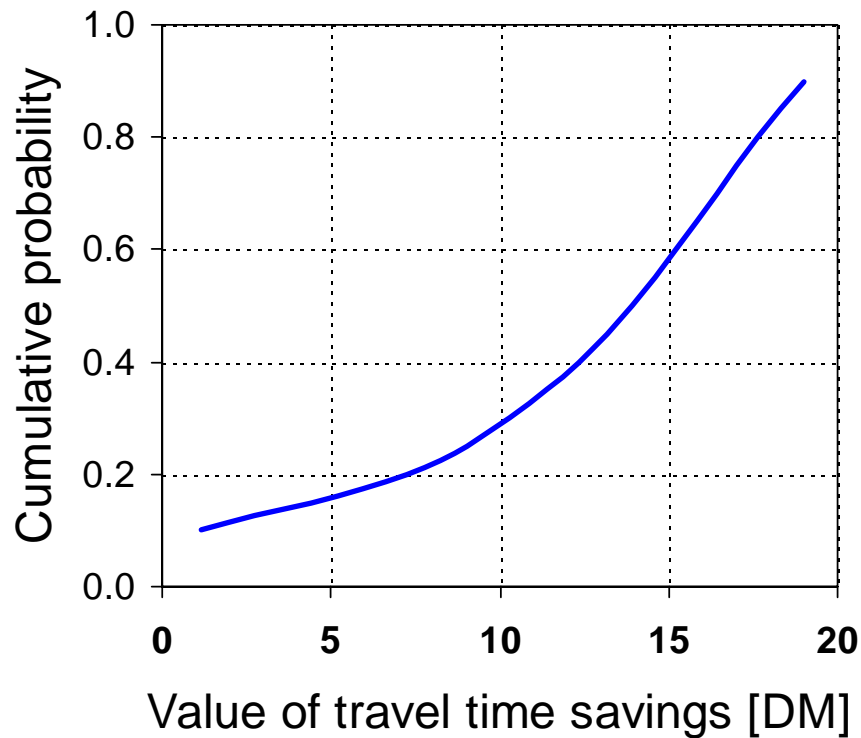
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Zur Verteilung der Zeitwerte: Ergebnisse aus einer sechs-wöchigen Tagebuchbefragung

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Kurzfassung

Dieser Aufsatz stellt die Ergebnisse einer Serie von Entscheidungsmodellen vor, in denen die Modellformulierung Aussagen über die Verteilung der Bewertung von Reisezeitveränderungen zulässt. Es zeigt sich im vollständigsten Modell, dass ein substantieller Anteil der Befragten (10%) keinen Wert auf solche Veränderungen legt, respektive sogar seine Reisezeit verlängern möchte.

Schlagworte

Zeitwert, Verteilung, MNL, Mixed logit, Mobidrive, Karlsruhe

Zitierungsver-schlag

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Abstract

This paper presents the results of a series of MNL and mixed logit models focusing on the distribution of the values of travel time savings. The full model, which also incorporates a number of time budget related variables, indicates that a small, but relevant share of the respondents does not value time savings, or would rather extend the journey. This 10% share is consistent with results from other studies. A series of models employing only time and costs to explain choices indicate even higher shares depending on the a-priori assumptions about the distributions of the parameters (normal, log-normal, normal, but censored at zero).

The RP data used is derived from the six week travel diary Mobidrive. The observations from Karlsruhe are summarised at the level of the tour.

Keywords

Value of travel time savings, mode choice, MNL, mixed logit, RPL, Time budget, Mobidrive, Karlsruhe

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1 Are negative values of travel time savings possible ?

It is one of the basic assumptions of transport planning, that time spent traveling should rather be spent on other things: working, education, shopping, leisure etc., which is another way of saying the travel is a derived demand and the people are willing to pay for the reduction in travel time. The obvious counterexamples to this assumption, i.e. all activities where movement is the actual purpose of the activity, e.g. walking, jogging, hiking, pleasure drive, can be argued away by pointing out, that the travel is the purpose here and that these travel times have to be categorized differently.

Still, when one considers the choices which are normally modeled to derive values of travel time savings (VTTS), it is not obvious, that these have to be strictly negative for all travelers at all time and for all trip purposes. Clearly, the VTTS should only be negative, if there is a binding time constraint, otherwise the VTTS should be zero. We can assume, that there is a binding time constraint in the overall leisure and work tradeoff from which our choice models are derived. It is binding, because it is understood that this trade-off concerns the long term, in which time is indeed fully allocated. The closest transport-related choice model to such a long-term choice is the joint work location, mobility tool ownership¹ and mode-to-work model². In this context, we would expect the travelers to make careful trade-offs between the alternatives to obtain a long-term combination of costs, travel times and comfort which reflects their preferences optimally. Both the budget and the time constraint should be binding here, resulting in negative values of time.

Unfortunately, it is clear, that the time constraint is unlikely to be binding in the usual one-day cross-sectional data, which are normally employed. The work of Doherty and others on activity scheduling and the planning horizon of activities has made it clear, that there is a large amount of buffer time and spontaneous activity performance in many persons' days. It is therefore consistent with theory, if we find persons who have a VTTS of zero. We would expect that this share varies by purpose and changes over the course of the day, as in most cases

¹ Mobility tools is the summary term for all services, to which a user can commit longer term and change his/her short run marginal cost of travel: car ownership, car leasing, public transport season tickets, public transport discount tickets, etc.

² The mode-to-work model estimated from one-day cross-sectional data is a much reduced form of the full model required. The day-to-day variability in mode use to work (see Mobidrive) adds additional random variation to the estimates.

the time table becomes lighter towards the evening or the night. We would also expect to find the same person having zero and positive values of time depending on the time constraints under she has to operate during the course of a day or longer period.

If we take the one-day cross-sectional data for what they are: short term decisions under time constraints, which are unknown to the outside analyst, even positive values of time become conceivable. It could indeed be the case, that for that particular trip the traveler would have like to extend it because he enjoyed the conversation with the passenger, liked the cycling home in the sun, dreaded the activity waiting at the end of walk. Therefore, one cannot a-priori exclude positive values of travel time savings.

There is no need to discuss the previous literature on the value of travel time savings, positive or otherwise, here. See the contribution of the editor of this special issue for this. Just one aspect needs some further discussion. Moktharian and her co-authors have suggested, that there is an optimal duration for the commute trip and by extension for other trips. Again, it is not possible to observe this optimal duration from cross-sectional data, as the home and work/school locations are fixed for this time horizon. Estimating it never-the-less from cross-sectional mode choice data should therefore lead to biased results. This paper makes therefore no attempt in this direction.

These changed assumptions lead to changed modeling assumption. It is obvious, that the model formulation should not exclude a-priori the possibility of positive values of time, as has been the rule in past exercises employing mixed logit formulations. The purpose of the paper is then to explore a particularly rich longitudinal data set to see, if there is any empirical evidence for zero or positive values of time.

The paper is structured as follows. In Section 2 we briefly recall the principal characteristics of the data set used and of the framework employed to structure the daily patterns. Section 3 is dedicated to the model specifications. Section 4 reports results of the logit and mixed logit mode choice models. Section 5 is dedicated to the value of travel time savings and to the differences in results between the specifications. Conclusions and future perspectives are presented in Section 6.

2 Data and framework

The data set used in this research work was collected in 1999 in two cities of Germany: Karlsruhe and Halle. The *Mobidrive* study, whose main objective was to observe the variabil-

ity and rhythms of daily life, involved 160 households and 360 individuals. Each individual was observed during six continuous weeks. For details on data collection techniques and on the descriptive results see (Axhausen, Zimmermann, Schönfelder, Rindsfuser and Haupt, 2002 and PTV AG, B. Fell, S. Schönfelder und K.W. Axhausen, 2000). Here we refer just to data collected in Karlsruhe for which data on the levels of service (LOS) for the used and non-used alternatives was added.

The days recorded were structured according to the framework proposed by Bhat and Singh, 2000 as extended by Cirillo and Toint, 2001. We recall briefly the principal elements of the schema adopted to describe the daily activity chains.

The population is divided into workers, i.e. individuals who commute or go to school on the day considered, and non-workers. All trips are grouped into tours. A tour is the sequence of trips performed by an individual, starting from a given base (usually home or workplace) until the individual returns to this base. In general, these tours employ only one mode. Each tour has a main activity defined by duration and purpose. It has also a main mode defined by the highest speed. This simplification is justified by the small share of tours employing multiple modes. Additionally, within a tour an individual might call at further locations to perform secondary activities.

For each daily chain we define the main activity of the day as work/education for workers/students; the longest duration out-of-home activity of the day for non-workers. All daily activity chains are represented in relation with this pivotal activity.

The work tour is divided into morning and the evening legs, which are called the *morning* and *evening commute*. All activities that take place before the morning commute will be referred to as *morning activities*, and the associated displacements grouped into one or more *morning tours*; they constitute the *morning pattern*. Similarly, all activities taking place after the return from work to home (the evening commute) will be referred to as *evening activities* and the associated displacements grouped into one or more *evening tours*; which together constitute the *evening pattern* (Hamed and Mannering, 1993). Additionally, all activities taking place outside the work location after the morning, but before the evening commute will be called *mid-day activities* and the associated displacements, whose origin and destination are at work, are grouped into one or more *midday tours*, themselves grouped into the *midday pattern*.

For non-workers, i.e. those not commuting on the day considered, we organize the daily pattern in a manner similar to that used for organizing workers' days. The morning pattern represents the activities and travel undertaken before leaving home to perform the principal activity

of the day. The *principal activity pattern* represents the activities and travel performed within the tour comprising the principal activity of the day. Note that this definition implies that the principal activity pattern always consists of a single tour. The (afternoon and) evening pattern comprises the activities and travel of individuals after their return home from their principal activity.

The morning and evening patterns of non-workers contain a main activity (not to be confused with the principal activity, which can be viewed as the main activity of the tour containing the principal activity).

A total of 5795 tours performed by 136 individuals belonging to 66 households was identified. The average number of tours per day is 1.72, while the average number of tours observed per week is about 7.60. Table 1 details the number of tours used for estimation by main mode and type.

Table 1 Number of tours by main mode and type

Type of tour	Main mode					Total(%)	
	Walking	Cycling	Vehicle driver	Vehicle passenger	Public Transport	All modes	
Non-workers							
Morning tour	286	328	638	182	138	1572	27.1%
Principal tour	250	203	541	264	207	1465	25.3%
Evening tour	51	31	89	25	25	221	3.8%
Worker							
Morning tour	9	10	31	1	4	55	0.9%
Midday tour	20	53	33	3	24	133	2.3%
Work tour	213	474	561	76	379	1703	29.4%
Evening tour	112	144	181	170	39	646	11.2%
All tour types	941	1243	2074	721	816	5795	
(Share in %)	16.3%	21.4%	35.8%	12.4%	14.1%		100.0%

3 The model specifications

The preferred tool to infer relative valuations of the elements of the generalized costs of travel is the discrete choice model. It allows the analyst to explain individual discrete choices (y) using observed variables (x) and unobserved factors summarized in an appropriate error term (ε). Since ε is not observed, the choice is not deterministic for the analyst, but if a distribution is imposed on it, one can treat the process as probabilistic.

Using the notation introduced by Train (2002) we can express this probability as follow:

$$P(y/x) = \int Prob(I[h(x, \varepsilon)] = y = 1) = \int I[h(x, \varepsilon) = y] f(\varepsilon) d\varepsilon \quad (1)$$

where:

h is a function of x and ε ,

$I[h(x, \varepsilon) = y]$ is equal to 1 when the statement between brackets is true, 0 when it is false, and

$f(\varepsilon)$ is the a-priori assumed density function of the unobserved term ε .

Depending on the specification of ε and h the integral takes different forms. With regards to the distribution of the disturbances we estimate logit models and mixed logit models, whose theoretical fundamentals are briefly recalled in the next sub-sections. With reference to the function form h we specify models linear in parameters and models non-linear in parameters, in which second order terms are introduced.

3.1 Logit

By assuming that ε is independently, identically distributed (IID) extreme value, a closed mathematical expression can be developed for the integral (1). The probability that individual n chooses the alternative i among a finite number of alternatives J is:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}} \quad (2)$$

which, is the logit choice probability (Ben Akiva and Lerman, 1985).

The IID hypothesis on the distribution of the error terms induces several limitations, which we summarize into four points:

1. logit models are homoscedastic.
2. logit models can handle just deterministic taste variations, but not random taste variation. This is the case when we estimate second order variables, allowing for example socio-economic variables to affect the marginal utility of the level-of-service variables (see Cherchi and Ortuzar, 2003 for an exhaustive discussions on the subject);
3. logit models implies proportional substitution patterns and exhibits the property of independence from irrelevant alternatives (Train, 2002);
4. logit model error terms are independent over times and cannot account for correlations in repeated choices observations. However some re-sampling techniques (Jack-knife and Bootstrap) have been used in logit models to eliminate the bias due to repeated observations (Cirillo et al, 2000).

3.2 Mixed Logit

The mixed logit formulation is rather more complex than logit, but much more flexible. It relaxes the IID hypotheses and resolves the four limitations presented in the previous section. In particular we are interested in the estimation of random coefficients and their distribution in the population.

Mixed logit probabilities are expressed by means of the integral of standard logit probabilities over a density of parameters:

$$P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta \quad (3)$$

where:

$L_{ni}(\beta)$ is the logit probability of equation 2.

$f(\beta)$ is a density function.

The mixed logit derivation that we will use in our application is based on random coefficients. $f(\beta)$ is specified to be continuous, in particular the density of β is normal with mean b and covariance θ . The choice probability under this assumption is:

$$P_{ni} = \int L_{ni}(\beta) \phi(\beta | b, \theta) d\beta \quad (4)$$

where $\phi(\beta/b, \theta)$ is the normal density with mean b and covariance θ .

The vector of unknown parameters is then estimated by maximizing the log-likelihood function, i.e. by solving the equation:

$$\max_{\theta} LL(\theta) = \max_{\theta} \frac{1}{I} \sum_{i=1}^I \ln P_{iz_i}(\theta) \quad (5)$$

where z_i is the alternative choice made by the individual i . This involves the computation of $P_{iz_i}(\theta)$ for each individual i , $i = 1, \dots, I$, which is impractical since it requires the evaluation of one multidimensional integral per individual. The value of $P_{iz_i}(\theta)$ is therefore replaced by a Monte-Carlo estimate obtained by sampling over β , and given by

$$SP_{iz_i}^R = \frac{1}{R} \sum_{r=1}^R L_{iz_i}(\beta_r, \theta) \quad (6)$$

where R is the number of random draws β_r , taken from the distribution function of β . As a result, θ is now computed as the solution of the simulated log-likelihood problem

$$\max_{\theta} SLL^R(\theta) = \max_{\theta} \frac{1}{I} \sum_{i=1}^I \ln SP_{iz_i}^R(\theta) \quad (7)$$

We will denote by θ_R^* a solution of this last approximation (often called Sample Average Approximation, or SAA), while θ^* denote the solution of the true problem (5).

A major drawback of Monte-Carlo methods is their slow convergence rate. Quasi Monte-Carlo methods attempt to speed up this convergence by being more directive in the choice of the sampling points used to evaluate the choice probabilities. This suggests the use of Halton draws (Bhat, 2001) instead of Monte-Carlo random draws. Bhat found that when the number of random parameters is small (typically less or equal to five), the approximation of the objective function based on Halton sequences usually succeeds in giving the same results as pure Monte-Carlo sampling with fewer random draws. Our model was calibrated with 125 Halton draws.

3.3 Mixed logit on panel data

We consider now the case in which an individual i chooses among alternative $j = 1, \dots, J$ in choice situations $t = 1, \dots, T$. Its utility can be expressed as:

$$U_{nit} = \beta_n x_{njt} + \varepsilon_{njt} \quad (8)$$

where ε_{njt} is iid extreme value, $\beta_n \sim g(\beta | \theta)$ is the vector of parameters randomly distributed in the population and x_{njt} are the independent variables. We observe for each individual the sequence of choices $y_n = (y_{n1}, \dots, y_{nT})$. The probability to observe the individuals' choices is given by the product of logit probabilities L_{nt} (Train, 2003):

$$P(y_n | x_n, \beta) = \prod_{t=1}^T L_{nt}(y_{nt} | \beta) \quad (9)$$

Again we need to integrate the probability (9) over the distribution of β and to solve the integral by means of Monte Carlo simulations. It should be noted that in the simulations we draw just one random number per each individual.

3.4 Bayesian procedures

Bayesian procedures are currently not very popular among transport modelers, but recently they have been introduced as an alternative method to estimate discrete choice models. Allenby (1997) employed them to estimate a mixed logit model with normally distributed coefficients. Train (2001) extended the Bayesian procedures to mixed logit models with non-normal distributions of coefficients: log-normal, uniform and triangular distributions. The exposition of this method below draws heavily from Train (2003).

The Bayesian approach does not require any function maximization. The classical approach to the estimation of mixed logit models simulates the maximum likelihood function and solves the optimization problem by way of the Monte Carlo method. Although faster methods have been proposed: quasi Monte Carlo maximum simulated likelihood (Bhat, 2001), variable sample size strategy (Bastin et al. 2003), solving the simulated problem can be very time consuming, as experienced by Hensher and Greene, 2003.

The property of consistency and efficiency of the maximum simulated estimators are attained respectively if the number of draws rises with the sample size, and if they rise faster than the square root of sample size.

The major difficulty in the application of the Bayesian procedures is the iterative process used to simulate the relevant statistics defined over a distribution. This process needs a sufficient number of iterations, however researcher cannot easily determine whether convergence has been reached.

It is important to mention that under certain conditions, the estimator that results from the Bayesian procedures is asymptotically equivalent to the maximum likelihood estimator. In this paper we use Bayesian procedures to estimate mixed logit models for the time and cost variables with log-normal parameter distributions and with censored normal distribution from below at zero distributions.

Let consider a model with parameters θ . Under Bayesian analysis, we need to identify a prior distribution of the value of these parameters (say the density of θ); then we collect data in order to improve our knowledge about θ . To achieve this goal we observe a sample of N independent decision-makers; if y_n is the observed choice of individual n , the entire set of observed choices is $Y = \{y_1, \dots, y_n\}$. By doing so we can update our knowledge about the density of θ , this new density is labeled $K(\theta | Y)$ and called the posterior distribution.

The Bayes rule establishes a precise relationship between the prior and posterior distribution. The probability of observing the Y or the likelihood function of the observed choices is:

$$L(Y | \theta) = \prod_{n=1}^N P(y_n | \theta) \quad (10)$$

By applying the Bayes rule that links conditional and unconditional probability in any setting we can write:

$$K(\theta | Y)L(Y) = L(Y | \theta)k(\theta) \quad (11)$$

where $L(Y)$ is the marginal probability of Y , marginal over θ :

$$L(Y) = \int L(Y | \theta)k(\theta)d\theta \quad (12)$$

By rearranging equation (11):

$$K(\theta | Y) = \frac{L(Y | \theta)k(\theta)}{L(Y)} \quad (13)$$

and since $L(Y)$ is the integral of the numerator of (13) we can say that the posterior distribution is proportional to the prior distribution times the likelihood function:

$$K(\theta | Y) \propto L(Y | \theta)k(\theta) \quad (14)$$

Equation (14) can be extended to estimate the parameters of a mixed logit model.

In discrete choice formulation the utility that person n obtains from alternative j in time period t is:

$$U_{njt} = \beta_n' x_{njt} + \varepsilon_{njt} \quad (15)$$

where ε_{njt} is iid extreme value and $\beta_n \sim N(b, W)$; suppose we have priors on b and W and a sample of N people. The chosen alternatives in all time periods for person n are denoted $y_n' = \langle y_{n1}, \dots, y_{nT} \rangle$, and the choices of the entire sample are labeled $Y = \langle y_1, \dots, y_N \rangle$. The probability of person n 's observed choices, conditional on β , is:

$$L(y_n | \beta) = \prod_t \left(\frac{e^{\beta' x_{ny_{nt}t}}}{\sum_j e^{\beta' x_{ny_{nt}t}}} \right) \quad (16)$$

The probability not conditional on β is the integral of $L(y_n | \beta)$ over all β :

$$L(y_n | b, W) = \int L(y_n | \beta) \phi(\beta | b, W) d\beta \quad (17)$$

where $\phi(\beta | b, W)$ is the normal density with mean b and variance W , $L(y_n | b, W)$ is the mixed logit probability.

The posterior distribution of b and W is, by definition:

$$K(b, W | Y) \propto \prod_n L(y_n | b, W) k(b, W) \quad (18)$$

where $k = (b, W)$ is the prior on b and W .

4 Mode choice model: ML estimation results

Using the *Mobidrive* data set collected in the city of Karlsruhe we model individual preferences on mode choice. The alternative choice set includes five modes: car driver, car passenger, public transport, walk and bike. Daily trip chains are divided into tours using the framework described in Section 2; we account for all tours observed from a single individual. This procedure allows the calculation of pattern specific variables. We include observations relating to workers and to non-workers (the same individual can belong to both categories depending on the principal activity of the day). All days of the week and all purposes are considered for model estimation. Table 2 lists the set of variables used.

We estimated several forms of mode choice model:

1. logit model on the full data set;
2. logit model on four purpose segments (work/education, shopping, leisure, other purposes);
3. logit model non-linear in parameters;
4. mixed logit;
5. mixed logit on panel data (accounting for correlation across tours observed on the same day by a single individual).

Table 2 List of independent variables used

Level	Variables	Categories
Household	House hold location	Urban
		Suburban
Individual	Age	Age 18-25 Age 26-35 Age 51-65
	Marital status	Married with children
	Professional Status	Full Time worker Female and employed part-time
	Use of car	Main car user Total annual mileage by car
Pattern	Use of Public Transport	Number of season tickets
	Time budget [min/100]	24 hours – time spent on previous activities (home stay included) and previous travel
	Sum of travel time [min]	Sum of time spent traveling
	Tour Duration [min]	Sum of tour travel time and activity duration.
	Number of stops	Number of secondary activities observed within each tour
LOS	Time [min]	
	Cost [DM]	Including any parking fees

We report in Table 3 the results of the models (1), (4) and (5). Coefficient estimates of logit models specified for the four purpose segments (model 2) are not shown; the model non-linear in parameters (model 3) and values of time relative to both specifications are described in Section 5.

In all three models we estimate 21 parameters, of which four are alternative specific constants (car driver is the base), two relate to household characteristics, nine to individual characteristics, two to the LOS variables (cost includes the parking fare) and four pattern variables. The mixed logit model specifications include estimate the mean and variances of the parameters of level of service and pattern variables; all are specified as normal. The socio economic characteristics are all added to the utilities as alternative specific.

Given that logit model and mixed logit do not differ substantially in the parameter estimates we concentrate the discussion on the latter model.

All parameters are significant except for being a full time worker and the standard deviation of tour duration. Looking at the effect of the socio-demographic on car driving; we observe that being an individual with young children, having the main use of a car, the miles traveled per year by car, the number of stops (or secondary activities) per tour have increase this utility. The only variable with a negative effect on the car driving utility is the number of season tickets owned by the respondent. An individual located in the suburban area of Karlsruhe or aged between 25 and 35 uses the car more frequently (both as driver or as passenger). Females with a part time job have a higher probability to be car passengers. We found that people aged between 18-25 or 51-65 years have a higher propensity to use public transport. The urban location of the household is also having a positive influence on the public transport utility. In contrast, being a full time worker affects the probability of public transport modes negatively.

For five variables we estimated mean and variance: the generic variables time and cost, and three alternative specific pattern variables: time budget (specific to car driver and passenger), sum of travel time (specific to bike) and tour duration (specific to public transport). We found time and cost variables strongly negative as expected, both the means and standard deviations are significant. The average value of the willingness to pay is 13.89 German Marks (about 7 €). The implied probability distribution of the VTTS will be discussed in the next Section.

The parameter of the time budget variable, defined as the total amount of time available in a day (24h) minus the time spent in previous activities (both at home and out of home) has a negative mean suggesting that individuals are more likely to use their own car as their time budget is decreases, their constraints become tighter. We also observe that the standard deviation is larger than the mean value: for 30% of the population this parameter has therefore a positive value. The ratio of time budget and the cost coefficient implies a low monetary valuation (between 0 and 10 € per 24 h), which indicates the low added value of in-home activities.

The parameter for the total time spent traveling so far, estimated as alternative specific to the bike mode, is more negative than the travel time parameter. One obtains a valuation with a mean of 20 € and an upper bound of 30 €. Fifteen percent of the population show a positive valuation of the travel time sum. The statement that some people enjoy the traveling as such (Richardson, 2003) could be particularly true for bicyclists.

The tour duration has a positive influence on the utility of public transport use. The standard deviation of this parameter is not significant and we therefore cannot make any suggestions about the distribution.

We have also estimated the same mode choice model accounting for correlations across tours observed along the day for the same individuals (mixed logit on panel data). We note that all the coefficients estimates keep the same sign and stay significant except for two socio-economic characteristics (full time workers and number of season tickets).

We finally compare the models' goodness of fit; in terms of ρ^2 adjusted the first three models perform almost equally, mixed logit on panel data gives the best results in terms of data fitting.

Table 3 Goodness of fit statistics of the estimated mode choice models

	Multinomial Logit (MNL)	MNL with interactions with socio- economic parameters	Mixed Logit	Mixed logit on panel data (day)
n. of obs.	5795	5795	5795	5795
L (0)	- 8179.88	- 8179.88	- 8179.88	- 8179.88
L (C)	- 7503.82	- 7503.82	- 7503.82	- 7503.82
L (β)	- 6465.11	- 6559.23	- 6446.88	- 6039.21
K	21	21	26	26
ρ^2 adjusted	0.2070	0.1955	0.2086	0.2585

Table 4 Parameter estimates of the mode choice models

Parameter	Alter- native	Multinomial logit		Mixed Logit		Mixed logit on panel data (day)	
		β	t-stat.	β	t-stat.	β	t-stat.
ASC Car passenger	CP	-0.897	-10.1	-1.139	-12.4	-1.665	-11.4
ASC Public Transport	PT	-0.762	-4.7	-0.723	-4.2	-0.822	-2.7
ASC Walk	W	1.138	7.6	1.336	8.0	1.666	5.7
ASC Bike	B	0.678	4.6	0.885	5.4	1.032	3.6
Sub-Urban Household location	CD,CP	0.398	5.1	0.442	5.1	0.411	2.3
Urban Household location	PT	0.150	1.5	0.199	1.8	0.477	2.7
Age 18-25	PT	1.231	1.9	1.323	7.9	1.402	4.1
Age 26-35	CD,CP	0.278	4.5	0.350	2.1	0.551	1.7
Age 51-65	PT	0.440	-1.4	0.491	4.8	0.527	3.1
Full time worker	PT	-0.136	9.5	-0.123	-1.2	-0.281	-1.4
Female and part-time	CP	0.908	10.5	0.725	6.9	1.156	6.7
Married with children	CD	0.820	10.5	0.793	8.9	1.305	7.6
Main car user	CD	1.106	12.6	1.073	12.0	1.356	8.6
Annual mileage by car	CD	0.025	7.9	0.027	7.4	0.034	4.2
Number of season tickets	CD	-0.217	-2.5	-0.192	-2.1	-0.134	-0.8
Number of stops	CD	0.130	3.3	0.161	3.7	0.328	4.9
Time (mean)	All	-0.019	-11.9	-0.028	-9.5	-0.061	-10.4
Time (s.d.)	All	-	-	-0.021	-5.9	-0.062	-10.9
Cost (mean)	CD,PT	-0.104	-9.5	-0.123	-8.1	-0.299	-9.3
Cost (s.d.)	CD,PT	-	-	-0.041	-2.4	-0.246	-7.9
Time Budget (mean)	CD,CP	-0.027	-1.9	-0.034	-2.0	-0.111	-3.9
Time Budget (s.d.)	CD,CP	-	-	0.064	1.7	-0.307	-13.7
Sum of Travel Time (mean)	B	-0.194	-8.6	-0.041	-6.5	-0.073	-9.0
Sum of Travel Time (s.d.)	B	-	-	-0.040	-5.1	-0.077	-7.9
Tour Duration (mean)	PT	0.370	17.5	0.396	16.9	0.563	13.0
Tour Duration (s.d.)	PT	-	-	0.002	0.05	0.087	0.8

5 The distributions of the values of travel time savings

In this section we examine the VTTS estimates of models introduced in the previous Section. We first present the VTTS point estimates and their confidence intervals for the multinomial logit model estimated on the full data set and then on four purpose segments: work/education, shopping, leisure, other. We then show the effect of socio-economic variables on the level of service variables and on the values of travel time savings. We finally present the distributions of the time and cost parameters and the resulting VTTS distribution.

5.1 VTTS by purpose

Table 5 shows the VTTS for multinomial logit parameters and their confidence intervals, both for all trip purposes and by trip purpose; the specification of the trip specific models is identical to that used for the mixed logit model. We adopt the asymptotic t-test formulation proposed by Armstrong, Garrido and Ortuzar (2001) for the calculation of the confidence interval. They point out that since model estimation yields an estimator of true values of their parameters, the computed VTTS also has a probability distribution.

The upper and lower bounds for the VTTS confidence interval are defined as follows:

$$V_{S,I} = \left(\frac{\theta_t}{\theta_c} \frac{t_c}{t_t} \right) \frac{t_t t_c - \rho t^2}{t_c^2 - t^2} \pm \left(\frac{\theta_t}{\theta_c} \frac{t_c}{t_t} \right) \frac{\sqrt{(\rho t^2 - t_t t_c)^2 - (t_t^2 - t^2)(t_c^2 - t^2)}}{(t_c^2 - t^2)} \quad (7)$$

where θ_t and θ_c are the time and cost coefficient estimates, t_t and t_c correspond to the t-statistics for θ_t and θ_c respectively, t is the critical value of t given the degree of confidence required and sample size and ρ is the coefficient of correlation between both parameters estimated. In their paper, Armstrong, Garrido and Ortuzar mentioned that the intervals calculated according to their suggestion are both asymmetrical and large.

We found that the VTTS on the full data set is about 11 DM (5.50 €) per hour and that the interval between lower and upper bound is about 6 DM (3 €) per hour, slightly lower than point estimate from the mixed logit formulation. Workers and students have a lower VTTS of about 8 DM (4 €), but a larger interval. The method does not produce precise estimates when one of the coefficients estimated is not significant at 95% confidence level. For the shopping segment, for which the cost coefficient is significant only at 90% confidence level we obtained,

as expected, a very large confidence intervals. Leisure and other purposes trips are associated with quite high VTTS, 15.30 DM (7.65 €) and 17.94 DM (8.97 €) respectively, but the confidence intervals are quite large.

Table 5 VTTS confidence intervals (MNL by trip purpose and for all purposes)

Variable	All purposes	Work or education	Shopping	Leisure	Other
Upper limit	14.47	13.57	757.09	80.61	50.74
Lower limit	8.60	4.50	13.02	7.07	9.09
VTTS point estimate	11.06	8.23	26.99	15.30	17.94
ρ	0.093	0.061	0.077	0.09	0.057
t	- 4.76	- 4.65	- 6.03	- 3.24	- 6.78
Number of observations	5795	1866	1252	1384	1293

5.2 Influence of the socio-economic variables on the VTTS

Logit models can capture systematic taste variations, but cannot handle tastes that vary randomly (Train, 2003). In the mixed logit specification we added socio-economic variables to mode choice utilities as alternative specific attributes, but we allowed the parameters of the level of service variables to vary randomly to capture random taste variations.

Alternatively, as presented in this section, one can interact the socio-economic variables with the level of service variables. This allows us to calculate the effect of the individual characteristics on the marginal utility of the level-of-service variables.

Table 6 MNL with socio-economic * LOS variable interaction terms

Parameter	Alternative	β	t-stat.	VOT
ASC Car passenger	CP	-1.379	-22.6	
ASC Public Transport	PT	-1.495	-11.6	
ASC Walk	W	0.239	1.7	
ASC Bike	B	-0.491	-3.8	
Annual mileage by car	CD	0.046	12.5	
Time Budget	CD, CP	-0.043	-2.9	
Tour Duration	PT	0.003	17.2	
Sum of Travel Time	B	-0.005	-2.8	
Time	All	-0.023	-9.4	12.04
Cost	All	-0.113	-10.5	
Interaction variables				
Time * urban household location	All	0.018	8.0	2.35
Time * Age18-25	All	0.021	5.7	0.82
Time * Age26-50	All	-0.001	-0.1	12.48
Time * Age51-65	All	0.003	1.3	10.35
Time * Full-time worker	All	-0.001	-0.2	12.31
Time * Female part-time	All	-0.032	-8.4	29.19
Time * Married with children	All	-0.027	-9.2	26.52
Time * Number of stops	All	0.015	6.3	4.19
Time * Season Ticket	All	0.002	0.9	10.79
Time * Main Car user	All	-0.006	-2.5	14.98

We estimate a generic time coefficient and 10 interaction variables (Table 6) between socio-economic characteristics and the time variable. The reference VTTS is 12 DM, almost identical to the value found in the simple MNL model with socio economic variables specific to the alternatives. We note that six second-order terms are significant. In five cases we found a VTTS in line (between 10.35 and 15 DM) with the value estimated with a multinomial logit on the full set of data. The VTTS associated to the interaction variables Time * Married with children and Time * Female and Part time are particularly high (about 29 and 26.5 DM). Three categories of persons have very low VTTS: young people, individual stopping for secondary activities and individuals whose home is located in an urban area. None of the groups identified by the interaction variables have a negative mean VTTS.

5.3 VTTS distribution

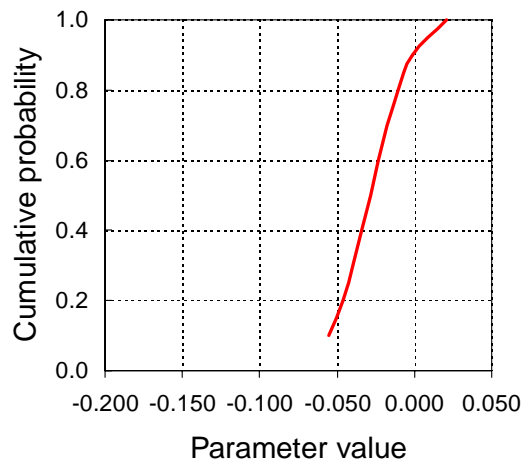
The mixed logit model identifies not only an average of the VTTS but also its standard deviation across the population. Looking at the estimated distribution of the time and cost parameters (Figure 1) we find that the time parameter is negative for about 90% of the population, while the cost parameter is negative, but for a very small share of the respondents. The distribution of the VTTS was approximated by dividing the n^{th} percentile values of the cost and time parameter distributions.

Our results of about 10% of respondents with zero or negative VTTS do not differ from those found by other authors who have tested the distribution of VTTS. Algers et al. (1998) report in their study that 11% of the population had a zero or negative VTTS. Richardson (2003) analyzing an adaptive Stated Preference survey found 14% of the respondents with a negative VTTS. The 95% percentile value of 20 DM is larger than the value found using the confidence interval of parameters estimated with the multinomial logit on the full data set.

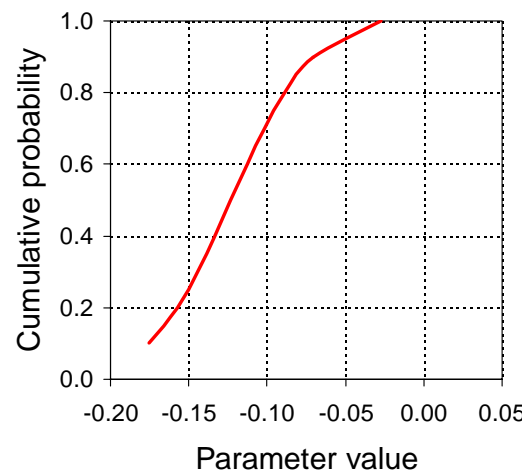
The percentage of people with negative value of time rises from 10% to 15% when we account for the correlation across the tours of the same person on the same day (model 5). The mean VTTS is 12.31 DM, very similar to the average value found when considering our observations as uncorrelated. The problem is that cost variable distribution also becomes positive for about 12% of the population, making further VTTS comparisons difficult.

Figure 1 Mixed logit model: Distribution of the parameters and of the VTTS

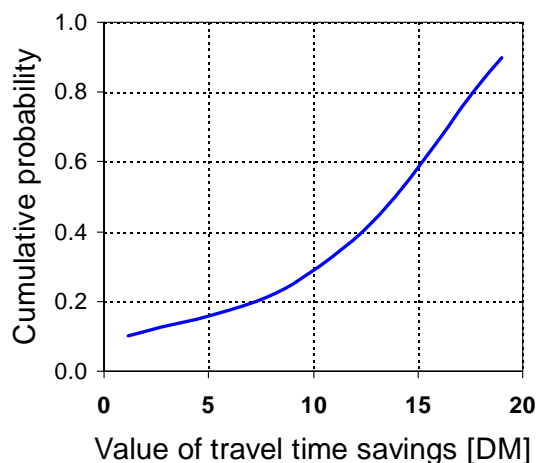
Distribution of the travel time parameter



Distribution of the cost parameter



Resulting VTTS distribution



We finally estimate travel time parameters as specific for each of the seven tour types defined by the framework of Section 2, assuming them to have a normal distribution. The model contains just alternative specific constants, cost and time by tour type as parameters. The estimates for the morning patterns and midday patterns for workers are not significant, which is not surprising given the limited number of such tours observed in the sample. All the other time variables have significant means and standard deviations (except for the standard deviation of the commute pattern). The adjusted ρ^2 is 0.1434.

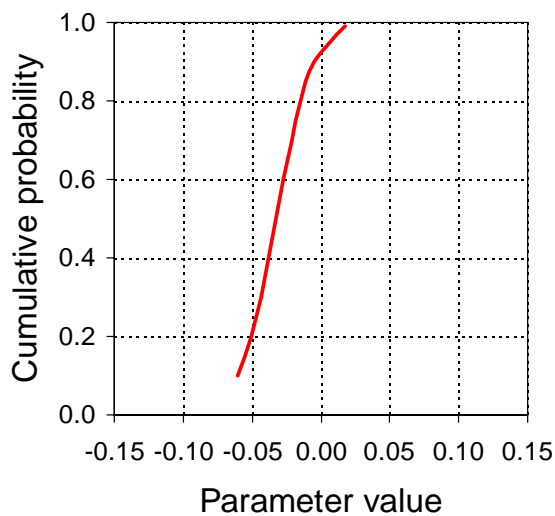
The results shown in Figure 2 and Table 7 are quite interesting. For non-workers in the morning pattern we have a low percentage of activity episodes with negative VTTS (6%). The

highest percentage (of about 25%) is found in the distribution of VTTS for the principal pattern, the percentage is lower (14%) for the evening patterns.

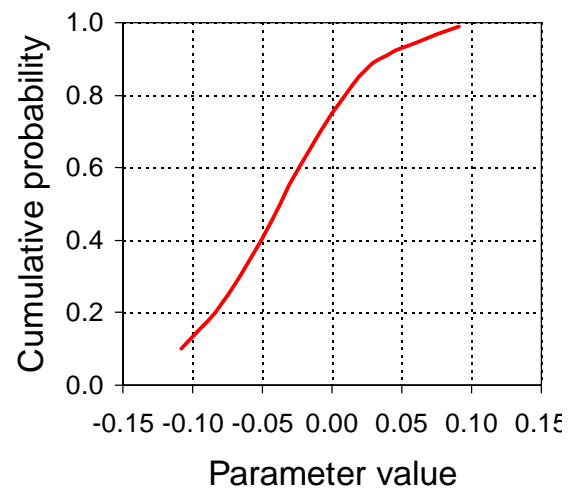
The average values are comparable with the values found in the general mixed logit model, except in the evening, where we calculate a willingness to pay of just 5 DM; here we can recall results of an earlier descriptive analysis, where we found that non workers go out in the evening especially for personal business.

Figure 2 Distribution of the travel time parameter by tour type for non-workers

Non-workers; Morning pattern



Non-workers; principal activity



Non workers; Evening pattern

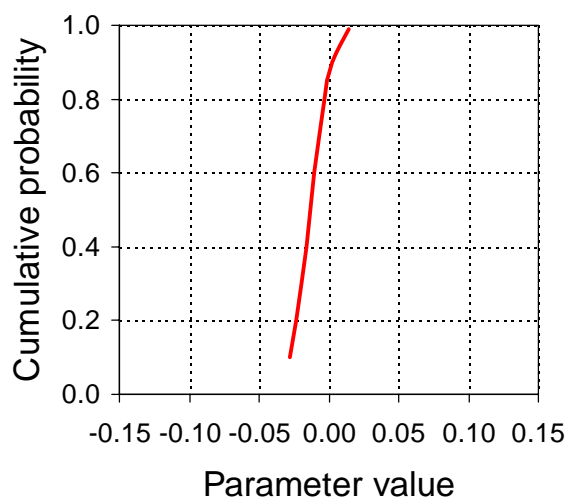


Table 7 VTTS distribution for non-workers by tour type

	Morning pattern	Principal pattern	Evening pattern
95 th percentile VTTS [DM]	15.7	28.1	7.4
Average VTTS [DM]	12.2	13.9	4.9
Share of % negative VTTS	6%	25%	14%

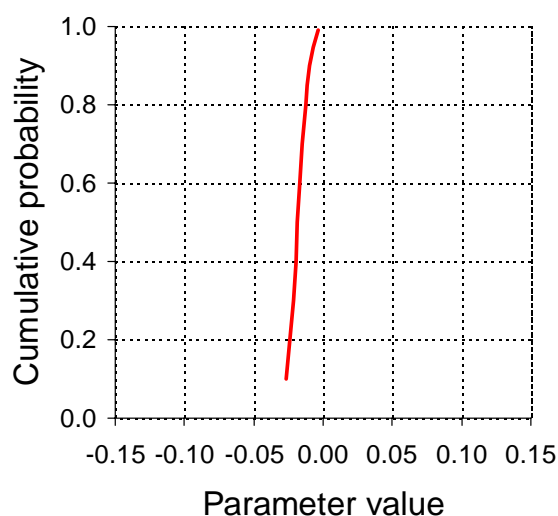
For workers (Table 8 and Figure 3) we do not observe negative VTTS for the commute pattern and a very small difference between the mean and the 95th percentile. In the evening workers have a much higher willingness to spend money with an average VTTS of about 20 DM and an 95th percentile of about 33 DM. While the evening tour is mostly shopping and leisure, the time constraints seems to be more binding, which is in line with the results for the time-budget variable earlier.

Table 8 VTTS distribution for workers by tour type

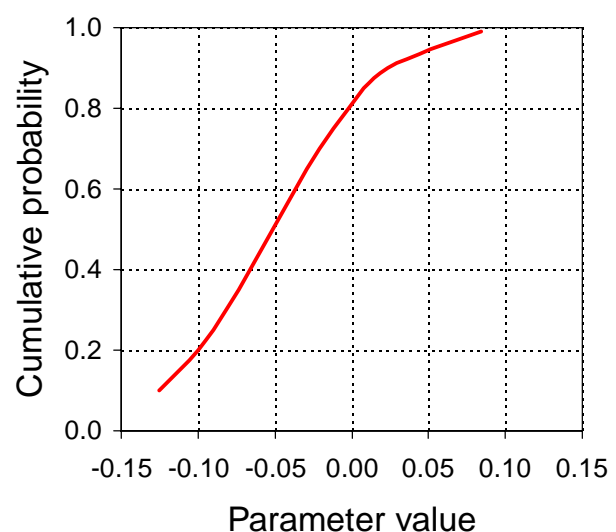
	Morning pattern	Principal pattern	Evening pattern
95 th percentile VTTS [DM]	n.a.	6.9	32.8
Average VTTS [DM]	n.a.	6.8	19.1
Share of % negative VTTS	n.a.	0%	19%

Figure 3 Distribution of the travel time parameter by tour type for workers

Workers; Commute pattern



Workers; Evening pattern



5.4 Bayesian estimation of time and cost parameters

We finally estimate time and cost parameters for individual respondents; the sample includes 136 individuals. Each performs on average 42 complete tours, but the number of repetitions varies substantially from person to person. Two estimation methods are used: mixed logit accounting for repeated observations by the individuals and the Bayesian procedure, which is especially well-suited to random parameter estimation (Train, 2003).

In Section 5.3 we used the mixed logit approach to estimate the distribution of five parameters, which are supposed to be normally distributed, but accounting only for correlations across individual days. Here the time parameter is positive for just 10% of the activity episodes, cost being essentially always negative.

In Table 9 we report the estimation results for mixed logit model accounting for repeated individual choices with normally distributed terms. It should be noted that this model is impoverished in its description of the travelers and their choice situations and employs only the two variables: time and cost. See also the low log-likelihood achieved. The ML probability was simulated with 500 Halton draws, which gave stable estimates. Time and cost coefficients are positive for a large part of the population (37% and 43%), both means and standard deviations are reported to be significant.

Table 10 gives the simulated mean of the posterior for the same parameters obtained applying the Bayesian procedure for the same impoverished description of the choice situation; 20000 iteration of the Gibbs sampling were performed, 1000 iterations were kept for averaging after convergence was reached (posterior).

Table 9 ML estimation on panel data (person) (normal distribution): Parameter estimates

	Estimate	s.e.	t-Statistic	< 0
Time mean	-0.0257	0.0059	-4.36	63%
Time s.d.	0.0765	0.0066	11.59	
Cost mean	-0.0731	0.0246	-2.97	57%
Cost s.d.	0.4008	0.0318	12.60	
Log-likelihood	-6877.27			

Table 10 Bayesian estimation on panel data (person) (normal distribution): Parameter estimates

	Estimate	s.e.	t-Statistic	< 0
Time mean	-0.0366	0.0145	-2.52	59%
Time variance	0.0286	0.0042	6.76	
Cost mean	-0.0552	0.0418	-1.36	57%
Cost variance	0.2064	0.0336	6.06	
Log-likelihood	-6911.89			

The two procedures provide quite similar results except for the standard deviation of time distribution, and almost the same percentages of positive parameter values. Bayesian procedure was substantially faster than classic maximum likelihood estimation.

It is not always true that the two methods give the same results. Ainslie et al. (2001) report that differences depend on the number of observations relative to the number of parameters, as well as the amount of variation that is contained in the observations. We judge that in our sample the number of observations is large enough to estimate two parameters; however it is difficult to measure the amount of variation. Mobidrive is a Revealed Preference (RP) experiment, work tour characteristics can be very similar from day to day, non-work tours could vary a lot along the same day, from a day to the following, and from person to person.

The large shares of respondents with the incorrect sign require further model tests. In a next step, the model was re-estimated with either an assumed log-normal or censored distribution for the parameters (Train, 2003).

The log-normal transformation is $c = \exp(\beta)$ and is bounded at zero. It is particularly well suited for parameters that affect every individual behavior. In order to estimate log-normal distributions for time and cost we entered negative value of those variables into the model. Results are in Table 11; mean and variance for both coefficients estimated are significant, mean values are negative because the median is between zero and one. However the log-likelihood is substantially lower than that for the model with all normal distributions.

Table 11 Bayesian estimation on panel data (person) (log-normal distribution): Parameter estimates

	Estimate	s.e.	t-Statistic	< 0
Time mean	-5.285	0.350	-15.10	0%
Time variance	7.873	1.930	4.08	
Cost mean	-4.567	0.638	-7.16	0%
Cost variance	15.11	5.341	2.83	
Log-likelihood	-7355.01			

Table 12 gives the results of the model with variables distributed normal, but censored from below at zero. With this distribution 63% of the population is not concerned about time, while 61% of the population is not concerned about cost. The four parameters have the correct sign, but the mean cost parameter is not strongly significantly different from zero. The value of the log-likelihood is in between those obtained with normal and log-normal distributions, but still substantially lower than with the normal distribution.

Table 12 Bayesian estimation on panel data (person) (normal distribution, censored at zero): Parameter estimates

	Estimate	s.e.	t-Statistic	= 0
Time mean	-0.0998	0.0362	-2.76	63%
Time variance	0.0748	0.0196	3.82	
Cost mean	-0.2106	0.1240	-1.69	61%
Cost variance	0.6245	0.2549	2.44	
Log-likelihood	-7338.19			

The results reported in this last section are not very satisfactory. The goodness of fit of the models is low in comparison with the earlier models, which is due to small number of variables included. The shares of respondents with either zero or below zero parameter VTTS were therefore overestimated, as the description of the person and the choice situations is incomplete.

6 Conclusions

The work presented here adds to the literature on the distribution of the values of travel time savings by demonstrating that there is a small share of the population which is interested in extending their travel time, especially during non-work tours. The interaction between the tour types, trip purposes or the time budgets/times spent and the value of travel time savings indicates that travelers respond according to their situation. This is in line with the usage patterns of the Californian HOT lanes, where again many travelers use them when they need them, because they are under time pressure.

The estimated shares of respondents with negative VTTS is in the relevant, full models comparable to other estimates reported in the literature. This about 10% share is difficult to assess, as there is little literature, which provides an independent assessment of how pleasurable travel is for travelers. If Csikszentmihalyi, 1990 results hold, which suggests, that driving is one of the most pleasurable everyday activities, then the 10% share might actually be too low.

The results are generally stable and do not vary too strongly with the increased sophistication of the modeling approaches. This increases their credibility

These strong situational impacts raise interesting questions for the interpretation of stated preference (SP) data. While most or at least many SP experiments use an observed trip as the basis for the construction of the choice situations, it is doubtful that they can fully recreate the situational constraints of the original situation without careful attention to its description of the trip in the written questionnaire. Very often the RP data are lacking the required details about timing, size of party, time pressure, etc. It is therefore unclear, in what frame of mind the respondents reply to an SP experiment. We would like to suggest, that they do so mostly without time pressure similar to the situation in which they decide about longer term choices. This supposed difference in time frame might also explain the differences typically found between SP and RP results.

The dependency of the VTTS on tour type, purpose and socio-demographic variables raises the question of how travel time change should be addressed in cost-benefit analysis. Traditionally, cost-benefit analysis did not differentiate at all, or maybe by mode. The demands made by the requirements of environmental justice and generally by a more detailed accounting of winners and losers of policy measures, should be matched by an increasing differentiation of the VTTS used to evaluate the losses and gains as well.

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