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A model for time of day and mode choice using error components logit

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Abstract

The severity of road congestion not only depends on the relation between traffic volumes and network capacity, but also on the distribution of car traffic among different time periods during the day. A new error components logit model for the joint choice of time of day and mode is presented, estimated on stated preference data for car and train travellers in The Netherlands. The results indicate that time of day choice in The Netherlands is sensitive to changes in peak travel time and cost and that policies that increase these peak attributes will lead to peak spreading.

Keywords: Time of day; Peak spreading; Error components model; Mixed multinomial logit model

1. Introduction

In the Netherlands, the Dutch National Model System for traffic and transport (LMS) has been used since 1990 to predict the responses of travellers to a wide range of developments, such as changing travel times (e.g. from congestion) or the imposition of time-dependent road user charging. One of the results of these simulations has been that the choice of when to travel (time of day choice) greatly affects the amount of congestion on the road network and that policies aiming at spreading out peak travel can be effective instruments to relieve congestion.

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However, these results rely to a large extent on a time of day choice sub-model within the Dutch National Model System, which is more than 10 years old. Moreover, this sub-model uses a rather simple and restrictive specification: only three time periods are distinguished within a working day, there are no links between the outward and inward leg of the same tour, and the model is multinomial logit (MNL). Since then, congestion has increased considerably, casting doubt about whether the old specifications will still hold, while modelling capabilities also improved.

In this paper, a new model for the joint choice of mode and time of day is presented and estimated on new stated preference data. The model is not restricted to shifts between large time periods and follows the error components logit (EClogit; also called mixed MNL) specification. Using this type of model, one can take account of the different degrees of substitution between time periods (e.g. greater substitution between nearby periods than between periods further away from each other) and between time of day alternatives and alternative modes. It is a tour-based model, in which outbound time of travel, duration of the activity at the destination and mode choice are determined simultaneously.

This new model was developed to become the basis of a new time of day choice sub-module of the Dutch National Model System. It also covers public transport users, whereas the old module only referred to the time of day choice of car drivers. [1]

The paper first describes the main outcomes of a literature survey into time of day choice (Section 2). Section 3 provides information on the stated preference survey. The estimation results for the EClogit model are in Section 4. Simulation results for the impact of changes in travel time on mode and period choice can be found in Section 5. Finally, Section 6 contains conclusions and recommendations for further work.

2. The literature on time of day choice models

2.1. Equilibrium scheduling theory and discrete choice models

Most empirical studies into the choice of time of day have considered only the demand of travellers for travel at different points of time or periods in time (mostly using discrete time periods) for given travel time and/or travel cost. Impacts on congestion and feedback to choice after assignment have usually been ignored.

An important exception is the literature, largely theoretical, building on the highly original contribution by Vickrey (1969). In his model, Vickrey assumes a single bottleneck (one link). For this bottleneck situation commuters decide on their time of travel (which can be different from the official work starting time because of a desire to travel at a less congested time) and the demand-supply equilibrium can be determined explicitly. Hyman (1997) and van Vuren et al. (1999) have

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called these type of models 'equilibrium scheduling theory' (EST). The basic trade-off for the travellers, which is the same for both the EST models following Vickrey and the discrete choice models following Small (1982), is between the disutility of arriving too early or too late (scheduling disbenefits, measured in clock time) and the disutility of travel time (measured in travel time, that is duration of travel).

The following formulation of this problem is based on Vickrey (1969):

$$V(t) = \alpha T(t) + \beta \max(0, (\mathrm{PAT} - t - T(t))) + \gamma \max(0, (t + T(t) - \mathrm{PAT})) \tag{1}$$

In which, $V(t)$ is the disutility (cost) to traveller with departure time t; $T(t)$ is the travel time associated with a departure at time t; PAT is the preferred arrival time at destination; α, β, γ are parameters to be estimated.

A traveller arriving precisely at his preferred arrival time will have no disutility from scheduling (second and third term are equal to zero), but $T(t)$ might be substantially higher. In the equilibrium of the Vickrey model (assuming homogeneous travellers with respect to preferred arrival time) the highest value of $T(t)$ will be at preferred arrival time. Arriving too soon (second term) will yield a disutility, as will arriving too late (third term), but the disutility gradients might be different (β can be different from γ). Travel cost could be included in $T(t)$, e.g. for tolls varying by time of day.

Whether departure time or arrival time is modelled does not really matter, as long as there is no unanticipated congestion. In the Vickrey model, as in most time of day models, it is assumed that the travellers are aware of the amount of congestion and its impact on travel times (e.g. from daily experience) and that they may respond to this by changing their departure time, which without unanticipated congestion, translates into an identical change in arrival time.

Some proposals on how to extend these theoretical models for single bottlenecks or simple networks to networks as used in operational transport models or even to dynamic assignment can be found in Bates (1996) and Hague Consulting Group et al. (1998). An empirical application of EST is the HADES (heterogeneous arrival and departure times based on EST) model (van Vuren et al., 1999; Hague Consulting Group et al., 2000). These models for time of day can be combined with existing assignment packages.

In Hague Consulting Group et al. (1998, 2000) the conclusion was drawn that HADES would probably be the final stage of EST development. Further developments are most likely to concentrate on an approach with discrete choice between time periods: 'The alternative (to EST) based on choice modelling seems to offer the best potential' (Hague Consulting Group et al., 2000). The general finding was that EST works best for small changes (5–10 min) in departure time whereas the choice approach is more suited for longer periods.

2.2. Combining time of day with other choices

The general rule in previous time of day models has been that no other choices are studied simultaneously, but some exceptions can be found. The EST studies include aggregate assignment as well as the demand-side component of time of day. Mannering (1989), Mahmassani et al. (1991) and Khattak et al. (1995) have developed models that not only explained time of day, but also the choice of route (by individual travellers, not the supply side problem of finding travel times that are consistent with the assignment of aggregate demand to the available routes at given capacities). Wang (1996) studied time of day and the scheduling of all daily activities and COWI et al. (1997) developed a model for long distance travel through the Storebælt corridor in Denmark for the choice of mode/route, travel day and time of day.

Three models could be found in the literature for the joint choice of travel mode and time of day. Of these three, Hendrickson and Plank (1984) used the most restrictive assumptions on the substitution patterns (MNL). A high degree of flexibility can be found in Bhat (1998a,b), which use EClogit and ordered generalised extreme value (OGEV) models.

Havnetunnelgruppen (1999) (see also Paag et al., 2000) used nested logit (NL) for route/time of day choice, and also used EClogit. These models for the Copenhagen area examined route choice (toll tunnel or untolled bridge) and time of day switching (two alternatives: switch from peak to off-peak, switch from off-peak to peak) for car travellers. The error components models reflected the relative elasticities of time-switching and route choice, in addition to random time and cost coefficients and repeated measurement corrections.

For the Dutch National Model System LMS, a model of choice of time of day was developed in 1989/1990 using stated preference data and was integrated with the other choices represented in the model system (e.g. mode and destination) using professional judgement. While this model has been successful in modelling policy options, its integration is clearly open to doubt, while the data on which it is based are from 1989 and a need for replacement is becoming more urgent. It is to meet this need that the present work has been undertaken.

About half of the time of day studies in the literature deal only with commuting. The reason for this is of course that the studies focus on congestion (or time-varying tolls); without these there would be no reason for arriving at other than the preferred arrival times. In many countries congestion is predominantly a peak phenomenon, and commuting traffic is the most important travel purpose in the peak periods. Nevertheless there are also studies focussing on other travel purposes (e.g. Bhat, 1998a,b) or dealing with the time of day behaviour for all purposes.

2.3. Model types used in time of day models

One of the disadvantages of using discrete choice models for time of day is that time periods are likely to be correlated. Especially if time periods are short, this situation becomes quite likely; intuitively speaking, the consecutive time periods then become very similar, not only with respect to the measured attributes but also with regard to the unmeasured influences in the disturbance terms. This problem does not appear to occur in a deterministic continuous time model, such as Vickrey's; in deterministic models the even stronger assumption of *no* unmeasured interpersonal variation is made. Most empirical models with a choice between discrete time periods use MNL in which the error terms are assumed to be independent (see Table 1). The possible dependence between similar alternatives can therefore not be accounted for. Some of the models used are NL, also called tree logit. In the NL model a uniform amount of correlation within a nest of alternatives is allowed, but alternatives not located in the same nest are uncorrelated.

The problem becomes even more complicated if mode choice is added to the time of day choice. For many travel purposes it is natural to expect that there will be more correlation (and substitution) between time of day alternatives than between time of day and mode alternatives. For the combination of mode and time of day, NL might still be an appropriate solution, but for the correlation within time of day alternatives, more flexible forms would be preferable.

Table 1
Model types used in time of day studies

Studies	Discrete (D) or continuous (C) time	Stated preference (SP) or revealed preference (RP) data	Model type used in time of day
Vickrey (1969)	C	–	Deterministic
Small (1982)	D	RP	MNL
Small (1987)	D	RP	MNL, NL and OGEV
Hendrickson and Plank (1984)	D	RP	MNL
Arnott et al. (1990a,b, 1994)	C	–	Deterministic
Mannering (1989)	D	RP	Poisson (for number of Changes)
Mahmassani et al. (1991), Hatcher and Mahmassani (1992), Jou and Mahmassani (1994) and Liu and Mahmassani (1998)	D	RP	Poisson (for number of changes); MNP (for time of day on consecutive days)
Chin (1990)	D	RP	MNL (NL did not converge)
Bates et al. (1990) and Martin Voorhees Associates (1990)	D	SP	MNL
Daly et al. (1990) and Hague Consulting Group (1991)	D	SP	MNL
Polak and Jones (1994)	D	SP	NL
Chin et al. (1995)	D	RP	Incremental logit (MNL)
Accent and Hague Consulting Group (1995)	D	SP	MNL
Khattak et al. (1995)	D	SP	Ordered probit (for changing)
De Palma and Rochat (1996)	C	RP	Ordered probit (number of changes)
Wang (1996)	C	RP	Weibull and log-logistic hazard
COWI et al. (1997)	D	SP	NL
De Palma et al. (1997)	D	SP	OLS & Tobit (for change in minutes)
Bhat (1998a)	D	RP	MNL, NL and OGEV
Bhat (1998b)	D	RP	MNL and EClogit
Bradley et al. (1998)	D	RP	NL
Havnetunnelgruppen (1999)	D	SP	NL and EClogit
van Vuren et al. (1999) and Hague Consulting Group et al. (2000)	C	RP	Deterministic, with segmentation; partially endogenous

MNL: multinomial logit, NL: nested logit, OGEV: ordered generalised extreme value, OLS: ordinary least squares and EClogit: error components logit.

Small (1982) noted the problem of possibly correlated error terms and designed a test to see whether adjacent alternatives are closer substitutes (higher correlation) than pairs of non-adjacent alternatives. In a later paper, Small (1987) designed a more flexible model than the MNL model that he had used in 1982: the OGEV model. This model belongs to the family of random utility models proposed by McFadden (1978, 1981) and known as generalised extreme value (GEV) models.

Both MNL and NL are special cases of the GEV model. The OGEV model allows for a correlation parameter, for a pair of alternatives, which depends on the distance between the alternatives along some natural ordering, such as the clock time in time of day choice. The highest correlation is expected to be found for adjacent alternatives. Alternatives at great distance from each other will be independent as in the common MNL. In practice the number of free parameters needs to be reduced to allow maximum likelihood estimation (with non-standard software). The simplest OGEV arises when all correlation parameters are equal and apply only to adjacent pairs of alternatives. When Bhat (1998a) estimated a model with MNL for mode choice and OGEV for time of day choice with two different correlation parameters (one more than in NL) he found that the MNL–OGEV performed significantly better than the MNL and the NL model. He concluded that the latter two specifications lead to biased level-of-service estimates and inappropriate evaluations of policy measures.

An even more general model than OGEV was presented by Koppelman and Wen (1999): the paired combinatorial logit (PCL) model. This model allows for a different correlation between each pair of alternatives. This correlation does not depend on the distance between the alternatives as in OGEV. This could be a useful step forward for modelling time of day because not only can we assume that time periods that follow shortly after other time periods will be correlated, but also similar but faraway periods (e.g. busiest hour of morning and evening peak) could be highly correlated. The OGEV is a special case of the PCL. Koppelman and Wen also use the PCL in estimation (non-standard software), though not on time of day choice but mode choice.

PCL has limits, but there are further more general models, even within the GEV family (Daly, 2001). An even more general discrete choice model is the multinomial probit (MNP) which could involve estimating a complete variance–covariance matrix for all alternatives. The major disadvantage of MNP is that with many alternatives (meaning 3 or more), estimation is very cumbersome due to the multiple integrals in the likelihood function. Therefore researchers have been investigating the possibilities—with some success—of simulating the likelihood function or the moments of the distribution by drawing from statistical distributions (e.g. Bolduc, 1999). Also the number of free parameters in the variance–covariance matrix in most empirical work is reduced considerably. Liu and Mahmassani (1998) used MNP for their time of day and route choice model for consecutive days, without applying such simulation methods, but they have access to a Cray supercomputer.

The EClogit or mixed MNL model has been known for some time (Cardell and Dunbar, 1980; Ben-Akiva and Bolduc, 1991) and was put forward by several authors (e.g. McFadden and Train, 1997; Bhat, 1998b) in the late nineties as a highly flexible, yet practical, model type. It is no less general than the MNP model in that it can also estimate a complete variance–covariance matrix. Unlike MNP it can also handle asymmetric disturbances. EClogit can approximate the MNP; MNP is the limiting case of EClogit. According to McFadden and Train (1997), EClogit can approximate as closely as one pleases not only MNP but also any other discrete choice model based on random utility maximisation, including OGEV and PCL. Therefore, although MNP, OGEV and PCL are not special cases of EClogit, EClogit can serve as an approximation for these. We therefore have chosen to use EClogit to model mode and time of day choice (also see Section 4).

The basic idea of any error components model is that it parameterises the variance–covariance matrix, by adding components to the MNL model. The utility function in the MNL is:

$$U_k = \sum_r \beta_r x_{kr} + \varepsilon_k \tag{2}$$

In which, U_k is the utility for decision-maker from alternative k; β_r is the parameter to be estimated for rth attribute; ε_k is the error term; follows extreme value type 1 distribution; x_{kr} is the measured attribute r for alternative k.

In the EClogit model, the utility function becomes:

$$U_k = \sum_r \beta_r x_{kr} + \sum_s \sum_t \eta_s w_{st}^k \xi_t + \varepsilon_k \tag{3}$$

In Eq. (3) the following new components are added to MNL: ξ_t is the error component, distributed $f(0,1)$, for which there can be several error components; η_s is the parameter to be estimated; w^k a general weighting matrix, based on data and/or fixed by the analyst, for alternative k, with rows s corresponding to the coefficients η and columns t corresponding to the error components ξ.

If ξ and ε follow the multivariate normal distribution, this model is MNP. In the EClogit specification with ε Gumbel distributed however, the choice probabilities *conditional on the error components* take the familiar MNL form. The unconditional choice probabilities are derived by integration of the conditional MNL choice probabilities over the distribution of the error components. The latter distribution is usually evaluated using Monte Carlo simulation (drawing from the distribution of ξ). The commonly used estimation method is called maximum simulated likelihood. Different assumptions on the structure of the variance–covariance matrix for error components can lead to different model specifications:

- MNL and NL are a special case of EClogit (NL by approximation).
- The varying and random coefficients model can be written as EClogit models.
- The model can be used for data sets with repeated measurements for the same individual (it is therefore an alternative to estimating the t-values using the Jack-knife method, providing we know the structure of the interpersonal variation) by including individual-specific components; the same specification can be used for panel data.
- It can approximate all other known discrete choice random utility models (e.g. MNP, OGEV and PCL).

3. The stated preference survey

The population from which respondents were recruited consists of persons travelling in the extended peak periods (6.00–11.00 and 15.00–19.00 h during working days) as car drivers or train passengers within The Netherlands. Respondents were recruited for participation in the actual stated preference survey from an existing panel or from short recruitment interviews at train stations and at a petrol station beside a motorway. The estimation sample contains information on more than 1000 travellers.

The stated preference survey itself was done by computer-assisted personal interviews (programmed in the WinMint software) at the residence of the respondent. Target numbers of interviews were used for strata by travel purpose and mode. During the stated preference interview, information was gathered first on attributes of a specific tour that the respondent made recently within a pre-specified mode and purpose combination. This information was used to customise the stated preference experiments.

Three different stated preference questionnaires were developed:

(1) a questionnaire for home-based (HB) tours by car drivers (travel purposes can be home to work, HB business or other, including education);
(2) a questionnaire for non-home-based (NHB) business trips by car drivers; and
(3) a questionnaire for HB tours by train travellers (purposes can be home to work, business, education and other).

The stated preference questionnaires for car drivers (both the one for tours and the one for trips) contain two choice experiments:

(1) a first experiment without road pricing focussing on the trade-off between departure time and travel time (especially influenced by congestion); and
(2) a second experiment with peak pricing.

For the interviews with train passengers, a similar two-experiment structure was set up:

(1) the first experiment deals with choices using the present fare system; and
(2) the second experiment includes extra peak charges (also taking into account that there are reduced fares for travel after 9.00 AM already).

In each of the stated preference experiments three or four alternatives were presented on the same screen:

- The first alternative contains departure time options close to the observed departure times (the same or a little earlier/later).
- The second alternative contains departure times which are considerably earlier (in the road pricing experiments all travel in the morning takes place before the morning peak charging period; the car trips in the afternoon might coincide with the afternoon peak charges; in the train peak charging experiments the travel takes place before the peak charging period, which refers to the morning peak only).
- The third alternative contains departure times that are considerably later, to travel after the end of the morning peak charging (using the same rules as mentioned above for earlier departure times).
- The fourth alternative refers to another mode than that observed (public transport for car travellers and car for train travellers) and is presented only to travellers who state they could use the alternative mode.

The attributes presented for these alternatives include:

(1) departure time from home;
(2) arrival time at destination;

(3) departure time from destination;
(4) arrival time at home;
(5) tour travel time;
(6) duration of stay at destination;
(7) travel cost not including (extra) peak charge;
(8) peak charge (second experiment only);
(9) probability of a seat (train only); and
(10) frequency (train only).

The stated preference survey contains both relatively small (10–20 min) shifts in departure time and large shifts (1 h or more).

By presenting the experiments this way, we have included the options that a respondent has in reality (and thereby made the experiment look as much as possible like 'reality') when facing (severe) congestion or peak pricing: staying with the chosen mode at or close to the chosen departure times, travelling earlier, travelling later and changing mode (stop making this tour can also be chosen). Furthermore, by presenting an alternative which is the same as the observed situation, or close to it on each screen, the respondent is reminded of the present circumstances with all the information on preferences and constraints that it contains, so that the choice will be 'tied to reality'. The number of screens per experiment is fixed at eight (giving eight choice observations for the experiment without peak pricing and eight for the experiment with peak pricing per respondent, all 16 screens with up to four alternatives per screen).

The four-alternatives-on-a-screen presentation departs from the standard presentation in transport applications of stated preference with binary choices. Comparing four alternatives at the same time is more difficult for the respondents, but recent experiments have shown that respondents are capable of giving consistent and plausible answers to complicated choice tasks (Louviere and Hensher, 2000). In the pilot we tested whether respondents can cope with this task of a four alternative comparison, and concluded that this was the case.

4. Estimation results

4.1. Model specification and estimation method

To account for the possible link between the outward and return legs of the same tour, we presented alternatives to respondents that refer to both legs of a tour. For commuters this will often coincide with a picture of the entire day. The link between both tour legs depends on the duration of the activity performed at the tour destination. If the activity duration is fixed, a shift in the time of travel for the outward leg will also affect the time of travel of the return leg. However it would be very unsatisfactory to use the behavioural assumption that the time of day choice for the return leg will follow automatically from decision-making about the time of day for the outward leg. Rational or boundedly rational behaviour will imply simultaneous decision-making about the time of day of both tour legs and activity duration. We estimated:

(1) simultaneous models for time of day choice for both tour legs; and
(2) simultaneous models for time of day choice for the outward trip and activity duration, with penalties for shorter or longer than preferred activity duration (following Polak and Jones, 1994).

Polak and Jones (1994) also used the tour concept for time-of-day choice instead of the commonly used trip concept. In their paper they establish a link between the timing decision for both legs of the tour and the activity scheduling, in which '... the timing of travel follows as a consequence of the interplay between time varying patterns of destination utility and travel cost'. This concept was implemented in the APRIL (assessment of pricing of roads in London) model to assess road pricing schemes in London.

These specifications did not lead to completely identical model results, presumably because of slight inconsistencies in preferences for activity duration and arrival time at home. The second category of models performed best for all four travel purposes, and was used in the models presented below. The utility functions of the estimated models are based on the Vickrey–Small utility functions (Eq. (1)), with scheduling penalty terms measured in minutes.

For a person observed making a car tour for some travel purpose, the *utility functions* considered in the estimations include:

$$\begin{aligned}
U_0 &= \alpha \mathrm{CARTIME}_0 + \beta^{\mathrm{o}} \mathrm{EARLY}_0 + \gamma^{\mathrm{o}} \mathrm{LATE}_0 + \beta^{\mathrm{r}} \mathrm{REARLY}_0 + \gamma^{\mathrm{r}} \mathrm{RLATE}_0 + \delta \mathrm{CARCOST}_0 + \cdots \\
U_1 &= \alpha \mathrm{CARTIME}_1 + \beta^{\mathrm{o}} \mathrm{EARLY}_1 + \beta^{\mathrm{r}} \mathrm{REARLY}_1 + \delta \mathrm{CARCOST}_1 + \eta_1 \mathrm{TIMDIF}_1 \xi_1 + \cdots \\
U_2 &= \alpha \mathrm{CARTIME}_2 + \gamma^{\mathrm{o}} \mathrm{LATE}_2 + \gamma^{\mathrm{r}} \mathrm{RLATE}_2 + \delta \mathrm{CARCOST}_2 + \eta_2 \mathrm{TIMDIF}_2 \xi_2 + \cdots \\
U_3 &= \alpha \mathrm{PTTIME}_3 + \beta^{\mathrm{o}} \mathrm{EARLY}_3 + \gamma^{\mathrm{o}} \mathrm{LATE}_3 + \beta^{\mathrm{r}} \mathrm{REARLY}_3 + \gamma^{\mathrm{r}} \mathrm{RLATE}_3 \\
&\quad + \delta \mathrm{PTCOST}_3 + \eta_3 \xi_3 + \cdots
\end{aligned} \tag{4}$$

Many more variables (especially socio-economic attributes) have in practice been included, but are not shown in this example to simplify the presentation. All utility functions include error terms that follow the extreme value type I distribution.

The subscripts 0, 1, 2, 3 refer to the four alternatives presented on a screen in the stated preference survey:

(1) observed mode and time of day;
(2) observed mode, considerably earlier;
(3) observed mode, considerably later; and
(4) different mode, observed time of day.

Furthermore α, β, γ, δ are the coefficients to be estimated (these can also be alternative-specific); the superscripts o and r denote the outward and the return leg; CARTIME is the travel time by car for both tour legs (minutes); CARCOST is the travel cost by car for both tour legs (guilders); PTTIME is the travel time by public transport for both tour legs (minutes); PTCOST is the travel cost by public transport for both tour legs (guilders); EARLY is the early schedule penalty for the outward leg: the difference in minutes between the preferred departure time and the presented departure time, if presented departure time is before the preferred departure time; otherwise zero;

LATE is the late schedule penalty for the outward leg: the difference in minutes between the presented departure time and the preferred departure time, if presented departure time is after the preferred departure time; otherwise zero; REARLY is the early schedule penalty for the return leg: the difference in minutes between the preferred departure time and the presented departure time, if presented departure time is before the preferred departure time; otherwise zero; RLATE is the late schedule penalty for the return leg: the difference in minutes between the presented departure time and the preferred departure time, if presented departure time is after the preferred departure time; otherwise zero; η_1, η_2 and η_3 are the coefficients for the error components to be estimated; $\mathrm{TIMEDIF}_1$ and $\mathrm{TIMEDIF}_2$ are the difference between presented time of day and observed time of day in minutes; ξ_1, ξ_2 and ξ_3 are error components drawn from a standard normal distribution.

For a person observed making a tour by train the utility functions (again for the four alternatives presented on a screen) could for example be:

$$\begin{aligned}
U_4 &= \alpha\mathrm{PTTIME}_4 + \beta^{\mathrm{o}}\mathrm{EARLY}_4 + \gamma^{\mathrm{o}}\mathrm{LATE}_4 + \beta^{\mathrm{r}}\mathrm{REARLY}_4 + \gamma^{\mathrm{r}}\mathrm{RLATE}_4 + \delta\mathrm{PTCOST}_4 + \cdots \\
U_5 &= \alpha\mathrm{PTTIME}_5 + \beta^{\mathrm{o}}\mathrm{EARLY}_5 + \beta^{\mathrm{r}}\mathrm{REARLY}_5 + \delta\mathrm{PTCOST}_5 + \eta_1\mathrm{TIMDIF}_5\xi_1 + \cdots \\
U_6 &= \alpha\mathrm{PTTIME}_6 + \gamma^{\mathrm{o}}\mathrm{LATE}_6 + \gamma^{\mathrm{r}}\mathrm{RLATE}_6 + \delta\mathrm{PTCOST}_6 + \eta_2\mathrm{TIMDIF}_6\xi_2 + \cdots \\
U_7 &= \alpha\mathrm{CARTIME}_7 + \beta^{\mathrm{o}}\mathrm{EARLY}_7 + \gamma^{\mathrm{o}}\mathrm{LATE}_7 + \beta^{\mathrm{r}}\mathrm{REARLY}_7 + \gamma^{\mathrm{r}}\mathrm{RLATE}_7 \\
&\quad + \delta\mathrm{CARCOST}_7 + \eta_3\xi_3 + \cdots
\end{aligned} \tag{5}$$

Finally for a person observed making a car trip (only for NHB business travel), the utility functions are:

$$\begin{aligned}
U_8 &= \alpha\mathrm{CARTIME}_8 + \beta^{\mathrm{o}}\mathrm{EARLY}_8 + \gamma^{\mathrm{o}}\mathrm{LATE}_8 + \delta\mathrm{CARCOST}_8 + \cdots \\
U_9 &= \alpha\mathrm{CARTIME}_9 + \beta^{\mathrm{o}}\mathrm{EARLY}_9 + \delta\mathrm{CARCOST}_9 + \eta_1\mathrm{TIMDIF}_9\xi_1 + \cdots \\
U_{10} &= \alpha\mathrm{CARTIME}_{10} + \gamma^{\mathrm{o}}\mathrm{LATE}_{10} + \delta\mathrm{CARCOST}_{10} + \eta_2\mathrm{TIMDIF}_{10}\xi_2 + \cdots \\
U_{11} &= \alpha\mathrm{PTTIME}_{11} + \beta^{\mathrm{o}}\mathrm{EARLY}_{11} + \gamma^{\mathrm{o}}\mathrm{LATE}_{11} + \delta\mathrm{PTCOST}_0 + \eta_3\xi_3 + \cdots
\end{aligned} \tag{6}$$

Here, CARTIME, CARCOST, PTTIME and PTCOST refer to a trip, not a tour.

Some respondents have a choice between three alternatives, because the alternative mode was not available (e.g. if no public transport available, or train users without a driving licence). Because we condition on car availability, we did not include a car availability measure, such as the cars to licences ratio, in the utility functions.

The *value of time* (VOT) is defined as α/δ. This gives the VOT in guilders/minute. After multiplying by 60 we obtain the VOT in guilders/hour. Furthermore we shall calculate *trade-off ratios* for the scheduling penalties versus the travel time coefficients:

(1) being early on outward leg ($\beta^{\mathrm{o}}/\alpha$);
(2) being early on return leg ($\beta^{\mathrm{r}}/\alpha$);
(3) being late on outward leg ($\gamma^{\mathrm{o}}/\alpha$); and
(4) being late on return leg ($\gamma^{\mathrm{r}}/\alpha$).

These ratios give the importance of being 1 min early or late in terms of a minute travel time. If these ratios are between zero and one, a minute scheduling delay is not as bad as a minute travel time.

The error components that were tested (the first three are represented in the above equations) are:

- A component that is proportional to the shift in departure time in the considerably earlier alternative (U_1, U_5, U_9, using the notation as in the utility functions in Eqs. (4)–(6)); the greater the shift, the lower the correlation between alternatives should be.
- A component that is proportional to the shift in departure time in the considerably later alternative (U_2, U_6, U_{10}); the greater the shift, the lower the correlation between alternatives should be.
- A component for mode shift (U_3, U_7, U_{11}); to test the hypothesis that shifting time is easier than shifting mode.
- A component that is proportional to the change in cost in the considerably earlier alternative (U_1, U_5, U_9); the greater the shift, the lower the correlation between alternatives should be.
- A component that is proportional to the change in cost in the considerably later alternative (U_2, U_6, U_{10}); the greater the shift, the lower the correlation between alternatives should be.
- A component that is proportional to the change in travel time in the considerably earlier alternative (U_1, U_5, U_9); the greater the shift, the lower the correlation between alternatives should be.
- A component that is proportional to the change in travel time in the considerably later alternative(U_2, U_6, U_{10}); the greater the shift, the lower the correlation between alternatives should be.

Below is a selection of the best time of day models obtained for each of the four purposes. Results are presented for models with Jack-knife [2] and without (called 'original model') Jack-knife estimation. The Jack-knife (see Cirillo et al., 2000) was used here to correct for the repeated measurements bias, which leads to overstated *t*-ratios and may correct for other specification errors as well. Future work may include using error components for this as well and comparing the outcomes with those of the Jack-knife. The models were estimated using the discrete choice model estimation software ALOGIT4. The error components are simulated from the normal distribution using 1000 pseudo-random draws.

4.2. Estimation results for commuting

The estimation results for commuting are in Table 2. After the Jack-knife estimation, all the estimated coefficients have the expected sign and are significant at the 95% confidence level, except for the dummy for working at home regularly and one of the car cost coefficients. The latter coefficient is significant at 90%. Younger persons, part-time workers and persons with a lower education level have a lower likelihood of shifting to earlier or later periods. Single workers travelling by train have an increased flexibility with regards to time of day choice.

[2] The Jack-knife method re-samples from the original sample by deleting a small number of observations each time. For each re-sample, statistics (e.g. estimated coefficients and standard errors) are calculated. The Jack-knife statistics are computed as averages of the re-sample averages.

Table 2
Estimation results for commuting (*t*-ratios in brackets)

Variable	Jack-knife estimates	Original estimates
Cost by car (in guilders) for households with gross annual income below 60,000 guilders	−0.0130 (−1.7)	−0.0143 (−7.5)
Cost by car (in guilders) for households with gross annual income above 60,000 guilders	−0.0111 (−2.6)	−0.0100 (−5.8)
Cost by train (in guilders) for persons not compensated by employer	−0.0429 (−2.8)	−0.0375 (−5.4)
Cost by train (in guilders) for persons compensated by employer	−0.0142 (−2.2)	−0.0132 (−5.4)
Travel time by car (in minutes)	−0.0141 (−5.2)	−0.0139 (−13.2)
Travel time by train (in minutes)	−0.0162 (−3.6)	−0.0155 (−12.7)
Early schedule penalty (in minutes) for the outward leg for persons with flexible working hours	−0.0153 (−5.7)	−0.0159 (−14.9)
Early schedule penalty (in minutes) for the outward leg for persons without flexible working hours	−0.0166 (−5.9)	−0.0172 (−14.2)
Late schedule penalty (in minutes) for the outward leg for persons with flexible working hours	−0.0191(−3.3)	−0.0210 (−15.6)
Late schedule penalty (in minutes) for the outward leg for persons without flexible working hours	−0.0290 (−6.6)	−0.0304 (−15.7)
Increased participation time penalty (in minutes) for persons with flexible working hours	−0.0098 (−4.7)	−0.0096 (−6.5)
Increased participation time penalty (in minutes) for persons without flexible working hours	−0.0071 (−2.6)	−0.0074(−4.7)
Decreased participation time penalty (in minutes) for persons with flexible working hours	−0.0041 (−4.2)	−0.0038 (−3.6)
Decreased participation time penalty (in minutes) for persons without flexible working hours	−0.0055 (−4.0)	−0.0063 (−4.5)
Constant for train earlier and later alternatives	−1.05 (−6.6)	−1.06 (−10.2)
Constant for car alternative for train users	−1.63 (−3.3)	−1.64 (−9.9)
Constant for train alternative for car users	−1.15 (−2.5)	−1.30 (−10.9)
1 if age under 40 years, 0 otherwise; for car earlier and later alternatives	−0.510 (−5.8)	−0.498 (−9.5)
1 if working part time (<32 h a week), 0 otherwise; for car and train earlier and later alternatives	−0.471 (−2.8)	−0.447 (−5.3)
1 if single worker; 0 otherwise; for train earlier and later alternatives	0.761 (3.0)	0.771 (4.2)
1 if low education level; 0 otherwise; for car and train earlier and later alternatives	−0.895 (−5.5)	−0.886 (−10.0)
1 if working home regularly; 0 otherwise; for car and train earlier and later and switch mode alternatives	−0.158 (−0.8)	−0.139 (−1.9)
Error component: departure time difference between the peak and the earlier retimed alternative	0.0093 (5.0)	0.0089 (11.2)
Error component: departure time difference between the peak and the later retimed alternative	0.0117 (2.8)	0.0123 (10.1)
Rho-squared (0)	0.333	0.333
Rho-squared (c)	0.096	0.096
Number of observations	6156	6156

Table 3
Trade-off ratios for commuting

Variable and mode	VOT in guilders/hour	
	Jack-knife	Original model
Car—gross annual income below 60,000 guilders	65	58
Car—gross annual income above 60,000 guilders	76	83
Train—not compensated by employer	23	25
Train—compensated by employer	69	71
	Schedule penalty coefficient divided by travel time coefficient	
Early schedule penalty		
Car—flexible hours	1.08	1.14
Car—non-flexible hours	1.17	1.23
Train—flexible hours	0.94	1.02
Train—non-flexible hours	1.02	1.11
Late schedule penalty		
Car—flexible hours	1.35	1.51
Car—non-working hours	2.05	2.18
Train—flexible hours	1.17	1.35
Train—non-flexible hours	1.79	1.96
Increased participation penalty		
Car—flexible hours	0.69	0.69
Car—non-flexible hours	0.50	0.53
Train—flexible hours	0.60	0.62
Train—non-flexible hours	0.43	0.48
Decreased participation penalty		
Car—flexible hours	0.29	0.57
Car—non-flexible hours	0.39	0.45
Train—flexible hours	0.25	0.24
Train—non-flexible hours	0.34	0.41

To judge the estimation results for travel time, cost and delay, one can have a look at the values of time and other trade-off ratios (see Section 4.1). In Table 3 are a number of trade-off ratios derived from the commuting model in Table 2.

The values of time are clearly higher than the values used in The Netherlands for project evaluation (about 17 guilders/h). [3] This has been found for some other time of day models as well and is also found for the other purposes in this study (except business). It appears that cost differences are not as strong in persuading travellers to shift time as are time differences, perhaps because the time differences already imply a change to activity schedules.

The scheduling trade-off ratio of 1.08 for car drivers with flexible working hours being early (Jack-knife estimation) in Table 3 is the result of dividing the coefficient −0.0153 from Table 2 by the car travel time coefficient −0.0141 (but at higher precision). This result implies that 1 min too early is valued to be slightly worse than 1 min of travel time. Most of the ratios of the schedule delay penalty coefficients, both for too early and too late, to travel time are between 1 and 1.5; half an hour earlier or later at work gives the same disutility as 30–45 min travel time. In the previous

[3] A guilder is an ancient currency that was worth approximately 0.45 EURO.

1989 time of day stated preference survey in The Netherlands, these ratios were generally between 0.5 and 1 for commuting. Time of day shifting appears to be less sensitive now, perhaps because many travellers have already shifted to less preferred time of day periods in response to increasing congestion. The disutility from arriving early is now very similar to that of being late. The above discussion referred to the outward leg. For the participation time decision, working too long or too short is generally preferred to an equivalent amount of travel time.

The error components used in the best model for commuting are:

(1) a component that is proportional to the shift in departure time in the considerably earlier alternative: the greater the shift, the lower the correlation between alternatives will be; and
(2) a component that is proportional to the shift in departure time in the considerably later alternative the greater the shift, the lower the correlation between alternatives will be.

For both error components, the closer the coefficient is to zero, the higher the degree of substitution. The sign of the error components is of no importance, but we would expect about the same absolute size for both departure time shift error components. This is indeed what we find in estimation. Error components proportional to the cost and travel time differences were tried as well but did not significantly improve the models; nor did an error component for mode shift for commuting. This finding implies that—all else equal—these models imply a greater elasticity for mode shifting than for time shifting.

4.3. Estimation results for business travel

The estimation results for HB business tours and NHB business trips are in Table 4.

In the Jack-knife estimates of the business model, the coefficients for the early and late schedule penalties for train are only significant at the 90% confidence level. Two participation time coefficients, the education dummy and one of the intercept terms are not significant at the 90% level. The other coefficients are significant at 95% and have the expected signs. Again younger persons are less likely to shift to off-peak. The trade-off ratios are in Table 5.

To calculate the VOT in these models, which used the log cost formulation, the ratio of the time coefficient to the log cost coefficient is divided by the average time travelled. This gives an approximate average VOT—in fact according to the model the VOT varies substantially among the travelling population, proportionately to the journey cost.

The values of time are somewhat higher than the officially recommended values (almost 55 guilders, but also including the valuation by the employer). Again, several of the outward leg scheduling penalty coefficients exceed the travel time coefficients, whereas for participation time, the penalty coefficients are lower than those for travel time.

4.4. Estimation results for education tours

The estimation results for education are given in Table 6. The reported model is a MNL model, not an error components model. Error components were tried but did not give a significant improvement for education tours.

Table 4
Estimation results for business (*t*-ratios in brackets)

Variable	Jack-knife estimates	Original estimates
Log of cost by car in guilders	−0.803 (−2.4)	−0.790 (−5.3)
Log of cost by train in guilders	−0.589 (−2.4)	−0.578 (−5.3)
Travel time by car (in minutes)	−0.0154 (−4.1)	−0.0151 (−9.2)
Travel time by train (in minutes)	−0.0185 (−3.6)	−0.0185 (−9.6)
Early schedule penalty (in minutes) for the outward leg for HB car tours	−0.0199 (−4.6)	−0.0200 (−13.5)
Early schedule penalty (in minutes) for the outward leg for NHB car trips	−0.0211 (−7.0)	−0.0206 (−12.0)
Early schedule penalty (in minutes) for the outward leg for train users	−0.0134 (−1.9)	−0.0140 (−7.1)
Late schedule penalty (in minutes) for the outward leg for HB car tours	−0.0252 (−4.8)	−0.0252 (−14.3)
Late schedule penalty (in minutes) for the outward leg for NHB car trips	−0.0235 (−5.0)	−0.0232 (−11.3)
Late schedule penalty (in minutes) for the outward leg for train users	−0.0106 (−1.9)	−0.0104 (−5.9)
Increased participation time penalty (in minutes) for HB car tours	−0.0083 (−1.7)	−0.086 (−4.5)
Increased participation time penalty (in minutes) for train users	−0.0041 (−1.2)	−0.0037 (−1.9)
Decreased participation time penalty for HB car tours	−0.0056 (−1.2)	−0.0060 (−3.0)
Decreased participation time penalty for train users	−0.0079 (−2.9)	−0.0078 (−5.3)
Constant for train earlier and later alternatives	−0.699 (−2.5)	−0.696 (−6.8)
Constant for car alternative for train users	−1.11 (−0.8)	−1.07 (−1.5)
Constant for train alternative for car users	−4.00 (−3.1)	−3.87 (−4.9)
1 if age under 40 years; 0 otherwise; car and train earlier and later alternatives	−0.559 (−3.7)	−0.553 (−7.8)
1 if low–medium education level; 0 otherwise; car and train earlier and later alternatives	−0.174 (−1.3)	−0.179 (−2.2)
Error component—departure time differences	0.0089 (2.3)	0.0070 (6.7)
Error component—mode switch dummy	1.92 (2.7)	1.65 (4.6)
Rho-squared (0)	0.313	0.313
Rho-squared (c)	0.116	0.116
Number of observations	3812	3812

Table 5
Trade-off ratios for business

Variable and mode	Approximate VOT in guilders/hour	
	Jack-knife	Original model
Car	92	92
Train	73	75
	Schedule penalty coefficient divided by travel time coefficient	
Early schedule penalty		
Car HB tours	1.29	1.32
Car NHB trips	1.37	1.36
Train	0.72	0.76
Late schedule penalty		
Car HB tours	1.64	1.67
Car NHB trips	1.53	1.54
Train	0.57	0.56
Increased participation penalty—car HB tours	0.54	0.57
Decreased participation penalty—train	0.43	0.42

Table 6
Estimation results for education (*t*-ratios in brackets)

Variable	Jack-knife estimates	Original estimates
Cost by car (in guilders)	−0.0831 (−2.4)	−0.0869 (−6.1)
Cost by train (in guilders), for persons without seasonal tickets	−0.0431 (−2.6)	−0.0505 (−8.2)
Travel time by car (in minutes)	−0.0140 (−2)	−0.0122 (−3.2)
Travel time train (in minutes)	−0.0375 (−7.1)	−0.0353 (−9.5)
Early schedule penalty (in minutes) for the outward leg for train users	−0.0107 (−1.9)	−0.0123 (−7.1)
Late schedule penalty (in minutes) for the outward leg for train users	−0.0088 (−2.2)	−0.0099 (−6.5)
Increased participation time penalty (in minutes)	−0.0024 (−0.7)	−0.0022 (−1.2)
Decreased participation time penalty (in minutes)	−0.0031 (−2.1)	−0.0032 (−2.6)
Constant for train earlier and later alternatives	−1.15 (−6.0)	−1.11 (−10.8)
Constant for car alternative for train users	−3.42 (−2.3)	−3.36 (−7.1)
Constant for train alternative for car users	3.66 (1.9)	3.23 (6.1)
1 if low education level; 0 otherwise; car peak alternative	2.17 (2.0)	2.47 (5.2)
Rho-squared (0)	0.439	0.439
Rho-squared (c)	0.163	0.163
Number of observations	1250	1250

In the model presented for education, some of the scheduling variables were clearly not significant, even before Jack-knifing. These have been removed and the model has been re-estimated without those variables. Persons with a low education level (going mostly to schools with fixed school hours starting and ending in the peak periods) have a higher probability of selecting the peak alternative.

The trade-off ratios for this travel purpose are in Table 7. The values of time for car are in line with official recommendations, but those for train are particularly high. For education all scheduling and participation penalty coefficients represent a lower disutility than travel time.

4.5. Estimation results for 'other purposes'

Finally, the estimation results for 'other purposes' are given in Table 8.

All the coefficients have the sign we expected and are significant at 95%, except for cost, two alternative-specific constants and one of the participation time penalties for train. The departure

Table 7
Trade-off ratios for education

Variable and mode	VOT in guilders/hour	
	Jack-knife	Original model
Car	10	8
Train	52	42
	Schedule penalty coefficient divided by travel time coefficient	
Early schedule penalty—train	0.28	0.35
Late schedule penalty—train	0.23	0.28
Increased participation penalty—train	0.06	0.06
Increased participation penalty—car	0.17	0.18

Table 8
Estimation results for other purposes (*t*-ratios in brackets)

Variable	Jack-knife estimates	Original estimates
Cost (in guilders)	−0.092 (−0.9)	−0.0129 (−7.2)
Travel time by car (in minutes)	−0.0157 (−2.6)	−0.0156 (−11.2)
Travel time by train (in minutes)	−0.0170 (−4.4)	−0.0179 (−12.4)
Early schedule penalty (in minutes) for the outward leg for car users	−0.0193 (−6.6)	−0.0197 (−13.3)
Early schedule penalty (in minutes) for the outward leg for train users	−0.0121 (−3.1)	−0.0094 (−5.5)
Late schedule penalty (in minutes) for the outward leg for car users	−0.0264 (−5.5)	−0.0249 (−13.9)
Late schedule penalty (in minutes) for the outward leg for train users	−0.0174 (−2.9)	−0.0124 (−5.2)
Increased participation time penalty (in minutes) for car users	−0.0056 (−3.1)	−0.0059 (−4.0)
Increased participation time penalty (in minutes) for train users	−0.0077 (−3.3)	−0.0090 (−5.5)
Decreased participation time penalty (in minutes) for car users	−0.0051 (−2.6)	−0.0050(−2.5)
Decreased participation time penalty (in minutes) for train users	−0.0057 (−1.6)	−0.0056 (−3.2)
Constant for train earlier and later alternatives	−0.125 (−0.5)	−0.265 (−2.7)
Constant for car alternative for train users	−0.689 (−1.2)	−0.849 (−3.8)
Constant for train alternative for car users	−1.78 (−4.3)	−1.76 (−10.6)
1 if housewife; 0 otherwise; car and train earlier and late alternatives	−0.340 (−3.4)	−0.342 (−4.2)
1 if low education level; 0 otherwise; car earlier and switch mode alternatives	−0.624 (−3.5)	−0.639 (−6.9)
Error component: departure time difference, earlier alternative	0.0100 (6.0)	0.0104 (10.2)
Error component: departure time difference, later alternative	0.0178 (3.3)	0.0107 (4.4)
Rho-squared (0)	0.262	0.262
Rho-squared (c)	0.108	0.108
Number of observations	3224	3224

time difference component coefficients have about the same size. A housewife has a lower probability of being able to shift departure time (presumably because of time constraints at home). Persons with a low education level have more difficulty in shifting departure time as well.

Trade-off values for other purposes are found in Table 9. The values of time are clearly higher than the officially recommended values (about 11 guilders), but cannot be based on a significant cost estimate. Three out of the four scheduling delay penalty coefficients exceed the travel time coefficient and all the participation penalty coefficients are lower than the travel time coefficient.

4.6. Overview of estimation results

Many different specifications were tested for all four purposes, with the following results:

- EClogit generally outperformed MNL and NL, except for education tours.
- A separate model for NHB business travel did not give acceptable coefficients (probably due to the limited number of observations); this was merged with HB business tours.
- For commuting, but not for all other purposes, quadratic scheduling penalties gave better results than linear scheduling terms only (to get comparable values of time and other trade-off values in the above tables we presented only linear models).
- For business travel, but not for the other purposes, logarithmic cost performed better than linear cost.

Table 9
Trade-off ratios for other purposes

Variable and mode	VOT in guilders/hour	
	Jack-knife	Original model
Car	102	73
Train	111	83
	Schedule penalty coefficient divided by travel time coefficient	
Early schedule penalty		
Car	1.23	1.26
Train	0.71	0.52
Late schedule penalty		
Car	1.68	1.59
Train	1.02	0.69
Increased participation penalty		
Car	0.36	0.38
Train	0.45	0.50
Decreased participation penalty		
Car	0.32	0.32
Train	0.33	0.31

- Splitting the cost coefficients by income group did not produce satisfactory results, except for commuting tours.
- A cost of zero for holders of seasonal passes worked best for education and other purposes, not for commuting tours and business travel.
- For train commuters, cost coefficients that differentiate between employees receiving compensation and employees not receiving compensation gave plausible values and a significant improvement in likelihood. Delay coefficients that differentiate between employees with and without flexible work hours did the same for commuters by train and car.

5. Simulation results

To get a good impression of the substitution patterns in the models estimated (nearby versus faraway periods, mode versus time of day alternatives), we carried out several simulation runs for car and train commuters. Fig. 1 shows the effect of an increase in the AM peak travel time (between 7:00 and 9:00) on the outward leg departure time (‘out change’ in the graph), on the return leg departure time (‘back change’) and on mode switching for commuters initially travelling by car. For the other purposes, the results were mostly rather similar to those for commuting. On the vertical axis are the percentage changes in the number of trips (car trips in Fig. 1 and train trips in Fig. 2), using the estimation sample. The horizontal axis gives the distribution over the time of day alternatives (aggregated to 11 time slices) during an entire 24-h day and the alternative to switch mode. Note that only the points in the graph indicate a value, the lines are drawn to improve readability.

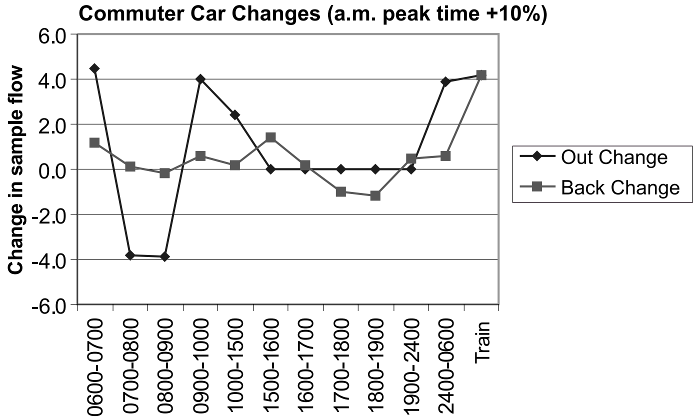

Fig. 1. Changes in time of day and mode choice (AM peak travel time + 10%), car commuters only.

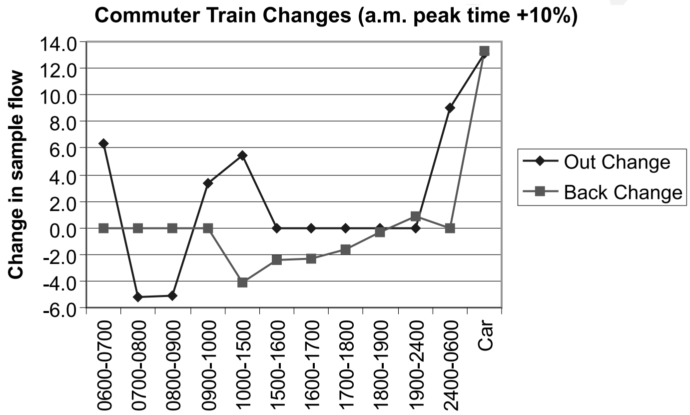

Fig. 2. Changes in time of day and mode choice (AM peak travel time + 10%), train commuters only.

Fig. 1 indicates that if the morning peak travel time increases, many commuters will change their departure time for the outward leg. Instead of departing in the affected periods (7:00–9:00) many will now depart during a neighbouring period, both of which increase by more than 4%. One can also notice that quite a few make major shifts in outbound leg to 10:00–15:00 or 24:00–6:00. As one could expect, this change has no impact on the travellers departing during the afternoon and the evening (15:00–24:00).

The effect on the return leg departure time is less important than on the outward leg, fewer travellers are switching period. We can notice interesting changes in profiles both out and return, e.g. small increases in returns between 6:00 and 7:00 and between 9:00 and 10:00 are presumably people returning home in AM peak, while increases in returns between 15:00 and 16:00 and between 19:00 and 24:00 are people affected on their outbound leg.

Some car commuters will also shift to the train. The number of train trips increases by 4%. Given the small initial number of choices for train in the data base for this purpose, not as many go to the train as to neighbouring periods (of course this is also affected by the fact that the train is also slowing down in the simulation).

Fig. 2 is similar to the previous one but deals with travellers initially using the train. Here the car is much more important as an alternative relative to time shifts. One could assume that train users are more scheduling-time constrained than car users and it is easier for them to change mode than departure time. Also we should keep in mind when comparing the above two figures that only for a limited number of trips where car (if available) is a good alternative there are good train connections.

Shifts to neighbouring periods are even larger than on the previous chart for the outward leg as well as for the return leg. No train users return in AM peak (night workers use cars), so all return shifts are consequent on outward effect. One can note how these are earlier than for car users. Many of those who change their choices switch to cars.

6. Conclusions and recommendations

A new stated preference survey into the time of day choice of travellers by car and train has been carried out in The Netherlands. In this paper, these data have been used to estimate error components models of time of day and mode choice.

In our estimation results, EClogit generally outperformed MNL and NL, except for education tours. In the estimated models, for commuting, business and other purposes, arriving 30 min too late or too early at the destination is valued to be worse than 30 min of travel time. For education tours, the opposite is found. Longer than preferred activity participation time is generally valued to be less important than an equivalent amount of travel time.

Simulation results with the estimated models show that for most purposes, the closer the two time of day periods are in clock time, the greater will be the degree of substitution. If travel time or cost in the peak increases, most travellers will shift to periods just before or after the peak. Many train travellers will also shift to the car (more than will shift from car to train).

The new results indicate that time of day choice in The Netherlands is sensitive to changes in peak travel time and cost and that policies that increase these peak attributes will lead to peak spreading. However, the time of day sensitivities to travel time and cost changes in the (selective) sample, in general seem to be lower than 10 years ago. [4]

In this paper we applied the Jack-knife method to estimate coefficient values and standard errors that do not suffer from the repeated measurements problem (multiple observations from the

[4] The error components model needs to be simplified for integration with the Dutch national model system (LMS) and to keep model run times within reasonable limits. For integration into the current NL framework of the LMS through logsum variables, the new time of day choice model needs to be a GEV model. Because mode choice was included in the joint mode and time of day choice model, an appropriate variance scaling between both models can be determined. A simplified model was developed that represents mode choice and choice among eleven time periods for each leg (outbound and return) of the tour, rather than the time-specific alternatives represented in the models of this paper. It was tested whether within time of day choice, similar alternatives (e.g. adjacent time periods) had a higher degree of correlation than other alternatives, by estimating the OGEV model specification (using the Biogeme software). However, the OGEV models had log likelihood values that were lower than those for NL models. The new simplified time of day models to be implemented into the LMS will therefore probably be NL models.

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same individual, taken to be independent) of the stated preference data. An alternative method would be to include individual-specific components, as are sometimes used in panel data models, in the error components model. Further research is needed to compare these two ways of solving the repeated measurement problem.

7. Uncited References

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