

Modelling departure time and mode choice

Andrew Daly
RAND Europe & ITS Leeds
Leiden
The Netherlands
daly@rand.org

Stephane Hess
Centre for Transport Studies - Imperial College London
London
United Kingdom
stephane.hess@imperial.ac.uk

John W. Polak
Centre for Transport Studies - Imperial College London
London
United Kingdom
j.polak@imperial.ac.uk

Geoffrey Hyman
Department for Transport
London
United Kingdom
geoff.hyman@dft.gsi.gov.uk

Charlene Rohr
RAND Europe
Cambridge
United Kingdom
crohr@rand.org

The opinions expressed in this paper are those of the authors and do not necessarily represent the views or policies of the UK Department for Transport.

ABSTRACT

Modelling the temporal response of travellers to transport policy interventions has rapidly emerged as a major issue in many practical transport planning studies and is recognised to hold particular challenges. The importance of congestion and its variation over the day, together with the emergence of time-dependent road user charging as a policy tool, emphasise the need to understand whether and how travellers will change the timing of their journeys. For practical planning studies, analysts face a major issue of relating temporal changes to other behavioural changes that are likely to result from policy or exogenous changes. In particular, the relative sensitivity of time and mode switching has been difficult to resolve.

This paper describes a study undertaken to determine the relative sensitivity of mode and time of day choice to changes in travel times and costs and to investigate whether evidence exists of varying magnitudes of unobservable influences in time of day switching. The study draws on data from three related stated preference studies undertaken over the past decade in the United Kingdom and the Netherlands and uses error components logit models to investigate the patterns of substitution between mode and time of day alternatives. It is concluded that the magnitude of unobserved influences on time switching depends significantly on the magnitudes of the time switches considered. With time periods of the magnitude generally represented in practical modelling, i.e. peak periods of 2-3 hours, time switching is generally more sensitive in this data than mode switching. However, the context of the modelling and the extent to which relevant variables can be measured will strongly influence these results.

1. INTRODUCTION

One of the main problems now confronting the users of roads is congestion, which is responsible for both loss of time and unreliability in journeys. Yet congestion is not a uniform phenomenon and varies over the day. Some travellers already adjust their departure times to avoid the worst congestion and planning authorities have begun to think about encouraging this retiming by applying peak hour charging to the most congested roads or areas. This idea is consistent with the economic concept of marginal cost pricing, whereby road users pay for the marginal congestion they impose on others, i.e. the charge needs to be higher in the peaks than at other times.

The specific interest in this research arises in the assessment of the value for money of transport policies and schemes. The UK Department for Transport issues guidance for planners developing models to forecast and appraise policies. These models need to incorporate the potential impact of time switching along with other behavioural responses to policy and the Department wishes to extend its guidance to cover such models. In order to contribute to this guidance, greater knowledge is required on the relative importance of time period and mode choice.

Consider demand models with a nested logit structure. All else being equal, if time of day choice is *lower* than mode choice in the nesting, a change in the cost of travelling at different times will be modelled to have a *greater* effect than changes in the costs of travelling on different modes. Conversely, if time of day choice were to be placed *higher* than mode choice, changes in the cost of travelling at different times will be modelled to have a *lesser* effect than changes in the costs of travelling on different modes. The need for nesting rules of this kind arises from the requirement for theoretically correct signs for the effects of cross-substitution between mode choice and time period choice.

Theory alone cannot determine which of the alternative nesting structures is correct; empirical evidence is required in order to resolve this dilemma. The investigation reported here arises from the need to provide such a body of evidence. The central aim of the research is thus to investigate the relative sensitivities to journey time and cost changes of departure time and mode switching.

Since both congestion and many of the consequent policy responses to congestion have strong time of day related components, as the salience of congestion as a policy concern has grown in recent years, so has the importance of developing theoretically sound yet practically applicable approaches to modelling the timing of travel, particularly the departure time of trips during congested peak periods.

A number of different modelling approaches have been proposed in the literature which was reviewed extensively in Bates (1997) for the UK Department of Transport. Building on ideas originally proposed by Vickrey (1969), several authors have presented frameworks in which the choice of departure time is modelled deterministically and as a continuous quantity (e.g., Arnott *et al.*, 1990; de Palma *et al.*, 1997; Hyman, 1997; van Vuren *et al.*, 1999). A related set of studies have modelled departure time jointly with route choice using model systems in which a continuously variable choice of departure time is linked to a discrete choice of route (e.g., Mannering *et al.*, 1990; Mahmassani and Chang; 1985, Mahmassani *et al.*, 1991). More recently, interest has also developed in formulating continuous models of departure time choice within the framework of hazard based duration models (e.g., Bhat and Steed, 2002; Wang, 1996). In addition, models of individual trip departure time are also increasingly being embedded in more general models of activity choice and scheduling behaviour (see, e.g., Ashiru *et al.*, 2003 and the work reviewed therein).

However, the dominant approach to modelling departure time, both in the academic literature and in practice, involves re-formulating the underlying continuous departure time choice problem as a choice problem involving a finite number of discrete time periods and modelling the choice between these periods within the framework of random utility theory. This approach, first proposed in the work of Cosslett (1977) and Small (1982), has been widely applied using both revealed preference (e.g., Abkowitz, 1981; Athanassiou and Polak, 2001; Bhat 1998a,b; Bradley *et al.*, 1998; Chin, 1990; Hendrickson and Plan, 1984; McCafferty and Hall, 1982; Small, 1982,1987) and stated preference (e.g., Bates *et al.*, 1990; Daly *et al.*, 1990; de Jong *et al.*, 2003; Hess *et al.*, 2005; Johnston *et al.*, 1989; Polak *et al.*, 1991; Polak and Jones, 1994) data sources.

Models based on this *time period choice* approach are typically formulated in terms of a trade-off between, on the one hand, the time of day varying travel times and costs experienced by travellers and on the other hand, travellers' inherent preferences for undertaking certain activities at certain times of day. The characterisation of these temporal preferences is challenging and the most commonly used approach is to use a version of the concept of schedule delay (Vickrey, 1969) to quantify the loss in utility associated with shifting a departure earlier or later relative to the preferred (or, more often, the actual) time of departure of the existing trip.

The schedule delay formulation works well in diagnostic and exploratory modelling, but when time period choice models are being used in long term forecasting applications, the embedding of this sample type information in the utility function can be highly problematic, since the notion of 'existing trip' is not meaningful in a forecasting context and, moreover, the characteristics of forecast trips are typically not available at the same level of temporal precision as that available in the estimation sample data set (a similar problem of course arises in the use of other sample information in forecasting applications). Hence when time period choice models are developed for forecasting applications, temporal preferences of travellers are captured by the use of a set of constants, associated with the different time-periods. Depending on the degree of granularity employed in the definition of the time periods, this formulation can lead to significant problems with identification and interpretation (Hess *et al.*, 2005), as well as heightened computational cost. These problems are compounded when time period choice models are specified in terms of tours rather than trips (e.g., de Jong *et al.*, 2003; Polak and Jones, 1994) since the number of alternatives and constants increases substantially. Similar issues apply in many other areas of research where a large number of constants are to be identified, such as in the analysis of spatial choice-processes.

A specific problem arising in SP data is that, because of its hypothetical nature, one cannot be sure that the extent of response is adequately captured. Experience suggests that trade-offs are captured reasonably well in SP data, but that the overall scale of response is often distorted. In other contexts, this problem is overcome by joint RP/SP analysis, but for the reasons explained, RP data of time choice is usually unsatisfactory. A solution may be found by using the SP data to conduct a simultaneous study of time and mode choice, with the aim of obtaining the ratio of sensitivities between these two choices. Apart from the fact that this ratio is of considerable importance in itself, this approach also gives the possibility of simultaneous analysis with RP mode choice data to obtain an overall correct scale of response. The approach relies on the assumption that any distortion of the scale by the SP data elicitation method is equal between time and mode choice, but this assumption appears more justified in the present state of understanding than an alternative which relies on equality between elicitation methods.

During the past decade, the authors have been involved in three substantial SP studies into the joint choice of mode and time of travel. These studies have been undertaken using a broadly similar approach to data collection but have been carried out with quite different populations (two in the UK, one in the Netherlands) and at different times. These data provide

an excellent opportunity for a more rigorous comparative assessment of evidence than has hitherto been possible. The objectives of the work described in this paper are therefore to determine the relative sensitivity of mode and time of day choice to changes in travel times and costs; to investigate whether evidence exists of varying magnitudes of unobservable influences in time of day switching; and to compare these results across different travel segments and data sets. The conclusions will inform the guidance issued by the UK Department for Transport to local planners in Britain.

The use of three different data sets, two of them collected in the UK, allows the Department to base its guidance on the widest range of information available. It would of course be desirable to use a larger number of data sets, but few data sets of suitable type are available. It was also necessary to anticipate, from the outset, that the use of a range of data sets would introduce inconsistencies in the results and the findings of the study are therefore based on the balance of the information and not always confirmed by all of the data used in the analysis.

The scales of response of the time and mode choices in these data sets are related to the unmeasured aspects of those choices, which are treated as random components in the models. The methods used in the present work are based on an 'error component' formulation that aims to characterise explicitly the structure of the unobservable influences on choice and hence the sensitivity of different choice dimensions to changes in observable travel times and costs. This allows greater flexibility and precision in the isolation of choice structure than was possible in most previous studies, which used more restricted modelling formulations.

This work forms the first of two stages in an attack on the problem and describes the more detailed attack on the issue using sophisticated modelling tools. The second stage, not reported in the current paper, simplifies these models to obtain tools which can be used in planning practice.

The paper is set out in four further sections. The first of these describes the three data sources that are used and the next describes the theoretical background and modelling approach employed. The modelling results are presented in the following section and a final section discusses these results and presents conclusions.

2. DATA SOURCES

This paper makes use of data from three separate studies of mode and time of day choice in which the authors took part over the past decade. Each of these data collection exercises formed part of larger urban, regional or national model development projects. These are (in chronological order of the collection date): the APRIL model for London (c.f. Bates and Williams, 1993; Polak and Jones, 1994), the Dutch National Model System (c.f. de Jong et al, 2003) and the PRISM model developed for the West Midlands region of the United Kingdom (RAND Europe, 2004). In the remainder of this paper, these three data sets will be referred to respectively as London, Dutch and West Midlands.

All three data sets were collected through Stated Preference (SP) surveys and these surveys shared a number of important features. These include:

- All three surveys concentrated principally on the re-timing and/or mode switching of existing car tours, although the Dutch survey also collected data from train travellers. A motivating policy interest in all three studies was the potential response of travellers to road user charging initiatives, so that this issue was highlighted in the survey rubric and protocols.
- In each survey, respondents were presented with a number of travel alternatives involving the re-timing of an existing tour or the switch of this tour to an alternative

mode. In the case of the Dutch and West Midlands data, the retiming alternatives were defined as “base”, “retimed earlier”, and “retimed later”, with the “base” alternative being close in departure time to the actual observed tour. A slightly different approach was adopted in the London data, where the retiming alternatives were constructed to present travellers with *inter alia* explicit trade-offs between retiming the departure of a tour and changing the amount of time spent conducting the destination activity. The choice-sets in the London survey also included a “not travel” alternative.

- In all the surveys, the travel alternatives were presented to respondents in the form of complete tours, comprising explicit and linked outbound and return legs, with the exception of non-home-based business travellers in the Dutch and West Midlands data sets, where only a one-way journey was considered. Aside from this subgroup, travellers are thus trading time and cost differences against retiming that would involve rescheduling the outbound *and* return legs, i.e. potentially involving a change in the amount of time spent at the destination. Although the detailed experimental design differed somewhat across the different surveys, in each of them respondents were presented with 12-15 SP replications.

The London data set was collected in 1992 from a sample of approximately 1000 car drivers contacted at various locations in central, inner and outer London. The Dutch data was collected in 2000 from a sample of approximately 1000 travellers, contacted at a selection of sites across The Netherlands, concentrating on areas where road and rail congestion was encountered in peak-period journeys. The West Midlands data set was collected in 2003 from a sample of over 550 car drivers undertaking journeys entirely within the West Midlands county region. In each survey, the main travel purposes distinguished were commuting, business and other. The data sets are related to each other in that the Dutch data was designed after a review which covered the London work (which itself was undertaken in the knowledge of earlier Dutch work), while the West Midlands data was explicitly designed to follow the main features of the Dutch work.

Although detailed differences exist amongst these data sets (for example in the associated socio-demographic information), there is thus an unusually high level of consistency in the treatment of key SP design features. This provides an excellent opportunity to undertake a comparative analysis of the mode and time of day substitution patterns in these data sets using similar model forms, whilst minimising concerns regarding the potential confounding influence of differences in the data collection process.

3. THEORETICAL BACKGROUND AND MODELLING APPROACH

The framework within which the present work falls is that of discrete choice. This framework is natural in the study of SP data, in which respondents are asked to choose among three or four alternatives (in the three data sets studied). However, for choice of departure time, the discrete choice framework requires the analyst to define periods within which choice is defined to fall. The application of the choice models developed in this work to practical studies will thus require time periods to be defined which aggregate the large number of moments at which the traveller could depart into a finite number of periods. This aggregation may affect the sensitivity of time choice, an issue to which we return subsequently.

3.1 Modelling flexible substitution patterns

Random utility models are the most widely used tools in discrete choice analysis of travel behaviour (c.f. Ben-Akiva and Lerman, 1985; Train, 2003). In this framework, a decision-maker chooses the alternative with the highest utility, where the utility of an alternative i is given as the random variable:

$$U_i = V_i + \varepsilon'_i = f(\beta, x_i) + \varepsilon'_i, \quad [1]$$

where V_i is the *observed* part of utility, and ε'_i is the unobserved part of utility. The observed utility is a function of a vector of tastes of the decision-maker, β , and a vector of attributes of the alternative and socio-demographic attributes of the decision-maker, x_i . Different assumptions about the joint distribution of the error-terms ε'_i ($i=1, \dots, N$) lead to different model structures, and thus different functional forms for the choice probabilities. The most well-known random utility model, the Multinomial Logit (MNL) model (McFadden, 1974), is obtained with the assumption that the individual elements in ε' are distributed independently following a type I extreme-value (Gumbel) distribution. More flexible model forms are obtained with more advanced distributions, notably by allowing for correlation between the individual elements contained in ε' . This leads to the family of Generalised Extreme Value (GEV) models (McFadden, 1978), of which the Nested Logit (NL) model (Williams, 1977; Daly and Zachary, 1978; McFadden, 1978) is the best-known example.

The sensitivity of the model to changes in the attributes of the alternatives will clearly depend both on the values of the taste parameters β and on the balance between the measured and unmeasured parts of the utility difference. Specifically, and whatever the precise form of the model and tastes, the sensitivity of the choice of one alternative over another is inversely proportional to the standard deviation of the utility difference between them, so that, in particular, the sensitivity of the choice between alternatives that share common unobserved components will be greater than that between alternatives that do not. When there are more than two alternatives, for example when a traveller may switch mode as well as time of travel, it is possible that the sensitivity is greater for changes to one alternative than to another. The analysis of this difference in sensitivity is the main topic of the present paper. This structural feature is represented in utility theory by the variance of the error difference, and the key issues for the present study are whether this variance is greater between time choices which differ by larger or smaller amounts of time and whether it is greater between time alternatives or mode alternatives.

In recent years, a number of flexible choice model specifications have been proposed that permit the explicit characterisation of the structure of the unobservable influences on choice. In this paper, we make use of one such model, the Mixed Multinomial Logit (MMNL) model (c.f. McFadden and Train, 2000; Train, 2003). In the MMNL model, the utility function is given by:

$$U_i = V_i + \eta_i + \varepsilon_i, \quad [2]$$

where V_i is defined as in equation [1] and where η_i represents one or more additional components of the unobserved part of utility, independent of ε_i , which is assumed to follow a Gumbel distribution, independent across alternatives and observations. The error components η_i will in general be specified to vary both across alternatives and individuals. The MMNL structure can be exploited in two distinct, though mathematically equivalent ways, using either a random coefficients or error components formalism (c.f. McFadden and Train, 2000). In this paper we adopt the latter approach in which some elements of η are allowed to be shared across some alternatives, thus inducing correlation in the unobserved part of utility for these alternatives (and hence greater choice sensitivity). This allows the error components logit (ECL) structure to closely replicate the correlation patterns in model systems using a nesting structure, such as NL, whilst at the same time accommodating additional effects, such as random taste heterogeneity and heteroskedasticity, which cannot be accommodated in the NL model.

In this paper, the ECL structure is used to estimate error components that measure the relative sensitivity of changes in mode and changes in departure-time and to accommodate heteroskedasticity in the unobservable influences on retiming. For the departure-time alternatives, the η_i component was used to represent the possibility that for a given mode, departure time alternatives share common disturbances which are such that departures close to one another in time would have utilities that were closely correlated; this was achieved by specifying that the relevant component of η_i should have a variance that was proportional to the time difference between the alternatives. For mode switching, a further component was included in η_i , representing the unmeasured difference in utility given by the alternative mode and experienced in common by all departure time alternatives using that mode. An examination of the variance of the error components can then give an indication of the relative sensitivity of mode and departure time switching.

Due to the differences in design between the surveys, the approach used was not entirely identical. In particular, while, for the Dutch and West Midlands data, the retiming error-components were associated with a variable giving the shift away from the base alternative, in the London data, the shift was measured from the observed departure time (given that no explicit *base* alternative was included in the London surveys). The differences between the two approaches should however be marginal, given that the *base* departure time was always close to the observed departure time. Finally, in all three data sets, the ‘schedule-delay’ coefficients (early and late departure changes) were associated with the shift away from the preferred departure times, in order to accommodate potential heteroskedasticity in the retiming response.

3.2 Generic Choice Model Specification

Drawing on the earlier work of Polak and Jones (1994) and de Jong *et al.* (2003), the generic model specification adopted in this study was based on the idea of simultaneously modelling the time of day of the outward trip in the tour and the activity duration at the destination, with (in addition to the normal travel cost and travel time elements) explicit penalties for shifts from the preferred departure time to earlier or later departure times (c.f. Vickrey, 1969, Small, 1987) and for shorter or longer than preferred destination durations. Thus, in our analysis, the generic form of the observed component of utility for a travel alternative takes the form of:

$$U_i = \beta_{TT} \cdot TT(i) + \beta_{TC} \cdot TC(i) + \beta_{SDE} \cdot SDE(i) + \beta_{SDL} \cdot SDL(i) + \beta_{PTI} \cdot PTI(i) + \beta_{PTD} \cdot PTD(i) + \dots \quad [3]$$

where $TT(i)$ gives the travel-time of alternative i , with $TC(i)$ giving the corresponding travel-cost. The early and late schedule-delay attributes $SDE(i)$ and $SDL(i)$ are defined as:

$$SDE(i) = \max(0, PDT - DT(i)) \quad [4]$$

and

$$SDL(i) = \max(DT(i) - PDT, 0), \quad [5]$$

where PDT gives the preferred departure time, and $DT(i)$ gives the departure time for alternative i . Finally, $PTI(i)$ and $PTD(i)$ give the participation-time increases and decreases respectively, when compared to the preferred participation time (difference between preferred outbound arrival time and preferred return departure time), PPT , such that:

$$PTI(i) = \max(0, PT(i) - PPT) \quad [6]$$

and

$$PTD(i) = \max(PPT - PT(i), 0), \quad [7]$$

where $PT(i)$ gives the participation time for alternative i . The various β parameters give the marginal returns of increases in the associated attribute by one unit. A number of different additional parameters were included in the models; these were mainly constants linked to socio-demographic attributes, and are not included in equation [3] for clarity of presentation. In some of the models, segmentations by socio-demographic or journey purposes were also used, for example specifying separate cost or time coefficients for different groups of travellers included in a common model. The success with using such segmentations and other interactions with socio-demographic variables was mixed, and varied across data sets, which is a reflection of the differences across data sets in the quality and level-of-detail of the socio-demographic information.

Note that this specification makes extensive use of disaggregate information regarding the characteristics of existing travel (e.g., via the shift variables), obtained from the SP sample. Since the principal objective of this paper is the development of diagnostic (rather than forecasting) models, this is considered appropriate. Ongoing work is exploring the implication of these results for forecasting.

Based on the discussions above, the following error components were added to this deterministic specification:

$$U_i = \dots + \sigma_E \cdot \xi_1 \cdot EDEP(i) + \sigma_L \cdot \xi_2 \cdot LDEP(i) + \sigma_M \cdot \xi_3 \cdot MODECHANGE(i) + \varepsilon_i \quad [8]$$

where ξ_1 , ξ_2 and ξ_3 are random variates drawn independently from the standard Normal distribution, σ_E , σ_L , and σ_M are the standard deviations of the error components, and ε_i is an error drawn from a type I extreme value distribution, independent across both alternatives and choice occasions. With this specification, $MODECHANGE(i)$ is a dummy variable that is set to 1 if alternative i represents a change of mode when compared to the observed trip. This dummy variable thus determines whether the mode-change error-component is included in the utility function of alternative i . The other two attributes $EDEP(i)$ and $LDEP(i)$ give the shift in departure-time; in the London models, this shift was relative to the preferred departure-time (such that $EDEP=SDE$, and $LDEP=SDL$, using the definition from equations [4] and [5]), while in the Dutch and West Midlands models, the shift was relative to the departure-time in the base alternative (such that $EDEP=0$ for the “retimed late” alternative, and $LDEP=0$ for the “retimed early” alternative). In each case, the utility of an alternative i contains at most one of these two error-components, where, due to the multiplication by $EDEP(i)$ and $LDEP(i)$ respectively, the variances of the error-components are thus proportional to the extent of the shift in departure-time. For the London data only, respondents were also offered the option to indicate that they would not travel. The utility function for this alternative consisted of a constant plus an error component ($\sigma_{NT} \cdot \xi_4$).

Estimation of this ECL model yields estimates of the substantive parameters (β_{TT} , β_{TC} , β_{SDE} , β_{SDL} , β_{PTI} and β_{PTD}), the standard deviations of the error components (σ_E , σ_L , σ_M and σ_{NT}), and the associated standard errors. The relative magnitude of the variances of the error components associated with the mode and time of day dimensions provide a measure of the relative sensitivity of these two dimensions to changes in the substantive attributes of travel (with smaller variances of the error components implying, *ceteris paribus*, higher sensitivity). It should be noted that the models presented in this paper do not include any treatment of the ‘repeated measures’ property of SP data (e.g., there are no individual level error components). Experience suggests that this is likely to lead to an overstatement (sometime substantially) of the significance of certain parameters, but not to major bias in the central estimates of the parameters themselves; see, for example, Cirillo *et al.* (2000). This should be borne in mind in interpreting the results presented below.

The aims of the work can be achieved by examining the results obtained for the σ terms:

- the significance and magnitude of σ_E and σ_L indicate the significance and magnitude of heteroskedasticity between time-shift alternatives as a function of the size of the shift in time;
- the relative values of σ_E and σ_L indicate whether earlier or later shifting is more sensitive;
- the relative value of σ_M to σ_E and σ_L (together with the size of time shifts) indicates the relative sensitivity of mode choice to time choice; thus if σ_M is larger than σ_E and σ_L , when the latter are multiplied by a given time shift, then we may conclude that, for time shifts of that size, mode choice is less sensitive than time shifting.

As the description of the aims suggests, the main interest in this paper lies in the estimates obtained for the variances of the different error-components, and their relative values across purposes and data sets. Consequently, the results for the β coefficients are of less concern. As such, the present paper is primarily concerned with analysing model structure for time-of-day modelling, and the estimates of taste coefficients should not necessarily be seen as definitive estimates of the marginal utilities of the associated attributes. This applies specifically to the calculation of value of time measures on the basis of estimates produced for the values of changes in travel-time and cost, where satisfactory estimates are available from other sources. However, the values estimated for schedule delay, where less information is generally available, may be of interest.

4. ESTIMATION RESULTS

For each of the three data sets, the generic model specification set out in equations [3] to [8] was separately estimated for commuting, business and other travel purposes. Where appropriate, further purpose-specific sub-segmentations were used. In addition, the generic specification was refined in a number of ways during the development of the estimation work. Such refinements included the introduction (where appropriate) of inertia dummy variables capturing the influence of existing choices, the testing for simple income effects via segmentation of cost variables and the introduction of socio-demographic factors as segmentation variables for certain travel attributes. A substantial body of empirical results were generated. The sections that follow summarise the main features of these results, placing particular emphasis on the findings in relation to the standard deviations of the error components (σ) associated with the time of day and mode choice dimensions.

4.1 London results

Table 1 summarises the estimation results for the London data set. These results are generally plausible, but with a rather variable pattern of significance across the different travel purpose segments. Overall, the implied values of time are plausible but a little low, notwithstanding that the data were collected over a decade ago. Problems were encountered in estimating a marginal utility of car travel-time for commuters, and public transport travel-time for business travellers. Similar problems were encountered in the use of a generic travel-time coefficient, such that only one mode-specific coefficient could be estimated in each of these segments.

Amongst commuters, there is a higher sensitivity to shifts to a later departure than to shifts to an earlier departure, and for the former, there are also significant differences between workers with flexible and fixed work-hours. Commuters are also sensitive to increases in the time spent at the destination, though not to reductions. By contrast, business travellers are sensitive to both increases and reductions in time spent at the destination and are also relatively more sensitive to retiming of the departure time to earlier or later times than is the case for

commuters. For all travellers, the ECL model yielded significant error components associated with a shift to a later departure time, indicating the presence of heteroskedastic unobservables affecting late shifts (perhaps related to unobserved variation in the degree of constraint in timing at the destination) but no error components were found for shifting to an earlier time, and only for 'other' travel was a significant error component found associated with a change of mode. The no-travel error component was significant for commuting and 'other', but not for business travel. The findings regarding choice structure and substitution patterns from the London data are rather mixed. The results for commuters and business travellers suggest a greater level of substitution between alternative modes than for switching to later (but not earlier) times of day, whereas the results for leisure and shopping purposes suggest the converse for this segment.

4.2 Dutch results

Table 2 summarises the estimation results for the Dutch data set. Initial model results suggested that it would be preferable to estimate separate models for commuters with fixed and flexible working hours and to distinguish between employment-related commuting and travel to and from education. In conjunction with the model for 'others' and business, this resulted in a total of five purpose segments. In contrast to the London data, where relatively few socio-demographic factors were found to be significant, in the Dutch data, there is evidence of significant variation in choice behaviour across different socio-demographic groups. This manifests itself both in the form of direct effects in the utility function (via dummies) and in the form of separate parameters for substantive travel attributes across segments. This may in part reflect the fact that the Dutch data included both car *and* train travellers and therefore may involve sampling from a more heterogeneous underlying population of both individuals and travel experiences than was the case with the London data.

For commuters with flexible working hours, all coefficients have the expected sign, although several of the constants, in addition to the cost coefficient for compensated rail travel, and the decreased participation time penalty, are not significant at the 95% level. The results in general indicate that travellers in this segment are sensitive both to changes in the timing of tours and in the amount of time spent at the destination. There is also evidence of differential sensitivity to changes in travel time by car and public transport and of significant variations in the sensitivity to changes in travel costs according to income. Two error-components, namely that associated with a shift in the early departure time and that associated with a change of mode, were found to be significant, suggesting that there is more heterogeneity of response to earlier times and to mode switch, causing lower aggregate elasticity for early departure and mode changes than for late departure. The results for commuters with fixed working time are broadly similar to those for flexible commuters, but as expected, those with fixed working time arrangements show relatively greater sensitivity to shifts in departure time and to decreases in participation time at the destination. In the fixed commuter segment, all three error components are significant, and their relative magnitudes suggest the greatest elasticity for changes to the early alternative, followed by the late alternative, and the mode-shift alternative (for an average shift of 90 minutes).

For business travellers, important gains in model fit were achieved by using a log-transform of the travel cost variable and by introducing segmentations based on home based or non home based travel (in a common model). For non-home based travel, no information is available on activity duration, such that no participation coefficients are estimated for this subgroup. The estimation results indicate that business travellers are sensitive both to the retiming of departures and to changes in the duration of the destination activity, with the former having a stronger effect than the latter, and that these sensitivities vary significantly between car and train travellers. The error-components associated with shifts in the earlier and later departure

time were virtually indistinguishable, such that a common error-component was used, leaving the model fit almost completely unaffected; the remaining two error-components suggest a greater elasticity for time-shifting than for mode-shifting (for an average shift of 90 minutes). For travel to and from education, the results show that the constant associated with the train alternative for car users has a positive value, while the constant associated with a switch from train to car is negative. The results also show a higher sensitivity to car cost than to train cost, while the value of time is higher for train than for car. The late departure penalty is higher than the early departure penalty for train travellers, while no significant early departure penalty could be identified for car users. No significant increased participation time penalty could be identified for either train or car users (nor could a common coefficient), and only a common decreased participation time penalty was found to be significant. No significant error-components could be identified for this model.

For those travelling on leisure, shopping and other purposes, the estimation results show significant effects associated with retiming and changes in duration at the destination, with train-travellers being less sensitive to changes in departure time but more sensitive to changes in participation time than car users, especially so for decreases. The error-components for early and late departure time shifts were almost indistinguishable, such that a common error-component was used and it was also possible to identify a significant error-component for mode-switching, where it is not clear why this was not possible in the original study (de Jong et al., 2003). The values suggest far greater elasticity for time changes than mode changes (for an average shift of 90 minutes).

The findings regarding choice structure and substitution patterns from the Dutch data show a more consistent pattern than those from London. With the exception of the segment for education related travel, all ECL analysis shows consistent evidence of heteroskedasticity in the unobservables associated with retiming alternatives and suggest a greater propensity for substitution amongst retiming rather than mode switching alternatives (for an average shift of 90 minutes).

4.3 West Midlands results

Table 3 summarises the estimation results for the West Midlands data set. As with the Dutch data, earlier results showed that it is preferable to estimate separate models for commuters with fixed and flexible working hours. In conjunction with the model for business travellers, and the model for “others”, this led to a total of four travel purpose segments. Several socio-demographic factors were found to be significant, though their influence was not as extensive as in the Dutch data.

For commuters with flexible working hours, all coefficients are significant and have the expected sign. The results indicate that travellers are sensitive both to shifts in departure time (very similar sensitivity to shifts in an earlier and later departure time) and to changes in the duration at the destination, with increases valued twice as negatively as decreases. All three error-components are significant and their values suggest a higher substitution effect (by a factor of around 2) between the base alternative and the retimed early and late departure alternatives, than between the base alternative and the mode-shift alternative (for an average shift of 90 minutes). The models for the fixed working time commuting segment are broadly similar in nature; the influence of timing constraints is reflected in the value of the coefficient associated with a shift in the late departure time, which is four times as high as the corresponding coefficient for a shift in the early departure time. The three error-components again lead to a significant increase in model fit, but, while, with an average shift of 90 minutes, the substitution between the base and the early departure alternative is highest, there is, with this group of travellers, a higher substitution between the base alternative and the mode-shift alternative than

between the base alternative and the retimed late alternative. This again reflects the fixed work-hours arrangement. Finally, the differences in the coefficients for increased and decreased participation time were not significant, so a common coefficient was used.

For business travellers, the estimation results indicate that business travellers are sensitive both to the retiming of departures and to changes in the duration of the destination activity, with, as in the case of the other data sets, the former having a stronger effect than the latter. The error component associated with a shift to a later departure time is not significant, while the remaining two error components indicate that the propensity to switch between departure times is far greater than the propensity to switch between modes (for an average shift of 90 minutes).

For those travelling on leisure, shopping and related other purposes, the estimation results show significant effects associated with retiming and with an increase in the duration at the destination. All three error components are significant, and the magnitudes of the variances suggest that these travellers have a substantially greater propensity for time shifting than for mode shifting (for an average shift of 90 minutes).

The findings regarding choice structure and substitution patterns from the West Midlands data show a consistent pattern which is very similar to that of the Dutch data. In particular, the ECL analyses show evidence of heteroskedasticity in the unobservables in each of the models, and the estimates of the error-components suggest a greater propensity for substitution amongst retiming rather than mode switching alternatives (for an average shift of 90 minutes), with the exception of late departures for commuters with fixed working-hours.

4.4 Comparison and discussion

By way of comparison, and primarily to indicate the general level of performance of the models, Table 4 summarises the implied values of time derived from the three data sets. It should be stressed that, as this analysis was concerned with model structure rather than the calculation of trade-offs, these values should in no way be seen as definitive VOT measures. Although the results from the different data sets are not directly comparable (given the different contexts, ages of the data, and currencies), they are generally plausible and show that (with the exception of the commuter and business segments in the Dutch data), as would be expected, public transport travel-time is valued more highly than car travel-time. We note however that the values of the Dutch data are rather large, though generally somewhat lower than in earlier analyses of these data (de Jong *et al.*, 2003). Furthermore, we note that, while in the West Midlands models, the VOT for commuters with flexible work-hours is higher than that for commuters with fixed work-hours, the opposite is the case for car-travellers in the Dutch models. Major differences in income between flexible and inflexible commuters were only observed for car-commuters in the Dutch data, where the income in the flexible group was higher, such that the differences in VOT cannot be explained on the basis of differences in income, but must be seen as being caused by some other, unmodelled socio-demographic attribute. Finally, it should be noted that the VOT measures in the 'other' purpose category are surprisingly high for car users in the West Midlands models, and public transport users in the Dutch data, when compared to the respective estimates in the *Business* models.

Table 5 shows the relative importance of the scheduling and participation attributes, compared to travel time. These results indicate that commuters generally have a greater sensitivity of shifts to later departure times compared to earlier ones. Although in most segments the scheduling and participation penalties are valued less negatively than travel-time increases, amongst both commuters and business travellers in London and amongst commuters with fixed working hours in the West Midlands, the converse is true. Additionally, travellers are in general less sensitive to changes in participation time than they are to changes in departure time.

Table 6 summarises the results of the ECL analysis, highlighting the finding of significant error components in the case of the Dutch and West Midlands data and the relatively limited role of error components in the models estimated on the London data.

Table 7 illustrates the effect of these error components in influencing the propensity for substitution between different dimensions (i.e., mode and time of day) of choice, by presenting the shift in departure time (in minutes) that is necessary in each case for the propensity to substitute amongst timing alternatives to be equal to that amongst modal alternatives. Specifically, Table 7 presents the equal-sensitivity time shifts, calculated as

$$q_E = \sigma_M / \sigma_E,$$

and

$$q_L = \sigma_M / \sigma_L.$$

For time shifts less than those cited in Table 7, the error components associated with modes dominate those associated with time of day, and hence the propensity for substitution amongst time of day alternatives is greater than that amongst modal alternatives. For London, we additionally present the ratio between the variances of the retiming error-components and the no-travel error-component, where available.

The results show that, except for the retimed later alternative for commuters with fixed work-hours in the West Midlands, a shift of more than the average 90 minutes used in the SP design is required for the substitution amongst modal alternatives to be as high as that amongst time of day alternatives. Aside from this, there are important differences across purposes and regions. Due to the different specifications used, the only direct comparison can be made in the case of commuters with fixed work hours; this shows that, as expected, a lower shift in the later departure-time is required (when compared to earlier departures) to reach sensitivity levels (to explanatory variables) that are as low as those for mode shifting, where the differences are more important in the West Midlands data, and where the shifts required are greater in the Dutch data. As mentioned above, it was not possible to estimate error components associated with mode shifts in the London models except for *other* travel, such that, for commuters and business travellers the results effectively indicate that the substitution amongst modal alternatives is greater than that amongst (late) time alternatives, whereas for shopping and other social/leisure travel, the substitution amongst time alternatives is greater than that amongst modal alternatives.

For wider modelling applications, i.e. the issues addressed by the guidance issued by the Department for Transport, the time shifts indicated in Table 7 are generally larger than that required for a traveller to move from one time period (of 120 to 180 minutes) to another; only commuters with fixed working hours in the West Midlands are less sensitive. It appears for these two data sets, therefore, that time shifting is generally more sensitive than mode shifting. The London data generally speaks against this conclusion, since the equivalent time shifts, where error components could be calculated, are effectively zero; however, the results for London are of inferior quality to those for the other two data sets.

5. CONCLUSIONS

The results presented in this paper highlight well some of the complexities associated with modelling travellers' time of day decision making. The ECL models fit the data well and render generally plausible results in terms of values of travel time savings and substantive attribute parameter relativities. In particular, it appears that the utility functions used for departure time choice analysis (based on the schedule delay concepts expounded by Vickrey and Small), provide adequate descriptions of some key aspects of the choice process, even in the discrete choice framework used in the work described in the present paper. The values, and relative

values, of the utility function coefficients are plausible on the whole. However, there is significant variation amongst the data sets and segments in terms of the substitution patterns between timing and modal alternatives and this has potentially important implications for large scale operational model development.

The procedure used in the present work, investigating the relative sensitivity of time and mode shifting by including both types of choice in the same SP experiments, appears to give reasonable results. The mixed logit approach has proved an effective means for analysing the data and obtaining results illuminating the main issues which the study addressed.

The principal, if unsurprising, conclusion is that the sensitivity of time shifting is significantly related to the size of the time shift. This effect was found in all the data sets and almost all of the purposes.

The conclusion on the sensitivity of time shifting means that the relative sensitivity of time and mode shifting also depends on the magnitude of time shifts. For two of the data sets, the time shifts required to make time and mode shifting equal in sensitivity were so large that time shifting could almost always be considered to be more sensitive than mode shifting. For practical work, however, it is necessary to aggregate departure time choices into time periods, to recognise that the data available will not be as detailed as that available for this study and to accept that mixed logit models will have to be replaced by simpler models to maintain an acceptable processing speed. The need to simplify the models for these reasons may lead to changes in the structural conclusions and the corresponding implications for practice. Such an investigation is being conducted and will be reported separately.

ACKNOWLEDGEMENT

The work reported in this paper was supported by the UK Department for Transport. The authors would like to thank the West Midlands local authorities and the Netherlands Ministry of Transport for their cooperation in granting permission to use their data. We would also like to thank Dr John Bates for helpful comments and suggestions during this work. The authors remain responsible for errors and interpretations contained in the paper.

REFERENCES

- Abkowitz, M.D. (1981), An analysis of the commuter departure time decision, *Transportation* 10, 283-297.
- Arnott, R., de Palma, A., and Lindsey, R. (1990), Departure time and route choice for the morning commute. *Transportation Research* 24 (3), 209–228.
- Ashiru, O., Polak, J.W. and Noland, R.B. (2003), The utility of schedules: A model of departure time and activity time allocation with application to individual activity scheduling, Paper presented at the 10th International Conference on Travel Behaviour Research, Lucerne, August 2003.
- Athanassiou, S. and Polak, J.W. (2001), Generalised extreme value models of time of travel choice, Proceedings of the European Transport Conference, AET, London.
- Bates, J.J., Shepherd, N.R., Roberts, M., van der Hoorn, A.I.J., and Pol, H.D.P. (1990), A model of departure time choice in the presence of road pricing surcharges. Proceeding of the 18th Summer Annual Meeting, Proceedings of Seminar H, PTRC, London, pp. 215–226.
- Bates, J.J. and Williams, I.N. (1993), APRIL - A strategic model for road pricing, Proceedings of Seminar D, PTRC Summer Annual Meeting, 1993. PTRC Education and Research Services Ltd, London.
- Bates, J.J. (1997), *Time Period Choice Modelling: a Preliminary Review*, HETA Division, Department of Transport, UK.

- Ben-Akiva, M. and Lerman, S.R. (1985), *Discrete Choice Analysis; Theory and Application to Travel Demand*, MIT Press, Cambridge MA.
- Bhat, C. (1998a), Analysis of travel mode and departure time choice for urban shopping trips, *Transportation Research* 32B(6), 361-371.
- Bhat, C. (1998b), Accommodating flexible substitution patterns in multidimensional choice modelling: formulation and application to travel mode and departure time choice, *Transportation Research* 32B(7), pp. 425-440.
- Bhat, C.R., and Steed, J.L., (2002), A continuous-time model of departure time choice for urban shopping trips, *Transportation Research* 36B(3), pp 207-224.
- Bradley, M.A., Bowman, J.L., Shiftan, Y., Lawton K., and Ben-Akiva, M.E. (1998), A system of activity-based models for Portland, Oregon. Report prepared for the Federal Highway Administration Travel Model Improvement Program, Washington, DC.
- Chin, A.T.H. (1990), Influences on commuter trip departure time decisions in Singapore, *Transportation Research* 24A(5), pp 321–333.
- Cirillo, C., Daly, A.J., Lindveld, K. (2000) Eliminating bias due to the repeated measurements problem in SP data. In: Ortúzar, J.D. (ed.) *Stated Preference Modelling Techniques: PTRC Perspectives 4*, PTRC Education and Research Services Ltd..
- Cosslett, S. (1977), The trip timing decision for travel to work by automobile, in *Demand Model Estimation and Validation, The Urban Travel Demand Forecasting Project*, McFadden, D.; Talvitie, A.; Cosslett, S.; Hasan, I.; Johnson, M.; Reid, F.; Train, K. (eds), Chapter III-3, pp. 201-221, University of California, Berkeley, CA.
- Daly, A. and Zachary, S. (1978), Improved multiple choice models, in D. Hensher and M. Dalvi, eds., *Identifying and Measuring the Determinants of Mode Choice*, Teakfields, London.
- Daly, A., Gunn, H., Hungerink, G., Kroes, E. and Mijer, P. (1990), Peak-Period Proportions in Large-Scale Modelling, paper presented at the PTRC Summer Annual Meeting.
- de Palma, A., Khatkhat, A.J., and Gupta, D. (1997), Commuters' departure time decisions in Brussels. *Transportation Research Record*, 1607.
- de Jong, G., Daly, A., Pieters, M., Vellay, C. and Hofman, F. (2003), A model for time of day and mode choice using error components logit, *Transportation Research* 29E(3), pp. 246–268.
- Hendrickson, C. and Plank, E. (1984), The flexibility of departure times for work trips, *Transportation Research* 18A(1) pp 25-36.
- Hess, S., Polak, J.W. and Bierlaire, M. (2005), Functional approximations to alternative-specific constants in time period choice-modelling, proceedings of the 16th *International Symposium on Transportation and Traffic Theory*, College Park, MD.
- Hyman, G. (1997), The development of operational models for time period choice. Department of the Environment, Transport and the Regions, HETA Division, London.
- Johnston, R.H., Bates, J.J. and Roberts, M. (1989), A survey of peak spreading in London, Proceedings of the PTRC Summer Annual Meeting.
- Mahmassani, H.S. and Chang, G.L. (1985), Dynamic aspects of departure time choice behaviour in a commuting system: Theoretical framework and experimental results, *Transportation Research Record* 1037 88-101.
- Mahmassani, H.S., Hatcher, S.G., and Caplice, C.G. (1991), Daily variation of trip chaining, scheduling and path selection behaviour of commuters. *Proceedings of the 6th International Conference of the Association for Travel Behaviour (IATB) Conference*, Vol. 2, pp. 29-45.

- Mannering, F.L., Abu-Eisheh, S.A. and Arnadottir, A.T. (1990), Dynamic traffic equilibrium with discrete/continuous econometric models, *Transportation Science* 24(2) pp 105-116.
- McCafferty, D. and Hall, F.L. (1982), 'The use of multinomial logit analysis to model the choice of time of travel' *Economic Geography* 58(3) pp 236-246.
- McFadden, D. (1974), Conditional logit analysis of qualitative choice behaviour, in P. Zarembka, ed., *Frontiers in Econometrics*, Academic Press, New York, pp.105-142.
- McFadden, D. (1978), Modelling the choice of residential location in A. Karlqvist, L. Lundqvist, F. Snickars and J. Weibull, eds, *Spatial Interaction Theory and Planning Models*, North-Holland, Amsterdam, pp.75-96.
- McFadden, D. and Train, K. (2000), Mixed MNL models for discrete response, *Journal of Applied Econometrics* 15 pp 447-4780.
- Polak, J.W., Jones, P.M., Vythoulkas, P.C., Meland, S. and Tretvik, T. (1991), 'The Trondheim Toll Ring: Results of a Stated Preference Study of Travellers' Responses', EURONETT Deliverable 17, Transport Studies Unit, University of Oxford.
- Polak, J. and Jones, P. (1994), "Travellers' choice of time of travel under road pricing", paper presented at the 73rd Annual Meeting of the Transportation Research Board, Washington D.C.
- RAND Europe (2004), PRISM West Midlands: Time of Day Choice Models. RED-02061-04.
- Small, K. A. (1982), The scheduling of consumer activities: Work trips, *American Economic Review* 72(3) pp 467-479.
- Small, K.A. (1987), A discrete choice model for ordered alternatives", *Econometrica* 55(2), pp 409-24.
- Train, K. (2003), *Discrete choice analysis with simulations*, Cambridge University Press, Cambridge, MA
- van Vuren, T., Carmichael, S., Polak, J., Hyman, G., and Cross, S., 1999. Modelling peak spreading in continuous time. Proceedings of the European Transport Conference, AET, London.
- Vickrey, W.S., 1969. Congestion theory and transport investment. *American Economic Review (Papers and Proceedings)* 59, pp 251–261.
- Wang, J.J., 1996. Timing utility of daily activities and its impact on travel. *Transportation Research* 30A(3), pp 189–206.
- Williams, H. (1977), On the formation of travel demand models and economic evaluation measures of user benefits, *Environment and Planning* A9, 285-344.

Table 1: Estimation results for London data

	Commute		Business		Other	
	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
<i>Attributes</i>						
Constant						
- public transport	-1.556	-9.5	-2.7992	-15.92	-12.8	-3.8
- no travel	-6.769	-8	-5.5889	-18.34	-27.3	-4
Travel time in minutes (β_{TT})						
- public transport	-0.0062	-5.3				
- car			-0.0039	-5.32		
- generic					-0.0096	-7.6
Cost in pence (β_{TC})						
- public transport					-0.0052	-4
- car					-0.0032	-16.3
- generic	-0.00065	-9.6	-0.0005	-8.11		
Early departure time change in minutes (β_{SDE})	-0.0068	-5.5	-0.0096	-5.41	-0.0008	-0.8
Late departure time change in minutes (β_{SDL})						
- Commuting: flexible work hours	-0.0120	-4.5				
- Commuting: fixed work hours	-0.0233	-13.8				
- Business			-0.0108	-5.7		
Increased participation penalty in minutes (β_{PTI})	-0.0067	-6	-0.0058	-3.52	-	-
Decreased participation penalty in minutes (β_{PTD})	-	-	-0.0059	-3.52	-	-
<i>Error components</i>						
Shift to later departure time in minutes (σ_L)	0.0422	12	0.0324	7.1	0.0115	2.8
Shift to earlier departure time in minutes (σ_E)	-	-	-	-	-	-
Mode-change (σ_M)	-	-	-	-	8.37	3.7
No travel (σ_{NT})	2.32	4.3	-	-	13.7	3.6
Observations	6,183		2,543		5,323	
Final log-likelihood	-5630.21		-2209.68		-4569.83	
Rho-Squared wrt 0	0.312		0.319		0.3285	

Table 2: Estimation results for Dutch data

	Commute: Flexible		Commute: Fixed		Business		Education		Other	
	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
<i>Attributes</i>										
Constant										
- train alternative for car users	-3.923	-4.9	-5.526	-5.7	-4.105	-4.8	1.74	3	-3.117	-6.2
- car alternative for train users	-5.36	-5.3	-2.47	-4.3	-1.678	-2.2	-3.079	-6.4	-1.387	-4.1
- switching from train peak to earlier/later	-0.3223	-2.2	-0.3903	-2	-0.2514	-2.1			0.2684	2.3
- switching from car peak to earlier/later for car-travellers aged under 40 years	0.1133	1.2	0.293	2.6	-0.2501	-3.1				
- switching from peak to earlier/later for respondents (car or rail) in part-time employment	0.1496	1.2	-0.2386	-1.8						
- switching from train peak to earlier/later for single workers	0.2931	1.1	1.273	4.5						
- switching from peak to earlier/later for respondents (car or rail) with medium education					0.05661	0.7				
- switching from peak to earlier/later for respondents (car or rail) with low education	-0.9472	-5.7	-0.01271	-0.1					-0.3192	-3.1
- switching from peak alternative to earlier/later or mode-change (car and rail) for travellers who regularly work from home	0.2011	2.1	0.4098	2.7						
- late departure	-1.168	-10.1	-1.615	-9.7	-0.8157	-8.9	-0.7838	-6	-0.6758	-8.5
- early departure	-0.6581	-6	-1.185	-8.5	-0.3986	-3.9	-1.66	-9.7	-0.339	-2.9
Travel time in minutes(β_{TT})										
- public transport	-0.03214	-7	-0.02068	-5.1	-0.02084	-9.4	-0.03542	-9.6	-0.02083	-10.3
- car	-0.01966	-8.6	-0.02637	-8.6	-0.0186	-9.5	-0.01414	3.7	-0.01996	-9.9
Cost in guilders (β_{TC})										
- train cost for travellers receiving no compensation from their employer	-0.0532	-3.3	-0.05203	-4.2						
- train cost & for travellers receiving compensation from their employer	-0.00957	-1.6	-0.02891	-4.8						
- car cost for travellers with income $\leq 60,000 f$	-0.04736	-4.8	-0.02161	-3.2						
- car cost for travellers with income $> 60,000 f$	-0.02619	-4.5	-0.01722	-2.4						
- Log car cost					-0.8176	-5.2				

- Log public transport cost					-0.6869	-5.8				
- car cost							-0.08435	-6		
- train cost							-0.04964	-8.1		
- generic									-0.01713	-5.7
Early departure time change (β_{SDE})										
- car tour					-0.02007	-11.1			-0.01918	-9.3
- train tour					-0.01542	-7	-0.00887	-5.1	-0.01384	-6.3
- car trip					-0.02095	-10.6				
- generic	-0.01756	-11.7	-0.01898	-8.3						
Late departure time change in minutes (β_{SDL})										
- car tour					-0.02005	-10.8	-0.01277	-1.6	-0.01877	-9.4
- train tour					-0.00938	-5.2	-0.01203	-7.5	-0.01103	-4.8
- car trip					-0.01882	-8.9				
- generic	-0.01245	-11.4	-0.03096	-9.1						
Increased participation penalty in minutes (β_{PTI})										
- car tour					-0.00763	-3.8			-0.00432	-2.9
- train tour					-0.00407	-2			-0.00691	-3.2
- generic	-0.00749	-4.5	-0.0063	-3.4						
Decreased participation penalty in minutes (β_{PTD})										
- car tour					-0.00443	-2.2			-0.00306	-1.5
- train tour					-0.00764	-5.1			-0.00678	-3.5
- generic	-0.00124	-1.4	-0.00769	-4.1			-0.00368	-3		
<i>Error components</i>										
Shift to later departure time in minutes (σ_L)			0.01735	7.9	0.007013	5.9			0.009887	8.7
Shift to earlier departure time in minutes (σ_E)	0.008451	6.2	0.01114	7.3						
Mode-change (σ_M)	2.834	4.2	3.939	5.2	2.005	5.1			1.727	3.9
Observations	3,050		3,106		3,812		1,250		3,224	
Final log-likelihood	-2574.69		-2436.58		-3278.42		-813.29		-2968.64	
Rho-Squared wrt 0	0.3332		0.3846		0.322		0.4463		0.2709	

- tour					-0.0197	-7.6		
- trip					-0.0221	-6		
- generic	-0.0285	-5.7	-0.1059	-7.3			-0.0374	-6
Increased participation penalty in minutes (β_{PTI})								
- tour					-0.0047	-2.1		
- generic	-0.00662	-2.3	-0.0025	-3.7			-0.0066	-2.4
Decreased participation penalty in minutes (β_{PTD})								
- tour					-0.006	-3.4		
- generic	-0.00329	-2.9	-0.0025	-3.7				
<i>Error components</i>								
Shift to later departure time in minutes (σ_L)	0.01537	3.2	0.05169	6.3			0.01947	3.2
Shift to earlier departure time in minutes (σ_E)	0.01666	5.4	0.02265	4.9	0.00955	6.3	0.02013	6.2
Mode-change (σ_M)	3.153	5.6	2.445	3.4	9.904	3.6	6.17	5.6
Observations	1,605		1,412		2,342		2,192	
Final log-likelihood	-1355.67		-981.54		-1779.37		-1616.24	
Rho-Squared wrt 0	0.3457		0.4358		0.3557		0.4118	

Table 4: Summary of implied values of time savings

		Commuters		Business	Education	Other ^b
		Flexible	Fixed			
West Midlands (£/hour @ 2003 prices) ^a	Car	2.13	1.21	2.81		2.14
	PT	3.47	1.69	13.98		2.86
Dutch (guilders/hour @ 2000 prices) ^c	Car			109.52	10.06	69.91
	PT			71.09	42.81	72.96
	Car, high income	45.04	91.90			
	Car, low income	24.91	73.25			
	Train, not compensated	36.55	23.85			
	Train, compensated	201.51	42.92			
London (£/hour @ 1992 prices) ^a	Car			4.68		1.80
	PT		5.72			1.11

a £1.00 = €1.40 to €1.80 (fluctuations in exchange rate between 1992 and 2003)

b 'Other' = Shopping and leisure for the London data

c 1 Guilder = €0.45 (fixed exchange rate, as of January 1st, 1999)

Note that these figures are derived from those in Tables 1-3 and approximate error margins can be deduced from the 't' ratios in those tables.

Table 5: Summary of marginal valuation of scheduling and participation attributes relative to travel time

		Commuters		Business		Education	Other
		Flexible	Fixed	Home based	Non-home based		
London	Early departure shift (β_{SDE}) - car - public transport - generic	1.097		2.46			1.1979
	Late departure shift (β_{SDL}) - car - public transport	1.935	3.758	2.77			
	Increase participation (β_{PTI}) - car - public transport - generic	1.081		1.49			
	Decrease participation (β_{PTD}) - car - public transport			1.51			
Dutch	Early departure shift (β_{SDE}) - car - public transport	0.893 0.542	0.720 0.918	1.079 0.740	1.126	0.250	0.961 0.664
	Late departure shift (β_{SDL}) - car - public transport	0.633 0.384	1.174 1.497	1.078 0.450	1.012	0.903 0.340	0.940 0.530
	Increase participation (β_{PTI}) - car	0.381	0.239	0.410			0.216

	- public transport	0.231	0.305	0.195			0.332
	Decrease participation (β_{PTD})						
	- car	0.063	0.292	0.238		0.260	0.153
	- public transport	0.038	0.372	0.367		0.104	0.326
West Midlands	Early departure shift (β_{SDE})						
	- car	0.777	1.700	0.823	1.176		0.674
	- public transport	0.476	1.219	0.166	0.236		0.504
	Late departure shift (β_{SDL})						
	- car	0.793	7.150	0.817	0.917		0.865
	- public transport	0.486	5.138	0.164	0.185		0.646
	Increase participation (β_{PTI})						
	- car	0.185		0.197			0.152
	- public transport	0.113	0.120	0.040			0.114
	Decrease participation (β_{PTD})						
- car	0.092		0.249				
- public transport	0.056	0.120	0.05				

Table 6: Summary of error components estimates

	West Midlands data			Dutch data			London data			
	EC early-shift (per min.) (σ_E)	EC late-shift (per min.) (σ_L)	EC mode-shift (σ_M)	EC early-shift (per min.) (σ_E)	EC late-shift (per min.) (σ_L)	EC mode-shift (σ_M)	EC early-shift (per min.) (σ_E)	EC late-shift (per min.) (σ_L)	EC mode-shift (σ_M)	EC not travel
Commuters flexible	0.0167	0.0154	3.153	0.0085	n.s.	2.834	n.s.	0.0422	n.s.	2.32
Commuters fixed working-hours	0.0226	0.0517	2.445	0.0111	0.0174	3.939				
Business travellers	0.00955	n.s.	9.904	0.0070		2.005	n.s.	0.0324	n.s.	n.s.
Other (Shopping and other social/leisure for London data)	0.0201	0.0195	6.17	0.0099		1.727	n.s.	0.0115	8.37	13.7
Education	N/A	N/A	N/A	n.s.	n.s.	n.s.	N/A	N/A	N/A	N/A

Table 7: Required departure time shift in minutes for sensitivity to time-shifting to be equal to sensitivity to mode-shifting, or to decision not to travel

	West Midlands data		Dutch data		London data	
	EC early-shift vs mode	EC late-shift vs mode	EC early-shift vs mode	EC late-shift vs mode	EC late-shift vs mode	EC late-shift vs no-travel
Commuters flexible	189	205	333			
Commuters fixed working-hours	108	47	355	226		55
Business travellers	1037			286		
Other	307	316		175	728	1191