Journal of Choice Modelling, 2(1), pp. 29-50
www.jocm.org.uk

Modelling the preference for scheduled and unexpected delays

Maria Börjesson*

Centre for Transport Studies, Royal Institute of Technology, S-100 44 Stockholm, Sweden

Received 8 August 2007, revised version received 1 July 2008, accepted 9 December 2008

Abstract

This paper describes a study undertaken to estimate a departure-time and mode-choice model for Stockholm. The model is segmented according to trip purpose, and a mixed - or error component - logit model is estimated. Estimation draws on stated preference data collected from drivers travelling toward the city centre during morning peak hours. The study uncovers drivers' preferences for scheduled delay, unexpected delay, travel time and cost as well the patterns of substitution between mode and time of day alternatives. The result indicates that disutility of unexpected delay depends on the scheduled deviation from preferred arrival time. The preference for scheduled delay is roughly proportional to the time shift and varies in the population, but is much more consistent within an individual. Another finding is that constraints at the destination mainly restrict late arrival, whereas constraints at the origin mainly restrict early departure.

Keywords: Stated Preference, Mixed Logit, Unobserved Heterogeneity, Travel Time Uncertainty, Scheduled Delay, Johnson's SB distribution

1 Introduction

Congestion problems, causing increasing travel times and travel time uncertainty, raise the need to evaluate policy measures. Since some of the latent demand avoiding congested time periods is diverted to other time periods, disregarding the effect of peak spreading in policy evaluation may result in over- or under-estimation of congestion. In a study carried out by SACTRA (1994) it was found that departure time shift is the second most common response, after changing route, to new travel conditions.

*T: +46 8 790 60 00, F: +46 8 688 77 32, maria.borjesson@wspgroup.se

Licensed under a Creative Commons Attribution-Non-Commercial 2.0 UK: England & Wales License
http://creativecommons.org/licenses/by-nc/2.0/uk/

ISSN 1755-5345

The congestion toll trial in Stockholm has demonstrated the need for a departure time model. A departure time choice model application needs to integrate a dynamic assignment model with a demand model. The objective of this paper is to develop and estimate a mode and departure time choice model for Stockholm that covers the extended morning peak period. This demand model is currently being implemented along with a dynamic assignment model. The fact that travellers face an uncertain travel time is also being taken into account.

Departure time models are usually estimated based on Stated Preference (SP) data, since Revealed Preference (RP) data with the required level of detail and quality is usually unavailable. There are only a few successful RP-based model estimations reported in previous literature: Small (1982), Small (1987), Bhat (1998a), Bhat (1998b) Lam and Small (2001) and Brownstone and Small (2005). In this study, estimation draws on data from a stated preference study undertaken in Stockholm. The target group was drivers travelling toward the city centre during the extended morning peak from 06.00-10.00.

There are a few published studies estimating departure time choice under uncertainty, such as Noland et al. (1998), Small et al. (2000) and Hollander (2005). These studies all use SP data and deal only with commuters. The departure time shifts considered in the studies were relatively small; in Small et al. up to 15% of the mean travel time (i.e. nine minutes assuming that the mean travel time is 60 minutes). Noland et al. used time shifts of similar magnitudes.

The vast majority of trip timing models adopt the framework developed by Vickrey (1969) and Small (1982), assuming that the traveller's utility depends on travel time and deviation from the preferred arrival time; the latter is sometimes referred to as earliness or lateness. However, earliness and lateness can be planned, i.e. scheduled, or unexpected. Planned and unexpected deviations from preferred arrival time are conceptually different, and the disutility arising from them is probably not equal. In the literature however this distinction is not always made clear.

de Jong et al. (2003) developed a trip timing model similar to the one developed in the present paper, but their model is tour based. Further they focus on scheduled delay only, whereas in the present study we consider both scheduled and unexpected lateness and earliness.

For the planned, or scheduled, departure time we used relatively large time shifts in the SP, of the same magnitude as de Jong et al., for several reasons. First, as the morning peak extends over a relatively long time, the effect on congestion levels will be very limited for small departure time shifts. Second, possible charging schedules for the tolls trial in Stockholm (see www.stockholmsforsoket.se), which will be evaluated using this application, are relatively crude. Most drivers thus have to make relatively large departure time shifts in order to reduce their charge. Third, our hypothesis was that a majority of commuters travelling toward the city centre have a flexible working schedule and thus more flexibility in their choice of departure time. A flexible working schedule here refers to a situation where there is no official starting or finishing time at work.

Many authors have noted that the MNL approach is inapplicable for departure time modelling, since it cannot accommodate the correlation structures in the alternatives. For this reason we apply a mixed logit model structure similar to those applied by de Jong et al. (2003) and Hess et al. (2006a), designed to induce correlation and heteroskedasticity between different departure time alternatives. One alternative to simulation-based models that would be faster in an application, but still be able to accommodate the desired correlation structures, is the closed form Ordered GEV (OGEV) model. Small (1987) was first in applying OGEV to departure time choice and Bhat (1998a) jointly modelled departure time and mode choice, applying a nested OGEV-MNL model. Since we use SP data for estimation however the OGEV model is less suitable, as this model cannot accommodate correlation in unobserved heterogeneity, which usually arises between repeated observations from the same respondent.

2 Model Formulation

2.1 Theory, terminology and literature

Following Vickrey (1969), Small (1982) and Bates et al. (2001) we first assume that the traveller's utility depends on travel time and deviation from the preferred arrival time, PAT. The majority of previous studies have used the official work starting time as preferred arrival time, but that cannot be used in this study since non-commuters are also included and also because a majority of the commuters travelling toward the city centre of Stockholm do not have an official work starting time. We have therefore sought to elicit a preferred arrival from the respondents in a different way. We first extracted information about the preferred departure time (PDT) by asking the drivers at what time they would have choosen to depart if there never were any queues on the road network. PAT was then computed by adding up PDT and the minimum travel time encountered under optimal travel conditions, as reported by the drivers.

In any case, the utility function is typically of the form

$$u(t_h, T) = \alpha T + \beta max[(PAT - t_h) - T, 0] + \gamma max[T - (PAT - t_h), 0] \quad (1)$$

where t_h is the departure time, T is the travel time, α is the direct utility of time spent on the trip. β is sometimes referred to as the disutility of being early, but it can also be viewed as the utility difference between time spent at the origin and time spent at the destination before the preferred arrival time and hence the (relative) opportunity cost of time. γ is the disutility of lateness, i.e. arrival after the preferred arrival time. Usually, the lateness penalty is assumed to be linear in the lateness, although some authors have suggested a step function (an extra penalty as soon as the traveller arrives after the preferred arrival time), and some authors have suggested that the marginal disutility of lateness may be either increasing or decreasing.

As mentioned in the introduction, there are in fact two possible interpretations of β and γ. One interpretation is that they represent the disutility of planned, or scheduled, deviation from the most preferred arrival time. Another interpretation in the literature is that these parameters refer to the valuation of unexpected lateness or earliness.

We first turn to the case when β and γ refer to the disutility of unexpected lateness or earliness. The direct disutility arising from the risk of arriving at a time different from planned arrival time, caused by the travel time uncertainty, can be captured by the expectation of the unexpected delay. The theory of this approach was first proposed by Garver (1968) and Polak (1987), with further development by Noland and Small (1995) and Bates et al. (2001), combined with the work of Small (1982).

Fosgerau and Karlstrom (2008) extend the results further by showing that as long as departure time can be chosen freely and travel time distribution is independent of departure time, the reduced-form utility function can always be written as a linear combination of the mean travel time and the standard deviation of travel time. They show further that this result generalizes approximately to the case where the mean and standard deviation of travel time depend on departure time. Another insight is that the direct utility of standard deviation will depend on the standardised travel time distribution. Standard deviation valuations that have been obtained in one context can thus not be directly transferred to another context with a different standardised travel time distribution.

In the original interpretation of β and γ these represent the disutility of planned deviation from the most preferred arrival time. The motive for a driver to make such a time shift is to move the trip to a time period with better travel conditions in heavy congested networks.

In the model developed in the present study we will include both the direct disutility of the *scheduled* deviation from the most preferred arrival time and the direct disutility of *unexpected* lateness or earliness. In accordance with the results of Fosgerau and Karlstrom, the disutility arising from unexpected lateness or earliness is represented as the width of the 95% confidence interval, i.e. the width between the 2.5 and 97.5 percentiles, which is proportional to the standard deviation for many travel time distributions. We chose this representation of travel time uncertainty for the SP, and therefore also in the utility function (see section 3).

The planned deviation from the most preferred arrival time is represented by the formulation used in eq. 1. We make the underlying assumption that some drivers have flexible schedules and are thus less constrained by a specific preferred arrival time, but have the option to choose a departure time so as to achieve better travel conditions. It is uncertain how large a share of the drivers have this option in reality. As mentioned however, and as will be shown later, a majority of commuters travelling toward the city centre have flexible working schedules and probably thus have some flexibility in their departure time choice.

A different but related issue is whether scheduled delay should be defined

with respect to departure (DT) or arrival time (AT). Defined with respect to departure time we have:

$$SDE_{DT} = max[PDT - t_h, 0] \tag{2}$$
$$SDL_{DT} = max[t_h - PDT, 0] \tag{3}$$

The deviation from the most preferred arrival time is stochastic if travel time is uncertain. However if the driver plans to shift arrival time significantly later than PAT, relative to the travel time variability, the distribution of SDL becomes a linear transformation of the arrival time. Hence E(SDL) can still be written as the difference between the expectation of arrival time and PAT, and E(SDE) becomes zero with certainty (or, equivalently, if the driver choose to arrive too early, E(SDL) becomes the difference between the expectation of arrival time and PAT):

$$E(SDE_{AT}) = max[(PAT - t_h) - \overline{T}, 0] \tag{4}$$
$$E(SDL_{AT}) = max[\overline{T} - (PAT - t_h), 0] \tag{5}$$

The choice of approach should be based on whether temporal constraints are more binding at origin or destination. Constraints at the origin and destination are most likely also working in different directions, so that earlier departure is constrained at the origin and later arrival is constrained at the destination. If so, SDE could be computed with respect to departure time and SDL with respect to arrival time. This is also most consistent with the view that the disutility of planned early time shifts corresponds to the opportunity cost of time spent at the destination before the preferred arrival time relative to time spent at the origin. These alternative approaches will be discussed further in the estimation section 4.3.

2.2 Model Formulation

We expect to find unobserved individual variation of scheduling constraints, and thus assume that the scheduled delay parameters are randomly distributed in the population. This assumption is formally equivalent to formulating an error component logit model in which a part of the unobserved utility difference is related to the proximity of the alternatives. In addition to the scheduling parameters, the cost parameter was assumed to be randomly distributed in the population. The expected utility function for the two departure time alternatives, for a given individual n, formulated as:

$$\begin{aligned} U_i =& \beta_n SDE_i + \gamma_n SDL_i + \delta_n COST_i + \\ & \alpha T_i + \lambda \Delta_i + \epsilon_{in} \end{aligned} \tag{6}$$

Index i refers to the two departure times in the SP choice situations. SDE and SDL represent planned deviations from PDT or PAT. COST is the monetary cost of the trip and T is mean travel time. Travel time uncertainty, or unexpected delay, is represented by the 95% confidence interval of the travel time duration, denoted Δ. ϵ_n are independent and identically distributed Gumbel terms.

We will also test the hypothesis that the disutility arising from unexpected delay depends on the scheduled delay. We will therefore replace Δ with the parameters Δ_{early} and Δ_{late}. Δ_{early} and Δ_{late} denote disutility of travel time uncertainty when the scheduled earliness and lateness, respectively, is non-zero. A dummy parameter for additional lateness penalty is not included because it is meaningless in a framework where we assume that many travellers deliberately choose to travel earlier or later than at the most preferred time in order to achieve better travel conditions.

The attractiveness of alternatives to car driving will obviously influence drivers' response to new travel conditions. To capture this dimension, a mode switch (to public transport) alternative is included in the model. The utility of this alternative is primarily described by the respondent's actual public transport time. The public transport cost is highly correlated with time and therefore omitted in the utility function. The expected utility function was formulated as:

$$U_{PT} = C_{PT} + \alpha_{PT} T_{PT} + \eta \xi_n + \epsilon_{PTn} \tag{7}$$

where C_{PT} is a constant and ξ_n is a [0,1] normally distributed error component, inducing a larger variance of the error components in the choice of mode relative to the choice between the car-based alternatives. The size of this variance is determined by η,, which is estimated. Comparing this specification with a nested logit model, this is equivalent to specifying separate nests for each of the two modes. T_{PT} is the public transport travel time. Public transport travel times are assumed not to vary very much within the extended morning peak.

3 Survey

An SP survey, designed to explore the trade-off that drivers make between shifts in preferred departure time, travel cost, travel time and travel time uncertainty, was administered to a sample of drivers travelling toward the city centre of Stockholm during the extended morning peak period (06.00-10.00). The main study took place in spring 2005, preceded by a pilot study in March the same year. Drivers were first registered by roadside number plate registration, after which a survey agency called them the same evening for an initial interview to collect certain prior information about the observed trip (i.e. purpose, departure time and travel time) as well as socioeconomic information (including income). The respondents were also asked at what time they would have departed, and how long the trip would have taken, if there never were any queues on the road network. This

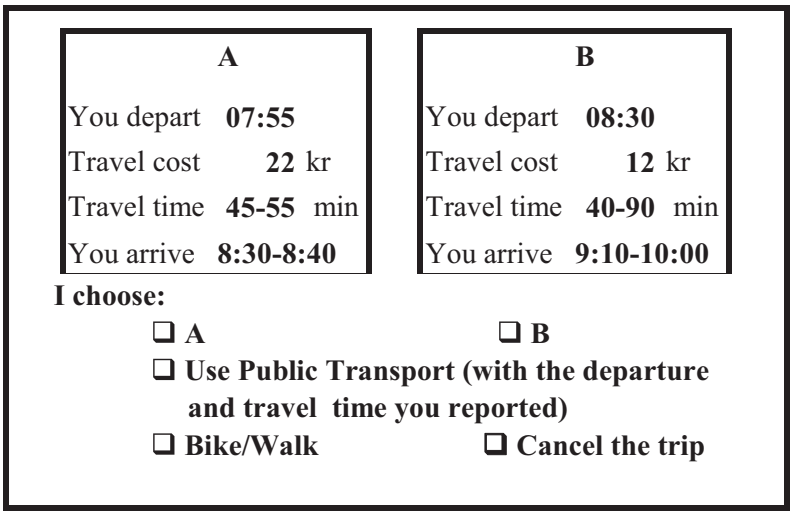

Figure 1: Example of the sample questions

information was used to identify the preferred departure time. The SP survey was mailed to them the following day.

The questionnaire first listed the information about the observed trip (i.e. actual departure and arrival time, trip duration and preferred departure time) to remind respondents about the circumstances of the trip. This information had also been used to customize the game. Then a number of questions followed that introduced the respondents to the concepts of travel time variability and departure time choice. The second part of the questionnaire included eight SP questions. For each question the respondents were instructed to choose one of two departure time alternatives. The option to switch to public transport, bicycle or walk, or cancel the trip were also offered, but the number of choices for the latter two was small and therefore not included in the model. For public transport time, respondents were instructed to assume their actual public transport time in the SP game. To code the respondents' actual public transport travel times, output from the EMME/2 network assignment package was used.

Travel time and travel time uncertainty were presented by a travel time interval, specified by a T_{max} and a T_{min} (see figure 1). The respondents were informed that the travel time might fall outside this interval about once a month if making the trip at the same time of day five days a week. We therefore interpret it as a 95% confidence interval.

The problem of representing travel time uncertainty in SP surveys, capturing the respondents' actual valuation of uncertainty and still making it both realistic and interpretable for non-professionals has been discussed by several authors (see Bates et al. (2001)). The present study adopted interval presentation because we believe it corresponds to the type of simplified information that many travellers

actually consider when choosing how and when to travel. The pilot and main survey further showed that the respondents are aware of the fact that their travel time normally varies within an interval. They were asked to report the minimum and maximum travel time of the particular trip, and their answers indicated that they understood and interpreted these questions correctly. Hence we may assume that an interval expresses travel time variability in a realistic and interpretable manner.

A further motive for adopting an interval representation of travel time is connected to the implementation of this model and to joint RP-SP estimation using this data, which have been carried out in subsequent studies. In the RP data travel time variability is measured with a 95% confidence interval because the standard deviation is too sensitive to measurement errors (see section 3).

Travel time variability in this case is represented by the difference between minimum and maximum travel time in the application because a very large number of observations with very good quality are required to measure the standard deviation accurately.

An interval representation of travel time uncertainty (difference between the 90th and the 50th percentile) was further found to have the best model fit in two studies on value of time and reliability, using RP and SP data from the HOT lane projects in California. In these studies standard deviation captured individual's preferences only imperfectly in RP data (Brownstone and Small 2005, Lam and Small 2001). They suggest that the poor results obtained from using the standard deviation may arise from incorrect measurements. However the interval representation implies that we need to make an assumption as to what mean travel time the respondents assume based on an earlier study of travellers' experiences of the travel time distribution.

An orthogonal design based on the difference between the two SP alternatives was used. Simulation over a wide range of parameter values, which also included the parameter values obtained in the pilot and main study, was undertaken to guarantee sufficient efficiency in parameter estimates. The observed departure and travel times, collected in the interview, were used to partially customize the game.

The pilot study, in combination with expert judgments, was used to arrive at the final levels of the attribute in the SP experiment. In the first of the two alternatives in each question, the departure time was shifted 5-15 minutes later or earlier from the actual departure time. The departure time in the second alternative was determined by assigning a departure time difference between the two alternatives. The departure time in the second alternative was shifted in the same direction, later or earlier, as in the first alternative. The difference between the departure times in the two alternatives was assigned four levels in the range of 5-60 minutes.

The travel time intervals were determined by two variables, mid-point and width, and the difference of the interval mid-points took four levels, ranging from 10-25 minutes. The interval width was derived as a percentage of the mid-

Table 1: Number of choices for each model segment†

	No. of obs	Shift to PT
Segment 1: Commuters with flexible schedule and other trips	*2732*	*268*
Trip purposes included:		
Commutes to work, flexible schedule	2034	185
Shopping	21	3
Drop or pick someone off	134	13
Other	519	67
Commutes home from work	24	0
Segment 2: Commuters with fixed schedule	*1133*	*112*
Trip purposes included:		
Commutes to work, fixed schedule	1071	111
To or home from school	62	1
Segment 3: Business	*521*	*36*
Total	4386	416

† The included purposes are listed for each segment. Number of choices corresponds to the number of respondents multiplied by the number of choices in the SP. The number of choices for which the public transport alternative was chosen is given explicitly

Table 2: Number of respondents categorized into trip purposes

Purpose	Frequency	Percent
Commutes to work, flexible schedule	456	43,7
Other trips	173	16,6
Commutes to work, fixed schedule & school trips	253	24,2
Business trips	162	15,5

point, with the four levels ranging from 0-80%. Cost differences between the two alternatives were assigned four levels in the range of SEK 10-40 (EUR 1-4).

The number of respondents interviewed, grouped with respect to purpose and temporal flexibility, is shown in table 1. The number of SP choices used in the model estimations, grouped into three segments, is tabulated in table 1.

4 Model Estimation

4.1 Segmentation

Based on a careful examination of the data, the population was segmented into three groups. The first segment included commuters with flexible working hours, the second commuters with fixed working hours and the third people taking business trips. School trips were included in the second segment and trips with other purposes were added to the first segment. The assumption of the latter's similarity, in scheduling flexibility, to trips for individuals with flexible work schedules is plausible since they, too, often lack a fixed starting time.

To summarise, separate models were estimated for 1) commuters with flexible working hours, with other trips added in 2) commuters with fixed working hours, with school trips added in and 3) business trips. Only the results from the estimation of the largest model segment, commuters with flexible working hours and other trips, will be presented in detail. Models for the other segments are presented in the appendix.

4.2 Mixing Distribution

In the introductory phase of the estimation, several mixing distributions for the scheduled delay and cost parameters were evaluated: triangular, normal, uniform and lognormal. The symmetric distributions were inappropriate since the true distributions proved to be highly skewed and it is clearly inconsistent to assume positive valuations for scheduled delay and monetary cost attributes. The lognormal distribution gave rise to convergence problems, most likely because of the extensive tail. Johnson's SB distribution, which has the advantage of being an unsymmetrical and bounded distribution, was therefore applied. It is a nonlinear transformation of the normal distribution:

$$l_1 + l_2 * \frac{e^{\theta}}{1 + e^{\theta}} \tag{8}$$

where l_1 is the lower bound and l_2 is the width of the interval. θ is a normally distributed variable with mean μ and variance σ that determine the shape of the density function. Johnson's SB approximate the normal and the lognormal distribution but can also be bi-modal.

However, applying Johnson's SB distribution implies that as many as four parameters can be estimated. Train and Sonnier comment that if the bounds (l_1 and $l_2 + l_1$) are treated as parameters to be estimated it is likely that the model runs into identification problems because l_2 is closely related to the variance of the normal term. We have therefore assumed fixed bounds, with the upper bound set at zero. For the lower bound we evaluated two different points, -1 and -2, and investigated the sensitivity of this assumption. No significant influence of

this assumption, in terms of model fit and shape of the density function, could be found and thus we chose the bounds [-1,0] for all random parameters, as will be shown below.

4.3 Estimation

For model estimation the software package Biogeme 1.4 (Bierlaire 2005) was applied. The model for commuters with flexible working hours and other trips was estimated using Modified Latin Hypercube Sample (MLHS) draws proposed by Hess et al. (2006b). A sum of 1000 draws proved to be sufficient to give stable estimates. The randomly distributed parameters are constant across all observations for the same individual in the estimation, i.e. the direct disutility of scheduled delay and cost are assumed to be constant across all choices for each individual.

For the three model segments three model specifications were initially estimated, differing in their definition of scheduled delay. In this initial examination all models were estimated using MNL models, which means assuming the coefficients to be constant across all individuals n in eq. (6-7). In specification 1) SDE and SDL were both defined with respect to departure time, eq. (2-3). In specification 2) SDE and SDL were both defined with respect to arrival time, eq. (4-5). In specification 3) SDE was defined with respect to departure time, eq. (2), and SDL was defined with respect to arrival time, eq. (5). The third model specification seems to be the most plausible one from a theoretical point of view. When defining SDE with respect to departure time, we may think of this cost as an opportunity cost of interrupting the activity at origin. SDL defined with respect to arrival time is opportunity cost of being late to the activity at the destination.

The Log Likelihood (LL) values of all specifications are presented in table 3. For two out of the three model segments, commuters with flexible and business, best model fit was achieved using specification 3). In these model segments, temporal constraints at the origin thus seem to primarily restrict early departure whereases constraints at destination primarily restrict late arrival. For commuters with fixed working hours, however, the LL values of specification 1) and 3) do not differ significantly. Since the third specification ins further the theoretically most sound specification this was applied in the final models. In the continuation of this paper SDE and SDL will refer to SDE_{DT} and SDL_{AT}, respectively.

The final model for commuters with flexible schedule and other trips are shown in table 4. α_{PTrep} is the public transport travel time parameter the for those respondents (18 in total) for whom the public transport time could not be coded (because of incorrect origin or destination address). The variable corresponding to this parameter is the travel time reported by the respondents themselves.

T_{Parent} is an additional direct disutility of travel time for parents with dependent children. PT_{Parent} is a dummy parameter in the public transport utility function, equalling one if parent and zero otherwise, indicating that parents have

Table 3: LL value for all model segments using different definitions of scheduled delay (MNL)

Specification	Flexible & Other trips	Fixed	Business
1) SDE_{DT}, SDL_{DT}	-2337,22	-957,67	-435,22
2) $E(SDE_{AT})$, $E(SDL_{AT})$	-2323,14	-926,45	-426,88
3) SDE_{DT}, $E(SDL_{AT})$	-2318,93	-926,63	-422,45

a lower propensity to switch to public transport. $SeasonTicket$ is a dummy variable, which is one if the respondents have a season ticket and zero otherwise. Beside this, no systematic socio-economic differences could be found. For instance, although cost sensitivity varies within each segment, no systematic differences between income groups could be found within each segment.

The disutility of travel time uncertainty depends on whether the expected arrival time of a specific alternative is shifted later or earlier. The parameter for travel time uncertainty was therefore segmented so that Δ_{early} and Δ_{late} denote the 95% confidence interval of the travel time in alternatives where expected arrival time is shifted earlier and later, respectively, than PAT. The parameter for travel time uncertainty was only significant in the choices where expected arrival time was shifted later than PAT, in segments 1 and 2. When departure time was shifted earlier, travel time uncertainty did not add a significant disutility. This seems plausible, since the risk of arriving later than PAT then is small. The estimates of travel time uncertainty depend on the way in which the mean travel time T is calculated as a linear combination of T_{min} and T_{max}. To show this we rewrite the last two terms in eq. (6):

$$\begin{aligned} &\alpha T + \lambda\Delta \\ =&\alpha(c(T_{max}) + (1-c)T_{min}) + \lambda\Delta \\ =&(\lambda + c\alpha)\Delta + \alpha T_{min} \end{aligned} \tag{9}$$

Hence, for any value of c (used to calculate the mean travel time) the estimated value of λ will adjust. c was set to 1/3, which is consistent with results from an earlier study on commuters' perception of the travel time distribution carried out in Stockholm (Transek 2000).

For earliness and lateness the parameter and not the variable names are given in table 4, since the parameters do not directly correspond to the variables. β_{COST}, β_{SDE} and β_{SDL} are the estimated means of the underlying normal distributions corresponding to the Johnson's SB-distributed coefficients of eq. (6 - 7). σ_{COST} is the standard deviation of the corresponding normal distribution. Since SDE and SDL are correlated, the standard deviations of the underlying normal distributions are not estimated directly. For technical reasons the elements of the Cholesky decomposition matrix are estimated instead. The Cholesky de-

Table 4: Departure time model for commuters with flexible schedules and other trips

Number of MLHS draws:	1000		
Number of observations:	2732		
Number of individuals:	359		
Null log-likelihood:	-3001.41		
Final log-likelihood:	-1996.02		
Rho-square:	0.3350		
Name	Value	Std err	t-test
β_{COST}	-2.815	0.095	-29.55
σ_{COST}	0.862	0.098	8.80
β_{SDE}	-4.304	0.360	-11.94
σ_{SDE}	2.010	0.261	7.71
β_{SDL}	-3.401	0.169	-20.17
σ_{SDL}	1.060	0.181	5.84
σ_{SDL_SDE}	0.549	0.167	3.29
$SDE_{7.30}$	0.017	0.005	3.34
T	-0.059	0.005	-12.69
T_{Parent}	-0.078	0.006	-13.00
Δ_{late}	-0.014	0.003	-4.81
C_{PT}	-7.401	0.895	-8.27
η	-5.052	0.566	-8.92
T_{PT}	-0.062	0.009	-6.73
T_{PTrep}	-0.206	0.048	-4.31
$SeasonTicket$	5.062	0.950	5.33
PT_{Parent}	-2.952	0.957	-3.08

composition was used as a method to generate a correlated multivariate normal distribution based on uncorrelated univariate normal draws (see for instance Press et al. (1987)) σ_{SDE}, σ_{SDL} and σ_{SDL_SDE} equal the lower triangular Cholesky factorisation matrix, where σ_{SDL_SDE} is the off-diagonal.

Using the Cholesky elements, the density functions of the Johnson's SB-distributed parameters of eq. (6 - 7) were simulated. Table 5 shows the corresponding simulated means, standard deviations and correlations of the simulated parameters. The corresponding density functions are plotted in figure 2. The plots reveal that the density functions of the random parameters are skewed, in particular SDE, indicating that many respondents have a low sensitivity to scheduled delay. Correlation of the scheduling parameters is positive, which is also the case in the model for business trips.

The standard deviations of the random parameters can be interpreted as error components. They allow for different levels of error between the alternatives. In

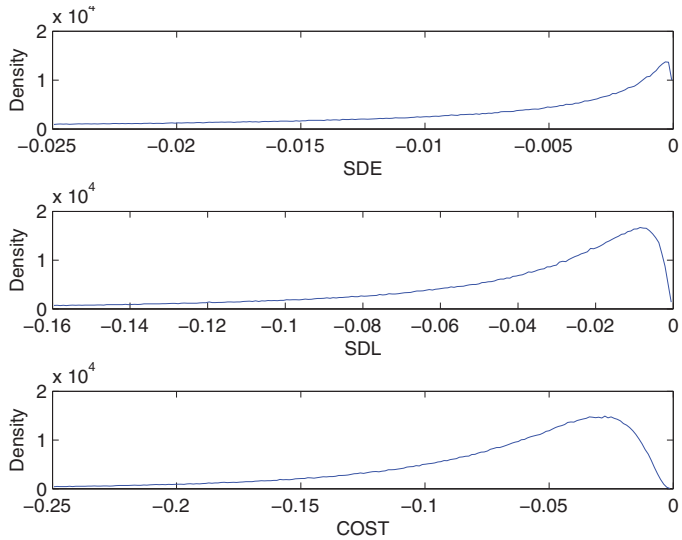

Figure 2: Commuters with flexible schedule and other trips: density of the Johnson's SB-distributed random parameters

turn this affects the sensitivity of departure time and mode choice, in response to changes in the observed part of the utility. The sensitivity is larger between alternatives that have smaller error difference. The error difference between two departure time alternatives equals the standard deviation of the scheduling variables multiplied by the departure time shift between them (de Jong et al. 2003).

Table 5 shows that the standard deviation of SDE is larger than that of SDL. Departure time shifts earlier are thus less sensitive to generalized cost changes than arrival time shifts later of the same magnitude. This means that there is more unexplained variation among drivers in constraints or preferences for earlier departure than late arrival. The standard deviation of the mode switch error component is 5.052 (see η in table 4). Hence, for time shifts smaller than 72 minutes later or 45 minutes earlier, time shifting is more sensitive than mode choice to travel cost changes.

The assumption that the random parameters are constant across all observations for the same individual appears to be crucial for achieving plausible substitution patterns in the present model. If, on the contrary, we treat all observations as independent from each other, the standard deviations of the random parameters SDE and SDL become insignificant. We can thus conclude that the disutility of departing earlier than PDT and shifting expected arrival time later than PAT is basically proportional to the time shift and varies in the population. It is consistent however across the observations from the same individual.

If we do not take repeated measures bias into account, variation in the random parameters thus becomes significantly underestimated and the model col-

Table 5: Mean and standard deviation of the random parameters for commuters with flexible schedule and other trips†

Parameter	Mean	Std. Dev.
COST	-0.0748	0.0626
SDL	-0.0563	0.0698
SDE	-0.0549	0.1108

† SDE and SDL are measured in [1/min] and COST has unit [1/SEK]

lapses to a nested logit model (the model is still nested since we have included mode choice). Note that we cannot apply the closed-form OGEV model to this data, which would have been faster in the application, since GEV models cannot accommodate correlation in unobserved heterogeneity.

4.4 Comparing the Segments

To facilitate a comparison between the different population segments, table 6 shows mean values of the random parameters as a proportion of the travel time parameters, for the three model segments. Taking the example of commuters with flexible schedule, these numbers should be interpreted as the disutility per minute of early departure being equivalent to 0.8 minutes of travel time (or 1 minute if departure time is shifted earlier than 7.30 a.m.), which means that on average commuters are willing to depart 10 minutes earlier to save 8 (or 10) minutes of travel time. For late arrival the corresponding value is about 8 minutes of travel time. For commuters with a fixed schedule both late arrival and early departure are more costly than in other model segments, in agreement with our a priori expectation.

Since the travel cost parameter can take values arbitrarily close to zero, the value of time cannot be computed directly. Still, we may compute valuation of money as a proportion of valuation of time. If the travel cost increased 10 SEK (1 Euro), 11 minutes' shorter travel times would, on average, compensate travellers with flexible schedules. In the segment for commuters with fixed schedules, the required compensation is 28 minutes of travel time. This is relatively high, and might be an effect of a policy bias against monetary cost. It is plausible however that commuters with a fixed schedule are more sensitive to travel cost, since this group has a lower average income.

Table 6 also shows that travel time uncertainty, relative to mean travel time, is less costly for travellers with flexible schedules as expected. For business trips, as opposed to the other segments, travel time uncertainty is costly also in choices where expected arrival time was shifted earlier than PAT.

Sensitivity for travel time uncertainty, or reliability, is normally computed as the ratio between sensitivity for standard deviation and sensitivity to mean

Table 6: Means of the random parameters expressed as a proportion of the parameter for the travel time (T)†

Parameter	Flexible schedule & Other trips	Fixed schedule	Business
$COST/T$	1.083	2.841	1.100
SDL/T	0.817	3.382	1.056
SDE/T	0.800	1.473	0.712
$(SDE_{7.30} + SDE)/T$	1.050		1.491
$(SDE_{7.00} + SDE)/T$		2.453	
Δ_{late}/T	0.198	0.528	0.472
Δ_{early}/T	*not sig.*	*not sig.*	0.292

† In the first column (Flex, Other) the values presented are weighted means between parents and others, who have different travel time parameters.

travel time (the reliability ratio). In the present study, the valuation of standard deviation of travel time is not estimated. If, however, assuming a lognormal distribution with the standard deviation of the underlying normal travel time is set to 1 for all departure times (which corresponds to the mean travel time we have assumed: $c = 1/3.$), standard deviation equals $\Delta_{late}/2.4$. The reliability ratio would thus be 2.4*0.20 = 0.48 for commuters with flexible schedule and $2.4 * 0.53 = 1.27$ for commuters with fixed schedule.For business trips the corresponding reliability ratio is 1.13 for late arrival and 0.70 for early arrival.

Note also that the valuation of the scheduled delay induce a higher disutlity per minute than the the unexpected delay, measured as the 95% confidence interval.

5 Validation

To assess the validity of the estimates of scheduling disutility we compare them with previous literature (see table 7), although the differences in definitions and data complicate the comparison. The time shifts used in Small (1982) and Noland et al. (1998) are much smaller than in the present analysis. However, because the model specifications and data differ between the studies we cannot isolate the effect of the larger departure time shifts on the scheduling disutility. The effect of larger time shifts could even work in different directions. On the one hand, they could imply a higher scheduling disutility per minute, since the whole day might have to be reorganised. On the other hand, larger shifts could imply a lower scheduling disutility per minute, if the cost of reorganising the day is reasonable. It is most likely however that large time shifts tend to increase the scheduling disutility for commuters with fixed working hours, since they presumably have

Table 7: Estimations of trade-off ratios of the parameter for SDE and SDL and the travel time parameters in the literature (studies referring to car users)

Studies	$SDE/TIME$	$SDL/TIME$
Small (1982), commuters	0.61	2.40
Noland et al. (1998), commuters	0.97	1.31
Dutch, commuters, flexible h	0.89	0.63
Dutch, commuters, fixed h	0.72	1.17
Dutch, other trips	0.96	0.94
West Midlands, commuters, flexible h	0.77	0.79
West Midlands, commuters, fixed h	1.70	7.15
West Midlands, other trips	0.67	0.87
Present study, commuters, flexible h / other trips	0.80	0.82
Present study, commuters, fixed h / school trips	1.47	3.38
Present study, business trips	0.71	1.06

smaller chances to reorganise the day.

The study by Small (1982) should be compared to the segment of commuters with fixed schedules, since few commuters had flexible working hours at that time. The scheduling disutility found in the present study is larger relative to travel time, which might be an effect of the larger time shifts. The scheduled delay parameters estimated in Noland et al. (1998) lie between those estimated for commuters with fixed and flexible hours in the present study. This makes sense since Noland et al. included commuters with both fixed and flexible hours.

The estimates further down in table 7 (labelled Dutch and West Midlands) are found in a tour-based study comparing the relative sensitivity of mode and departure time choice (Hess et al. 2006a). In these studies the time shifts are of about the same magnitude as in the present analysis. The estimated scheduling costs found in the present study are also well in line with those found by Hess et al. Scheduling disutility differs notably between commuters with fixed and flexible schedules, and shifts to later departure times are more costly than earlier ones. The error components also show a similar pattern as in Hess et al. The mode choice is less sensitive than the departure time choice to changes in observed generalized travel costs, unless the time shifts considered are large (45-90 min). Further, earlier time shifts are more sensitive to changes in the observed generalized travel costs than later departure time shifts of the same magnitude.

In comparing the valuations of travel time uncertainty using so called reliability ratios, the difference between studies seems to be even larger. Typical reliability ratios from the literature are 1.1-2.2 according to Bates et al. (2001). However, in the earlier study by Black and Towriss (1993), the values 0.7 and

0.55 are found. Noland and Polak (2002) suggest that the way of presenting travel time uncertainty to respondents might be an important source of the large discrepancies in the estimates of its valuation. This study indicates that the reliability ratio is dependent not only on population segment but also on planned deviations from most preferred time, which could be an explanation for the large variability of the reliability ratios estimated in the literature.

6 Conclusions and further work

The purpose of this study is to estimate a departure-time and mode-choice demand model for Stockholm. The main result is that the preference for scheduled delay is roughly proportional to the time shift and varies in the population, but is much more consistent within an individual. Another interesting finding is that scheduled delay induce a much higher disutlity per minute than unexpected delay, the latter measured as the 95 interval. The disutilty arising from an uncertain travel time also depend on the scheduled delay.

Since the model included error components for mode and time of scheduled delay shifts the patterns of substitution between was estimated. For time shifts smaller than 72 minutes later or 45 minutes earlier, time shifting is more sensitive to generalized cost changes than mode choice. Departure time shifts earlier are more sensitive than arrival time shifts later, which means that there is more unexplained variation among drivers in preferences for earlier departure than late arrival.

The estimated demand model is currently being implemented together with a dynamic assignment model (Kristoffersson 2007). However, to control for the fact that the response scale normally is distorted in SP data, the implemented model has been re-estimated, combining the SP data with RP data (see Brjesson (2008)).

Acknowledgement

This research was funded by the Swedish Agency for Innovation Systems (VINNOVA) and the Swedish Road Administration. I am indebted to Staffan Algers, Andrew Daly, Leonid Engelson and Jonas Eliasson for providing many useful insights and comments on the work. Thanks also to Fredrik Davidsson for providing traffic supply data. I would also like to thank Pia Koskenoja for comments on earlier versions of this paper. Finally, I would like to thank anonymous referees for useful observations.

A Models for other segments

Table 8: Departure time model for commuters with fixed schedule and school trips

Number of MLHS draws:	2000		
Number of observations:	1133		
Number of individuals:	149		
Null log-likelihood:	-1244.73		
Final log-likelihood:	-759.485		
Rho-square:	0.38894		
Name	Value	Std err	t-test
β_{COST}	-2.824	0.201	-14.08
σ_{COST}	1.271	0.202	6.28
β_{SDE}	-3.702	0.457	-8.09
σ_{SDE}	1.348	0.333	4.05
β_{SDL}	-2.377	0.159	-15.00
σ_{SDL}	0.950	0.171	5.55
$SDE_{7.00}$	0.033	0.010	3.22
T	-0.034	0.006	-5.44
Δ_{late}	-0.018	0.006	-3.20
$C_P T$	-6.921	2.019	-3.43
η	-4.994	0.836	-5.97
T_{PT}	-0.098	0.031	-3.16
T_{PTrep}	-0.045	0.029	-1.54
$SeasonTicket$	6.837	1.761	3.88

Table 9: Mean and standard error of the random parameters for commuters with fixed schedule and school trips

Parameter	Mean	Std. Dev.
$COST$	-0.095	0.110
SDL	-0.113	0.095
SDE	-0.049	0.072
Correlation of SDE and SDL is not sig.		

Table 10: Departure time model for business trips

Number of MLHS draws:	5000		
Number of observations:	521		
Number of individuals:	74		
Null log-likelihood:	-353.13		
Final log-likelihood:	-282.27		
Rho-square:	0.21837		
β_{COST}	-4.342	0.929	-4.67
σ_{COST}	2.277	0.820	2.78
β_{SDE}	-4.079	0.732	-5.57
σ_{SDE}	2.474	0.806	3.07
β_{SDL}	-3.059	0.314	-9.75
σ_{SDL}	-0.190	0.761	-0.25
σ_{SDL_SDE}	0.937	0.341	2.75
$SDE_{7.30}$	-0.047	0.011	-4.19
T	-0.061	0.009	-6.46
Δ_{late}	-0.029	0.007	-4.07
Δ_{early}	-0.018	0.008	-2.36

Table 11: Mean and standard error of the random parameters for business trips

Parameter	Mean	Std. Dev.
$COST$	-0.067	0.137
SDL	-0.064	0.062
SDE	-0.043	0.172
Correlation of SDE and SDL is 0.936		

References

Bates, J., Polak,J., Jones, P. and Cook, A.J, 2001. The valuation of reliability for personal travel. *Transportation Research Part E*, 37 (2-3), 191-229.

Bhat, C., 1998a. An Analysis of Travel Mode and Departure Time Choice for Urban Shopping Trips. *Transportation Research Part B*, 32 (6), 361-371.

Bhat, C., 1998b. Accomodating flexible substitution patterns in multidimensional choice modelling: formulation and application to travel mode and departure time choice. *Transportation Research Part B*, 32 (7), 455-466.

Bierlaire, M., 2005. *BIOGEME Version 1.4.*
Available from: http://roso.epfl.ch/biogeme

Black, I.G., Towriss, J.G., 1993. Demand Effects of Travel Time Reliability. Centre for Logistics and Transportation, Cranfield Institute of Technology.

Brownstone, D., Small, K, 2005. Valuing time and reliability: assessing the evidence from road pricing demonstrations. *Transportation Research Part A*, 39 , 279-293.

Brjesson, M., 2008. Joint RP-SP Data in a Mixed Logit Analysis of Trip Timing Deci-

sions. *Transportation Research Part E*, 44 (6) , 1025-1038.

Cirillo, C., Daly, A.J., Lindveld, K., 2000. Eliminating bias due to the repeated measurements problem. *In:* J.D. de Ortzar, eds. *Stated Preference Modelling Techniques.* London: PTRC, 137-154.

Fosgerau, M. and Karlstrm, A., 2007. *The value of reliability.* Available from: http://mpra.ub.uni-muenchen.de/5733/1/MPRA_paper_5733.pdf

Garver, D.P., 1968. Headstart Strategies for Combating Congestion. *Transportation Science*, 2 (3), 172-181.

Hess, S., Polak, J.W., Daly, A., Hyman, G., 2007 Flexible Substitution Patterns of Mode and Time of Day Choice: New Evidence from the UK and the Netherlands. *Transportation*, 34 (2), 1572-9435.

Hess, S., Train, K., Polak, J.W., 2006. On the use of a Modified Latin Hypercube Sampling (MLHS) Method in the Estimation of a Mixed Logit Model for vehicle choice *Transportation Research Part B*, 40, 147-163.

Hollander, Y, 2005. Direct versus indirect models for the effects of unreliability. *Transportation Research Part A*, 40 (9), 699-711.

de Jong, G., Daly, A., Pieters, M., Vellay, C., Bredley, M. And Hofman, F., 2003. A model for time of day and mode choice using error components logit. *Transportation Research Part E*, 39 (3), 245-268.

Kristoffersson, I, 2007. *Implementation of Model for departure time Choice.* Presented at the TRISTAN VI conference, Phuket Island, Thailand 2007

Lam, T.C, Small, K.A, 2001. The value of time and reliability: measurement from a value pricing experiment. *Transportation Research Part E*, 37 (2-3), 231-251.

Noland, R.B. and Small K.A., 1995. Travel-Time Uncertainty, Departure Time Choice, and the Cost of Morning Commutes. *Transportation Research Record*, 1493, 150-158.

Noland, R.B., Small K.A., Koskenoja, P.M., Chu, X., 1998. Simulating travel reliability. *Regional Science and Urban Economics*, 28, 553-564.

Noland, R.B., Polak, J.W., 2002. Travel time variability: a review of theoretical and empirical issues. *Transport Reviews*, 22 (1), 39-54.

Polak, J.W., 1987. *Travel time variability and departure time choice: A Utility Theoretic Approach.* Polytechnic of Central London: Transport Studies Group, Discussion Paper No. 15.

Press, W.H., Flannery, B.P., Teukolsky, S.A.,Vetterling, W.T., 1988. *Numerical Recipes in C: The Art of Scientific Computing.* Cambridge University Press, Cambridge

SACTRA (Standing Advisory Committee on Trunk Roads Assessment), 1994. *Trunk Roads and the Generation of Traffic.* London: Department of Transport, United Kingdom.

Small, K.A., 1982. The scheduling of consumer activities: work trips. *American Economic Review.* 72 June 467-479.

Small, K.A., 1987. A discrete choice model for ordered alternatives. *Econometrica*, 55-2, 409-424.

Small, K.A., Noland, R., Chu, X.,Lewis, D., 2000. *Valuation of Travel-Time Savings and Predictability in Congested Conditions for Highway User-Cost Estimation.* NCHRP Report 431. Washington: Transportation Research Board, US National Research Council.

Train, K., Sonnier, G., 2005. Mixed logit with bounded distribution of correlated partworths. *In:* A. Alberini and R. Scarpa, eds. *Applications of Simulation Methods in Environmental Resource Economics.* Dordrecht, The Netherlands: Springer, 117-134.

Transek, 2000. *Bilisters tids- och kostnadsuppfattning - Intervjuer med arbetspendlare.*

Stockholm: Transek, Sweden.
Vickrey, W.S., 1969. Congestion theory and transport investment. *American Economic Review (Papers and Proceedings)*. 59, 251-261.
99