A model of departure time choice with latent classes and peak-hour avoidance rewarding

Eran Ben-Elia *Centre for Transport and Society, University of the West of England, UK.* Eran.Ben-Elia@uwe.ac.uk

Michel Bierlaire *Transport and Mobility Laboratory, Ecole Polytechnique Fédérale de Lausanne, Switzerland.* michel.bierlaire@epfl.ch

Dick Ettema *Urban and Regional Research Centre, Utrecht Faculty of Geosciences, Univ. of Utrecht, The Netherlands.* d.ettema@geo.uu.nl

Abstract

This paper presents a model of departure time choice based on the notion of a latent preferred arrival time using the peak-avoidance data of the Dutch Spitsmijden project. Spitsmijden involved the use of rewards for encouraging drivers to avoid commuting during the peak-hours. Rewarding (either by money or by Smartphone credits) was investigated in the context of a longitudinal field experiment lasting 13 weeks in which the electronic detection of participant s vehicles was used to verify change of behavior i.e. shift of traveling time. Using 15 minute interval to discrete time, we estimated several choice models to identify the choice of departure time when rewards are provided. We use these interim models to generate starting values for a new modeling framework based on the vehicle detection data to estimate the choice of departure time and assuming a latent preferred arrival time based on a latent class construct. This study is a work in progress and presents interim results.

Keywords: discrete choice, departure time choice, latent class, rewards

1 Introduction

Too many people traveling in their car at the same times and even to the same places are a main cause for road congestion. The prognosis for Europe is far from satisfactory. Congestion levels on urban roads throughout the European Union are rising (European Commission, 2006a, European Commission, 2006b). Overloading of the Transportation System has considerable external costs such as pollution, noise and road user safety (Mayeres et al., 1996) and results in increasing frequency of incidents, interrupted vehicle flow and uncertainty regarding travel times (Lomax and Schrank, 2003). Transportation Demand-based solutions (e.g. promoting modal alternatives, parking policy and land use planning policy) have been suggested to reduce congestion (Shiftan and Golani, 2005). Another possible remedy is to encourage travelers to shift to other times i.e. change of departure times to less congested time frames either before or after the rush-hour. That is to influence their choice of departure time.

Convincing travelers to change their departure times is far from easy as it disrupts their common daily schedule. Without a stimulus there would be no real motivation to change normal behavior. Transport economists have been arguing for implementation of road pricing as a first-best solution to efficiently alleviate congestion externalities (Nijkamp and Shefer, 1998; Rouwendal and Verhoef, 2006; Small and Verhoef, 2007). However, road pricing is controversial and insight is lacking in key domains. First, as suggested initially by Vickrey (1969), optimal pricing requires that tolls are designed to be variable making it quite complex for drivers' comprehension (Bonsall et al., 2007; Verhoef, 2008). Second, it raises questions regarding social equity (Giuliano, 1994), fairness and public acceptability (Banister, 1994; Viegas, 2001; Eriksson et al., 2006). Third, psychologists assert people are more motivated when rewarded rather than punished (Kahneman and Tversky, 1984; Geller, 1989).

In The Netherlands the notion of using rewards to achieve desired outcomes in travelers' behavior has been recently implemented in the context of the Spitsmijden (translated freely as peak avoidance) program (Ettema and Verhoef, 2006; Knockaert et al., 2007; Ettema et al., 2010). A pilot study, involving 340 participants and lasting over 13 weeks, was organized in the second half of 2006. Its objective was to investigate, in an empirical field study (or revealed preference - RP), the potential impacts of rewards on commuters' behavior during the morning rush-hour. Participants were rewarded, either with money or with credits (to be eligible to keep a handy Smartphone called 'Yeti'),for changing their behavior. Behavior change was defined as shifting commuting times from the morning rush-hours to earlier or later times, changing travel modes or for working from home. Further details of the design are presented in section 3. Initial results provided evidence of substantial behavior change in response to the rewards, with commuter shifting to earlier and later departure times and more use of public transport and alternative modes or working from home (Ettema et al., 2008; Ettema et al., 2010).

Further research, based on discrete choice modeling for aggregate alternatives (peak driving, driving before the peak, driving after the peak and not driving), suggests the main effect of the reward is to encourage the shift from peak-hour driving. In this sense the rewards triggers a response to avoid the peak-hour. However, the choice of alternatives to rush-hour driving is influenced by different factors: First, certain socio-economic characteristics like gender and education were found to be significant. Women were found to be less responsive to change behavior. Higher education was also associated with lower peak avoidance rate. Second, scheduling considerations including work and home related constraints or flexibility were found to influence behavior. Work time flexibility such as ability to start working later was associated with driving after the peak. Third, the gaps between the change of behavior and habitual behavior as reflected in the, usual peak commuting frequencies (reference behavior), usual departure time and preferred start of work time are relevant. The larger the difference (e.g. earlier usual departure time associated with driving before the peak) the lower is the rate of peak-avoidance. Use of other modes except the car for traveling to work was also associated with encouraging not driving. Fourth, perceptions about effort involved in avoidance behavior and beliefs regarding the non-motorized alternatives (cycling and public transport) were found to have significant effects. Positive beliefs about alternatives were associated with less driving. Perceptions of high effort in change of behavior were associated with less peak avoidance. Fifth, greater use travel information was associated with a greater degree of peak avoidance and especially with driving after the peak. Further results are discussed by Ben-Elia and Ettema (2010). The research into Spitsmijden, so far has provided remarkable results. However, to date it has mainly focused on the analysis of participants aggregate choice of mode and avoidance preference (before/after the peak-hour), whereas the dynamics of departure time choice during the course of the program have been less understood.

Departure time choice modeling has been part of main stream travel behavior research for more than three decades. Congestion management schemes are based on the assumption that travelers optimize their departure time choice. Ever since Vickrey formulated the 'bottleneck' model in the late 1960's (Vickrey, 1969) and later updated by Small in the 1970's (Small, 1982; Small and Verhoef, 2007), the concept of schedule-delays (early and late) has been the focus of most modeling endeavors. The main idea is that travelers scheduling revolves around a preferred arrival time. The bottleneck model shows how a queue is formed from the departure time decisions of individual travelers and how a time-dependent toll could in theory dissolve it efficiently. Several theoretical extensions have included variable demand and supply and heterogeneity but the fundamental logic remains the same (Arnott et al., 1990, Arnott et al., 1993). Several empirical investigations applied schedule-delay specifications using discrete choice models (Bates et al., 2001; de Jong et al., 2003; Ettema and Timmermans, 2006; Jou et al., 2008). Most of these models used discrete time units in different intervals to represent continuous time. A different approach was applied by Bhat and Steed (2002), who used a hazard specification to model departure time for shopping trips. However the behavioral representativeness of this approach can be questioned. In this paper we continue with this line of research with a focus on departure time choice behavior during the experiment. We apply the schedule-delay framework albeit in more flexible manner using a latent preferred arrival time construct.

The main challenge standing before any departure time choice model is lack of sufficient and accurate data on travelers' departure and arrival times. Usually surveys based on stated behavior of travel diaries are applied. Surveillance techniques to capture real departure and arrival times are less frequently adopted probably due to both high costs of the infrastructure and privacy issues. In this respect the database of Spitsmijden provides researchers a remarkable data set of revealed preference. The rest of the paper is organized as follows: Section 2 presents the design of the Spitsmijden pilot experiment and the data collection. Section 3 presents the modeling framework and the estimation results. Section 4 presents discussion and future work.

2 Design and data collection

The Dutch 'Spitsmijden' experiment is, thus far, the largest systematic effort to analyze the potential of rewards as a policy mean for changing travel behavior. The experiment was conducted by a public-private partnership consisting of three universities, private firms and public institutions. Its purpose was to collect a large sample of empirical or revealed preference (RP) data regarding the effects of a reward on daily commuting behavior during the morning rush-hour. A pilot study was launched in October 2006. The study area was the heavily congested Dutch A12 motorway stretch from Zoetermeer westbound towards The Hague. During a period of 13 consecutive weeks, 341 recruited volunteers (221 men and 120 woman) living in the town of Zoetermeer, a satellite city of The Hague, participated in a scheme whereby they would receive daily rewards, either of money (between 3-7 €) or of credits to earn a Smartphone called 'Yeti'. 232 participants chose to receive a monetary reward ("Money") and 109 the Smartphone reward. Participants could avoid peak-hour travel, defined between 7:30-9:30 AM and earn a reward, either by driving at off-peak times (before or after the peak), switching to another travel mode (cycling or public transport) or by working from home. Participants that opted for the Yeti option were also provided with real-time traffic information regarding travel times on the Zoetermeer – The Hague corridor.

Data was collected during the 'Spitsmijden' experiment in three stages. The first and third stages consisted of surveys. The second stage consisted of the actual experiment. The second stage was the actual experiment, lasting 13 weeks (of which weeks 3-12 were with rewards). It consisted of tracking participant's revealed (i.e. observed) behavior. Detection equipment using in-vehicle installed transponders and electronic vehicle identification (EVI) as well as backup road-side cameras was installed at the exits from Zoetermeer to the A12 motorway and on other routes leaving the city.

This equipment allowed detecting each and every car passage during the course of the day, minimizing the ability of participants to cheat by trying to access alternative routes. In addition, participants were instructed to fill in their daily web-based logbook. They recorded whether or not they had commuted to work (and if not, why not), which means of transport they used and at what slot time they made their trip. This information was used to gain insight into situations in which the participant was not detected by the EVI. It was necessary in these cases to know whether they had used some other means of transport (public transport or bicycle) or whether they had not made a commute due to vacation, illness, etc. The first two weeks were without reward (pre-test). The data collected during the pre-test was used to determine participants' reference travel behavior. The final week (post-test) was also without rewards.

Those participants who opted for money were the subject of three consecutive reward "treatments" lasting 10 weeks in total: a reward of 3€(lasting three weeks), a reward of 7€(lasting four weeks) and a mixed reward (lasting three weeks) of up to 7€- of which 3€for avoiding the high peak (8:00-9:00) and an additional 4€for avoiding also the lower peak shoulders (7:30-8:00, 9:00-9:30). The order of the reward "treatments" followed a block design which allocated participants roughly randomly to the 6 possible schemes. Some exceptions were applied to couples using the same vehicle.

Participants in possession of the Yeti could acquire credit during a period of five consecutive weeks. If they earned enough credit relative to a known threshold they could keep the Smartphone. This threshold was determined by their reward class (see below). The other five weeks were without credits but participants could still have access to traffic information. Participants were divided between two schemes in relation to which of the first or second set of 5 weeks credits could be awarded. Participants in possession of a Yeti also had 24 hour access to travel information via the handset during 11 weeks: the credit treatment, the no-credit treatment as well as the post-test. This information consisted of real-time travel times on the A12 motorway on the Zoetermeer – The Hague corridor and an online map showing congestion levels on other roads in the area. Information availability was not dependent on the reward itself. In contrast, participants in the money group had access to information available to all other drivers: pre-trip through internet and media and en-route from variable message signs along the motorway.

The third stage of the study was a posterior evaluation survey. In this survey questions were asked about the participant's subjective experience during the course of the experiment. This dealt, on the one hand, with their retrospective assessment of behavior adjustment (was it easy / difficult to adjust travel behavior and how). On the other hand, other questions were asked about their experience with the organization of the trial (provision of information, performance of the project's back office, etc.

Another important feature in the design was the participants' allocation to reward class determined by his or her (reference) behavior during the pre-test. .For the participants who chose the monetary reward, the reward class defined the maximum number of rewards they could receive each week (1, 2, 4, 5). The rationale was that not all participants drive during the rush-hour five days per week. For the participants in the Yeti group, the class defined the threshold value for the number of days on which the participant could avoid the morning rush-hour. If the participant met or exceeded the threshold value, he/she would be able to keep the Yeti. If the participant failed to meet the threshold value, he/she would have to return the phone, but not until the end of the experiment. As all days on which the participant's car was not detected in the morning rush-hour counted towards meeting the threshold, this threshold value was designed to be regressive in nature - larger for participants who drove less during the rush-hour. The key aim was to discourage any possible increase in the number of commuting trips during off-peak periods that were not offset by existing rush-hour trips. Based on the information above, each participant was allocated into one of four possible classes. Once determined these classes were fixed throughout the rest of the experiment. The majority of participants belonged to classes A (3.5-5 trips/week) and B (2.5-3.5 trips/week) and the minority to classes C (1-2.5 trips/week) and D (0-1 trips/week). Table 1 presents the number of participants (by gender) in each class.

3 Models

The time is discretized into intervals of 15 minutes each. By convention, the time interval k starts $15k$ minutes after midnight and ends $15(k+1)$

		Money			
		A	B	C	D
Rush-hour trips/week at reference		3.5–5	2.5–3.5	1–2.5	0–1
Threshold*		5	4	2	1
N	Men	83	33	13	11
		62%	54%	57%	79%
	Women	51	28	10	3
		38%	46%	44%	21%
	Total	134	61	23	14

Table 1: Breakdown of the participants to reward classes by gender and reward group

* Money: maximum number of eligible rewards per week; Yeti: number of credits at the end of 5 weeks required to keep the phone.

minutes after midnight. We consider intervals 24 to 43, corresponding the period between 6:00 and 11:00. The peak hour spans intervals 30 to 37, that is from 7:30 to 9:30.

We consider the following variables, where $k = 24, \ldots, 43$ denotes the departure time interval:

- $\texttt{TT}_k$: travel time when departing during time interval k, as provided by the traffic information system (in seconds, min: 173, max: 3069, mean: 311.7);
- $\texttt{RFTIM}_n$: reference detection time of individual n (in minutes after midnight, min: 421 (7:01), max: 592 (9:52), mean: 492 (8:12));
- $\texttt{RFTRAV}_n$: reference travel time of individual n (in seconds min: 173, max: 3069, mean: 411.68) adapted from the traffic information system;
- $\texttt{PAT}_n = \texttt{RFTIM}_n + \texttt{RFTRAV}_n/60$: reference arrival time of individual n (in minutes after midnight), used as a proxy for preferred arrival time;
- $\texttt{XE}_{kn} = \max(0, \texttt{PAT}_n - (15(k+1) + \texttt{RFTRAV}_n/60)$: early arrival, where $15(k+1) + \texttt{RFTRAV}_n/60$ is the latest possible arrival time when departing in time interval k,

- $\mathtt{XL}_{kn} = \max(0, 15k + \mathtt{RFTRAV}_n/60 - \mathtt{PAT}$: late arrival, where $15k + \mathtt{RFTRAV}_n/60$ is the earliest possible arrival time when departing in time interval k,
- EURO: reward in money (in euros),
- CREDIT: reward in credits.

3.1 Logit

We estimate first a linear-in-parameter logit model with 20 alternatives with the following specification. The utility function for time intervals within the peak hours (k=30,...,37) are defined as

$$V_k = \mathtt{A}_k + \mathtt{BT}\ \mathtt{TT}_k + \mathtt{BE}\ \mathtt{XE}_{kn} + \mathtt{BL}\ \mathtt{XL}_{kn},$$

The utility functions for time intervals off peak hours (k=24,...,29 and k = 38,...,43) are defined as

$$V_k = \mathtt{A}_k + \mathtt{BT}\ \mathtt{TT}_k + \mathtt{BE}\ \mathtt{XE}_{kn} + \mathtt{BL}\ \mathtt{XL}_{kn} + \mathtt{BEUR}\ \mathtt{EURO} + \mathtt{BCR}\ \mathtt{CREDIT}.$$

The estimation results are presented in Table 2. All coefficients are significant and have the correct sign.

3.2 Logit mixture

We investigate a first improvement of this model using a specification with error components and random coefficients. An error component, normally distributed, is added to all alternatives corresponding to a time interval before the peak period (EC_EARLY). Another one, EC_LATE, is associated to alternatives after the peak period. Moreover, the coefficient BE and BL are normally distributed, with standard error S_BE and S_BL, respectively. The estimation results, obtained from a panel data specification, are reported in Table 3. A clear improvement of the fit is obtained. Again, all parameters are significant with the correct sign.

3.3 Latent class

We investigate a second type of improvement for the logit model, based on a latent class specification. Due to the long estimation time for the mixture model, we will combine these two improvements in a later stage.

Parameter number	Description	Coeff. estimate	Robust Asympt. std. error	t-stat	p-value
1	A25	-0.436	0.199	-2.19	0.03
2	A26	0.698	0.175	3.99	0.00
3	A27	0.649	0.190	3.41	0.00
4	A28	1.37	0.213	6.42	0.00
5	A29	1.94	0.242	8.04	0.00
6	A30	1.17	0.273	4.27	0.00
7	A31	0.823	0.304	2.71	0.01
8	A32	0.785	0.335	2.35	0.02
9	A33	0.954	0.369	2.58	0.01
10	A34	0.865	0.399	2.17	0.03
11	A35	0.869	0.435	2.00	0.05
12	A36	0.779	0.474	1.64	0.10
13	A37	0.782	0.511	1.53	0.13
14	A38	1.78	0.540	3.30	0.00
15	A39	1.53	0.578	2.65	0.01
16	A40	1.28	0.620	2.06	0.04
17	A41	1.43	0.661	2.16	0.03
18	A42	1.75	0.701	2.49	0.01
19	A43	1.89	0.747	2.53	0.01
20	BCR	1.31	0.0762	17.25	0.00
21	BE	-0.0278	0.00282	-9.87	0.00
22	BEU	0.196	0.00747	26.27	0.00
23	BL	-0.0355	0.00290	-12.25	0.00
24	BT	-0.0116	0.00388	-3.00	0.00

Number of observations = 10315

$\mathcal{L}(0) = -30900.978$

$\mathcal{L}(c) = -26328.662$

$\mathcal{L}(\hat{\beta}) = -22518.767$

$\rho^2 = 0.271$

$\bar{\rho}^2 = 0.270$

Table 2: Estimated parameters for the logit model

The penalization for early and late arrival is related to the actual existence of a preferred arrival time. Many participants in the experiment reported that they have flexible schedules and, therefore, do not necessarily have a preferred arrival time. We test this assumption by specifying a latent class model.

We assume that there are two classes of individuals. One class is penalized by an early or a late arrival, while the second class is not. Therefore, the parameters BE and BL are constrained to zero for individuals belonging to the second class.

The class membership model is a binary logit model. We define V to be a linear combination of the following variables (the associated coefficient is reported in parentheses):

- Gender of participant (1 if woman, 0 otherwise, coefficient: `ClassFemale`),
- Dummy variable for early departure constraints due to child care at home (coefficient: `ClassChildCare`),
- Dummy variable for arrangements with employer made prior to beginning the experiments to support flexible working times (inquired in the posterior survey, coefficient: `ClassFlexWorkTime`).

The probability to belong to the first class (penalized by early or late departure) is

$$P(\texttt{WithPenalty}) = \frac{e^V}{1+e^V} = \frac{1}{1+e^{-V}}.$$

The probability to belong to the second class is therefore

$$P(\texttt{WithoutPenalty}) = 1 - P(\texttt{WithPenalty}) = \frac{1}{1+e^V}.$$

Also, the choice model has been improved by adding some characteristics to capture part of the heterogeneity using observed variable:

- Dummy variable for whether the participants is allocated to classes A or B (see Table 1) in the money group: alternatives 30 to 37. Coefficients: $\texttt{BCABM}_i$.
- Dummy variable for whether the participants is allocated to classes A or B (see Table 1) in the phone group: alternatives 30 to 37. Coefficients: $\texttt{BCABP}_i$.

- Gender of participant (1 if woman, 0 otherwise): alternatives 30 to 37. Coefficients: $\mathtt{BGN}_i$.
- Dummy variable for ranking the effort involved in behavioral change as high (inquired in the posterior survey): alternatives 30 to 37. Coefficients: $\mathtt{BEF}_i$.
- Number of days per week starting work late is possible: associated with after-peak departure time (alternatives 38 to 43). Coefficients: $\mathtt{BDL}_i$.
- weekly frequency of consulting pre-trip of traffic information: associated with after-peak departure time (alternatives 38 to 43). Coefficients: $\mathtt{BCI}_i$.

This specification for the variables is based on previous work (Ben-Elia and Ettema, 2010) and after corrections of trial and error estimation and clearing out of non-significant coefficients.

The model has been estimated using the new version of the software package Biogeme (Bierlaire and Fetiarison, 2009). The coefficients of the attributes of the choice models are again all significant and with the correct sign. The coefficient of the class membership model are also significant and with the correct sign. Table 3.3 reports the probability to belong to the class of individuals with a preferred arrival time for each segment of the population.

Assuming that the sample is representative of the population under interest, we can compute aggregate quantities using sample enumeration based on the 10315 observations.

If $\Pr(\mathrm{PAT}|n)$ is the probability that individual n has a preferred arrival time, the share of such individuals in the population is given by

$$\frac{1}{N}\sum_{n}\Pr(\mathrm{PAT}|n) = 85.4\%.$$

We are also interested in computing elasticities with respect to the rewards. Among the 10315 observations, 5443 are associated with a reward in cash, and 1145 with a reward in Yeti credits (which leaves 3727 without reward). We report here elasticities for time-interval 30 (7:30-7:45), which is the first interval of the peak period. The disaggregate elasticity for observation n

is given by

$$e_n = \frac{\partial P_n(30)}{\partial \mathtt{REWARD}} \frac{\mathtt{REWARD}}{P_n(30)},$$

where $P_n(i)$ is the probability that departure time interval 30 is selected for observation n. The aggregate elasticity is given by

$$e(\text{cash}) = \frac{\sum_n \delta(\mathtt{cash}, n) P_n(30) e_n}{\sum_n P_n(30)} = -0.384,$$

$$e(\text{yeti}) = \frac{\sum_n \delta(\mathtt{yeti}, n) P_n(30) e_n}{\sum_n P_n(30)} = -0.0525,$$

where $\delta(\mathtt{cash}, n)$ is 1 if observation n corresponds to a reward by cash, and 0 otherwise. $\delta(\mathtt{yeti}, n)$ is defined similarly. The large difference is due to the lower number of observations influenced by the credits. We report also the elasticities computed for relevant observations, that is

$$e(\text{cash}) = \frac{\sum_n \delta(\mathtt{cash}, n) P_n(30) e_n}{\sum_n \delta(\mathtt{cash}, n) P_n(30)} = -0.907,$$

$$e(\text{yeti}) = \frac{\sum_n \delta(\mathtt{yeti}, n) P_n(30) e_n}{\sum_n \delta(\mathtt{yeti}, n) P_n(30)} = -0.922.$$

4 Discussion and future work

This paper presents a work in progress for developing a model of departure time choice based on the Spitsmijden's database of peak avoidance behavior. The Spitsmijden data provides a unique opportunity to estimate departure time based on revealed preference. Three models have been presented based on a variant of the schedule-delay construct: a logit model, a mixture model and a latent class model regarding arrival time preference.

The results indicate that the rewards, both monetary and in-kind (Yeti smartphone) have a substantial effect on increasing off-peak travel. This effect was evident in all three models estimated. This result was expected and is in line with previous findings. In addition, other factors some already discussed in previous research, appear to have a significant influence on shaping departure time choice (Table 4, 5). The significance of gender suggests that even when rewarded , woman are less likely to change departure time compared to men. This effect is visible for the main peak travel times between 7:30-9:00. After 9:00 the differences are less apparent and loose significance. Furthermore, in the latent-class specification, we can see that women are more likely to have a preferred arrival time compared to men. This is an interesting finding, which invokes further exploration of gender-specific considerations in incentive-based programs. The relevance of work time flexibility in encouraging compliance with the reward is also evident. The ability to start work later has a significant effect on encouraging departure times after the peak-hour. In the latent class model, prior arrangements with employers regarding flexible work time also decreased the probability of having a preferred arrival time. In contrast, time-use constraints such as childcare, have positive effect on fixed schedules and preferred arrival time. Reference class was also found to be significant. Especially in the case of money, it seems that higher frequencies of peak-hour commuting (classes A and B), are less likely to change departure times. The strongest effects are observed for the 7:30, 7:45 quarters. In the case of the Yeti the (significant) effects are quite similar. This result emphasizes, similarly to previous findings, the importance of habitual behavior in travelers choices. Another important factor is that of effort involved in behavior changes. Following on previous findings, we find that a high perceived effort is positively associated with peak-hour departure. It is especially strong in the mean departure time around 7:45. Travel information has a mostly significant and positive effects on departing after the peak. Heterogeneity in behavior is also apparent in the mixture model (Table 3). Both the random terms of early and late schedule delays are highly significant, as well as, the error-components of departing before/after the peak, asserting that there is a large degree of variation amongst the participants. Regarding the latent-class model, we can see in Table 7, that being a woman with child care responsibilities and no flexibility in working time, as expected, will lead to a preferred arrival time association. Whereas, men without responsibilities and with flexible work times have a 25% chance not to have a preferred arrival time. Although not surprising, the results elucidate, the complexity involved in motivating voluntary changes in travel behavior that involve modifications of daily schedules.

The richness of the Spitsmijden dataset is likely to reveal more details about the complex behavior in terms of departure time choice. The main challenge is the estimation of the complex models. Indeed, the maximum likelihood estimation of models involving random parameters, latent variables, latent classes, and correlated error terms is extremely complex, especially with a relatively large choice set.

A new version of the software package Biogeme (Bierlaire, 2003; Bierlaire and Fetiarison, 2009 has been developed, which has allowed to investigate the models presented in this paper. We hope that it will allow us to investigate more complex models.

5 Acknowledgments

This study was undertaken as part of the Spitsmijden project, which was funded by Transumo, the Ministry of Transport in the Netherlands, Bereik, RDW, NS, Rabobank, ARS T&TT, OC Mobility Coaching, Vrije Universiteit Amsterdam, TU Delft, Universiteit Utrecht. Some of the ideas were discussed during the Fifth Workshop on Discrete Choice Models, August 27–29, 2009, EPFL, Lausanne, Switzerland.

References

Arnott, R., de Palma, A. and Lindsey, R. (1990). Economics of a bottleneck, *Journal of Urban Economics* **27**: 111–130.

Arnott, R., de Palma, A. and Lindsey, R. (1993). A structural model of peak-period congestion: a traffic bottleneck with elastic demand, *American Economic Review* **83**: 161–179.

Banister, D. (1994). Equity and acceptability questions in internalising the social costs of transport. Internalising the Social Costs of Transport, OECD.

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

Ben-Elia, E. and Ettema, D. (2010). Commuters choice behavior with rewards for avoiding peak-hour driving, *89th Annual meeting of the Transportation Research Board*, Washington D.C.

Bhat, C. and Steed, J. L. (2002). A continuous-time model of departure time choice for urban shopping trips, *Tranportation Research B* **36**: 207–224.

Bierlaire, M. (2003). BIOGEME: a free package for the estimation of discrete choice models, *Proceedings of the 3rd Swiss Transportation Research Conference*, Ascona, Switzerland. www.strc.ch.

Bierlaire, M. and Fetiarison, M. (2009). Estimation of discrete choice models: extending biogeme, *Proceedings of the 9th Swiss Transport Research Conference*, Ascona, Switzerland.

Bonsall, P., Shires, J., Maule, J., Matthews, B. and Beale, J. (2007). Responses to complex pricing signals: Theory, evidence and implications for road pricing, *Transportation Research A* **41**(7): 672–683.

de Jong, G., Daly, A., Pieters, M., Vellay, C., Bradley, M. and Hofman, F. (2003). A model of time of day and mode choice using error components logit, *Transportation research E* **39**: 245–268.

Eriksson, L., Garvill, J. and Nordlund, A. M. (2006). Acceptability of travel demand management measures: The importance of problem awareness, personal norm, freedom, and fairness, *Journal of Environmental Psychology* **26**: 15–26.

Ettema, D., Knockaert, J. and Verhoef, E. (2008). Using incentives as traffic management tool: Empirical results of the "peak avoidance" experiment, *87th Annual meeting of the Transportation Research Board*, Washington D.C.

Ettema, D., Knockaert, J. and Verhoef, E. (2010). Using incentives as traffic management tool: empirical results of the "peak avoidance" experiment, *Transportation Letters* **2**: 39–51.

Ettema, D. and Timmermans, H. (2006). Costs of travel time uncertainty and benefits of travel time information: Coneptual model and numerical examples, *Transportation Research. C* **14**: 335–350.

Ettema, D. and Verhoef, E. (2006). Using rewards as a traffic management tool: Behavioural effects of reward strategies, *IATBR*.

European Commission (2006a). Keep europe moving – sustainable mobility for our continent. (mid-term review of the european commission's 2001 transport white paper). Communication from the Commission, European Commission, COM(2006)314.

European Commission (2006b). Raising awareness of ict for smarter, safer and cleaner vehicles. Communication from the Commission, European Commission, COM(2006)59.

Geller, E. (1989). Applied behavior analysis and social marketing: An integration for enviormental preservation, *Journal of Social Issues* **45**: 17–36.

Giuliano, G. (1994). Equity and fairness considerations of congestion pricing, *in* T. R. Board (ed.), *Special Report 242: Curbing gridlock: Peak-period fees to relieve traffic congestion*, Vol. 2, Washington DC.

Jou, R.-C., Kitamura, R., Weng, M.-C. and Chen, C.-C. (2008). Dynamic commuter departure time choice under uncertainty, *Transportation Research A* **42**: 774–783.

Kahneman, D. and Tversky, A. (1984). Choices values and frames, *American Psychologist,* **39**(4): 341–350.

Knockaert, J., Bliemer, M., Ettema, D., Joksimovic, D., Mulder, A., Rouwendal, J. and van Amelsfort, D. (2007). *Experimental design and modelling Spitsmijden*, Bureau Spitsmijden, The Hague.

Lomax, T. and Schrank, D. (2003). 2002 urban mobility study, Texas Transportation Institute.

Mayeres, I., Ochelen, S. and Proost, S. (1996). Marginal and external costs of urban transport, *Transportation Research D* **1**(2): 111–130.

Nijkamp, P. and Shefer, D. (1998). *Urban Transport Externalities and Pigouvian Taxes: A Network Approach*, Edward Elgar Publishing, Cheltenham.

Rouwendal, J. and Verhoef, E. T. (2006). Basic economic principles of road pricing: From theory to applications, *Transport Policy* **13**(2): 106–114.

Shiftan, Y. and Golani, A. (2005). Effect of auto restraint on travel behavior, *Transportation Research Record* **1932**: 156–163.

Small, K. A. (1982). The scheduling of consumer activities: Work trips, *American Economic Review* **72**(3): 467–479.

Small, K. A. and Verhoef, E. T. (2007). *The Economics of Urban Transportation*, Routledge, London.

Verhoef, E. (2008). Road transport pricing: Motivation, objectives and design from an economic perspective, *in* E. Verhoef, M. Bliemer, L. Steg and B. van Wee (eds), *Pricing In Road Transport: A Multi-Disciplinary Perspective*.

Vickrey, W. S. (1969). Congestion theory and transport investment, *American Economic Review* **59**: 251–261.

Viegas, J. M. (2001). Making urban road pricing acceptable and effective: searching for quality and equity in urban mobility, *Transport Policy* **8**(4): 289–294.

Parameter number	Description	Coeff. estimate	Robust Asympt. std. error	t-stat	p-value
1	A25	0.945	0.773	1.22	0.22
2	A26	3.18	0.915	3.47	0.00
3	A27	3.83	0.972	3.95	0.00
4	A28	4.84	1.03	4.69	0.00
5	A29	5.41	1.07	5.06	0.00
6	A30	5.17	1.12	4.62	0.00
7	A31	4.76	1.15	4.14	0.00
8	A32	4.66	1.19	3.93	0.00
9	A33	4.71	1.26	3.74	0.00
10	A34	4.55	1.31	3.48	0.00
11	A35	4.49	1.37	3.27	0.00
12	A36	4.37	1.44	3.03	0.00
13	A37	4.37	1.53	2.86	0.00
14	A38	5.36	1.63	3.29	0.00
15	A39	5.21	1.71	3.04	0.00
16	A40	4.97	1.83	2.72	0.01
17	A41	4.99	1.94	2.57	0.01
18	A42	5.06	2.06	2.45	0.01
19	A43	4.87	2.17	2.25	0.02
20	BCR	1.66	0.177	9.37	0.00
21	BE	-0.0715	0.0106	-6.76	0.00
22	S_BE	0.0606	0.00615	9.85	0.00
23	BEU	0.308	0.0251	12.28	0.00
24	BL	-0.0405	0.00892	-4.54	0.00
25	S_BL	0.0438	0.00410	10.66	0.00
26	BT	-0.0114	0.00494	-2.30	0.02
27	EC_EARLY	1.53	0.180	8.49	0.00
28	EC_LATE	2.02	0.332	6.10	0.00

Number of observations = 10315

$$\begin{aligned}
\mathcal{L}(0) &= -30900.978 \\
\mathcal{L}(c) &= -26328.662 \\
\mathcal{L}(\hat{\beta}) &= -19447.815 \\
\rho^2 &= 0.371 \\
\bar{\rho}^2 &= 0.370
\end{aligned}$$

Table 3: Estimated parameters for the mixture model

Description	Coeff. estimate	Robust Asympt. std. error	t-stat	p-value
A[25]	-0.215	0.195	-1.1	0.27
A[26]	1.03	0.157	6.55	0.0
A[27]	0.961	0.151	6.36	0.0
A[28]	1.57	0.145	10.84	0.0
A[29]	2.0	145.13	82.0	0.
A[30]	0.146	0.212	0.69	0.49
A[31]	-1.05	0.267	-3.92	0.0
A[32]	0.16	0.217	0.74	0.46
A[33]	0.403	0.212	1.9	0.06
A[34]	0.155	0.241	0.64	0.52
A[35]	-0.107	0.262	-0.41	0.68
A[36]	-0.438	0.276	-1.59	0.11
A[37]	-0.322	0.275	-1.17	0.24
A[38]	0.454	0.21	2.16	0.03
A[39]	0.177	0.216	0.82	0.41
A[40]	-0.376	0.249	-1.51	0.13
A[41]	-0.498	0.271	-1.84	0.07
A[42]	0.133	0.233	0.57	0.57
A[43]	-0.386	0.251	-1.54	0.12
BCABM[30]	1.13	0.157	7.24	0.0
BCABM[31]	1.65	0.215	7.65	0.0
BCABM[32]	0.465	0.158	2.95	0.0
BCABM[33]	0.374	0.155	2.42	0.02
BCABM[34]	0.384	0.185	2.08	0.04
BCABM[35]	0.514	0.211	2.44	0.01
BCABM[36]	0.434	0.229	1.9	0.06
BCABM[37]	0.706	0.233	3.03	0.0
BCABP[30]	0.831	0.172	4.84	0.0
BCABP[31]	1.65	0.227	7.28	0.0
BCABP[32]	0.00843	0.176	0.05	0.96
BCABP[33]	-0.175	0.169	-1.04	0.3
BCABP[34]	-0.202	0.199	-1.01	0.31
BCABP[35]	0.472	0.217	2.17	0.03
BCABP[36]	0.884	0.226	3.91	0.0
BCABP[37]	0.788	0.239	3.3	0.0

Table 4: Estimated parameters for the latent class model (part 1)

Description	Coeff. estimate	Robust Asympt. std. error	t-stat	p-value
BCI[38]	-0.00393	0.0178	-0.22	0.82
BCI[39]	0.0265	0.0163	1.63	0.1
BCI[40]	0.0492	0.0175	2.82	0.0
BCI[41]	0.0683	0.0176	3.88	0.0
BCI[42]	0.0542	0.0201	2.69	0.01
BCI[43]	0.0746	0.0197	3.79	0.0
BDL[38]	0.215	0.024	8.96	0.0
BDL[39]	0.192	0.0289	6.63	0.0
BDL[40]	0.238	0.045	5.3	0.0
BDL[41]	0.257	0.0521	4.93	0.0
BDL[42]	0.0838	0.0511	1.64	0.1
BDL[43]	0.177	0.0552	3.21	0.0
BE	-0.0474	0.00151	-31.48	0.0
BEF[30]	0.404	0.186	2.18	0.03
BEF[31]	1.38	0.146	9.41	0.0
BEF[32]	0.595	0.173	3.44	0.0
BEF[33]	0.747	0.16	4.68	0.0
BEF[34]	0.746	0.184	4.04	0.0
BEF[35]	1.09	0.174	6.25	0.0
BEF[36]	1.08	0.175	6.21	0.0
BEF[37]	0.203	0.311	0.65	0.51
BGN[30]	0.363	0.0858	4.23	0.0
BGN[31]	0.476	0.0974	4.88	0.0
BGN[32]	0.315	0.0992	3.17	0.0
BGN[33]	0.0527	0.0999	0.53	0.6
BGN[34]	0.266	0.107	2.48	0.01
BGN[35]	0.032	0.12	0.27	0.79
BGN[36]	0.212	0.135	1.57	0.12
BGN[37]	-0.258	0.17	-1.51	0.13
BL	-0.0405	0.00227	-17.81	0.0
BRewardAmountMoney	0.253	0.0101	25.01	0.0
BRewardAmountPhone	1.33	0.0938	14.16	0.0
BT	-0.0134	0.00419	-3.2	0.0
ClassChildCare	0.449	0.13	3.46	0.0
ClassCte	1.77	0.1	17.7	0.0
ClassFemale	0.789	0.159	4.97	0.0
ClassFlexWorkTime	-0.72	0.113	-6.38	0.0

Table 5: Estimated parameters for the latent class model (part 2)

Number of observations = 10315

$$
\begin{aligned}
\mathcal{L}(0) &= -30900.978 \\
\mathcal{L}(\hat{\beta}) &= -21954.34 \\
\rho^2 &= 0.290 \\
\bar{\rho}^2 &= 0.287
\end{aligned}
$$

Table 6: Estimation results for the latent class model

Male	Childcare	Flex. Work time	81.7%
Male	Childcare	No flex. Work time	90.2%
Male	No childcare	Flex. Work time	74.1%
Male	No childcare	No flex. Work time	85.4%
Female	Childcare	Flex. Work time	90.8%
Female	Childcare	No flex. Work time	95.3%
Female	No childcare	Flex. Work time	86.3%
Female	No childcare	No flex. Work time	92.8%

Table 7: Latent class model: probability to have a preferred arrival time