A BEHAVIOURAL DEPARTURE TIME CHOICE MODEL WITH LATENT ARRIVAL TIME PREFERENCE AND REWARDS FOR PEAK-HOUR AVOIDANCE

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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' experiment. It involved the use of rewards for encouraging drivers to avoid commuting during the morning peak-hours. The impact of 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 behaviour i.e. shift of travelling time. Using (20) 15-minute intervals to discrete time, we estimate several models to identify car drivers' choice of departure time when rewards are provided. We use these interim models to generate starting values for a new modelling framework to estimate the choice of departure time and assuming latent class (LC) in preferred arrival time. The LC model suggests that both types of reward are effective in discouraging peak driving. In addition, the latent class asserts preferred arrival time is associated (positively) with gender, childcare responsibilities and (negatively) with flexible working time. These results indicate that responding to the reward is very much influenced by situational factors.

***Keywords**: discrete choice, departure time choice, latent class, peak avoidance rewards*

1. INTRODUCTION

With too many people travelling in their car at the same times and even to the same places the prognosis for Europe's transport 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, Ochelen & Proost 1996) and results in increasing frequency of incidents, interrupted vehicle flow and uncertainty regarding travel times (Lomax & Schrank 2003). Transportation Demand-based solutions (e.g. promoting modal alternatives, parking policy and land use planning policy) have been advocated to combat congestion (Shiftan & Golani 2005). Another possible solution is to encourage travellers to shift to other times i.e. to change their departure times to less congested time intervals either before or after the rush-hour.

However, changing departure times is far from easy as it undoubtedly disrupts one's daily schedule. Without an incentive there is no real motivation to change one's usual behaviour. Transport economists have been arguing for implementation of road pricing as an efficient solution to alleviate congestion externalities (Nijkamp & Shefer 1998); (Rouwendal & Verhoef 2006); (Small & 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, fairness and public acceptability (Banister 1994; Viegas 2001; Giuliano 1994; Eriksson et al. 2006). Third, psychologists assert people are more motivated when rewarded rather than punished (Kahneman & Tversky 1984; Geller 1989).

The notion of using rewards has been recently implemented in The Netherlands in the context of the Spitsmijden (translated freely as peak avoidance) program (Ettema & Verhoef 2006; Knockaert et al., 2007; Ettema et al., 2010). 'Spitsmijden I' organized in the second half of 2006, was the first study, involving 340 participants and spanning 13 week. Its objective was to investigate, in an empirical field study (i.e. revealed preference - RP), the potential impacts of rewards on commuters' behaviour during the morning rush-hour. Participants were rewarded for changing their behaviour, either with money or with credits (to be eligible to keep a handy Smartphone called 'Yeti'), Behaviour change was defined as shifting commuting times from the morning rush-hours to off-peak times, changing travel modes or working from home. Further details of the design are presented in section 3. Initial results provided evidence of substantial behaviour changes in response to the rewards, with commuters shifting to earlier and later departure times and more use of public transport and alternative modes or working from home (Ettema et al., 2008; 2010). Further research, based on discrete choice modelling with aggregate alternatives (peak driving, driving before the peak, driving after the peak and not driving) indicated that the main effect of the reward was to encourage the shift from peak-hour driving. However, the choice of rush-hour driving alternatives was influenced by other (situational) factors: First, certain socio-economic characteristics like gender and education were found to be significant. Women were found to be less responsive to change behaviour. Higher education was also associated with a lower peak avoidance rate. Second, scheduling considerations including work and home related constraints or flexible working times were found significant. Third, the gaps between the change of behaviour and habitual behaviour are relevant. The closer the difference (e.g. an earlier usual departure time is more associated with driving before the peak) the higher is the rate of peak-avoidance. Use of other travel modes to work was also associated with avoiding driving. Fourth, perceptions about the (low) effort involved in avoidance behaviour and (positive) beliefs regarding the non-motorized alternatives (cycling and public transport) were found to encourage peak avoidance. Fifth, greater use of 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 & 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 modelling has been part of main stream travel behaviour research for more than three decades. Congestion management schemes are based on the assumption that travellers will optimize their departure time choice. Ever since Vickrey formulated the 'bottleneck' model in the late 1960's (Vickrey, 1969) updated later by Small in the 1970's (Small 1982; Small & Verhoef 2007), the concept of schedule-delay (early and late) has been the focus of most modelling endeavours. The main idea is that travellers scheduling revolves around a preferred arrival time (PAT). Several theoretical extensions have included variable demand and supply and heterogeneity (Arnott et al., 1990; 1993). Several empirical investigations also applied schedule-delay specifications using discrete choice models (Bates et al., 2001; de Jong et al., 2003; Ettema & Timmermans, 2006; Jou et al., 2008).

Most of these models used discrete time units with different intervals to represent continuous time. A different approach was applied by Bhat & Steed (2002), who used a hazard specification to model departure time for shopping trips. However the behavioural representativeness of this approach can be questioned. In this paper we continue with the first line of research with a focus on departure time choice behaviour during the peak-avoidance 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 travellers' departure and arrival times. Usually surveys based on stated behaviour derived from travel diaries are applied. Surveillance techniques to capture real departure and arrival times are less frequently adopted due to both high costs of the infrastructure and privacy issues. In this respect the database of Spitsmijden provides researchers a remarkable set of revealed preference data. 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 modelling framework and the estimation results. Section Accounting **only for the relevant observations, the estimated elasticity suggests that both types of reward are quite effective in decreasing peak-hour driving. In fact the elasticity of both reward measures is quite close to unity.**

4 presents a discussion, conclusions and future work directions.

2. EXPERIMENT 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 behaviour. 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 during the morning rush-hour. The study was launched in October 2006. The heavily congested Dutch A12 motorway stretch from Zoetermeer westbound towards The Hague was selected as the study’s trajectory. 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. In the first survey, data was collected regarding socio-economic characteristics, usual travel behaviour and work time arrangements. In the second survey questions were asked about the participant’s subjective experience during the course of the experiment, the amount of effort involved and support measures assisting behaviour change. The actual experiment lasted 13 weeks (of which in weeks 3-12 rewards were provided). It consisted of tracking participant’s revealed (i.e. observed) behaviour. 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 cheating 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 time slot 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. As noted, the first two weeks were without reward (pre-test). The data collected during the pre-test was used to determine participants’ reference travel behaviour. The final week (post-test) was also without rewards.

Participants who opted for money participated in 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 was randomized (blocks). 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. This information consisted of real-time travel times on the A12 motorway and an online map showing congestion levels on other roads in the area. Information availability was not dependent on the reward itself. Participants in the money group only 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.

Participants' were also allocated to reward classes which were determined by his or her (reference) behaviour during the pre-test. The reward class defined the maximum number of rewards they could receive each week. The rationale was that not all participants drive during the rush-hour five days per week. The main aim was to discourage any possible increase in the number of commuting trips during off-peak periods that were not offset by a decrease in 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.

	Money				Yeti				Total
	A	B	C	D	A	B	C	D	
Rush-hour trips/week at reference	3.5-5	2.5-3.5	1-2.5	0-1	3.5-5	2.5-3.5	1-2.5	0-1	
Thresholds*	5	4	2	1	15	20	23	25	
N Men	83	33	13	11	34	27	13	7	221
	62%	54%	57%	79%	72%	87%	59%	78%	65%
Women	51	28	10	3	13	4	9	2	120
	38%	46%	44%	21%	28%	13%	41%	22%	35%
Total	134	61	23	14	47	31	22	9	341

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.

3. CHOICE MODELLING

We assume that the time a participant's car was detected by the EVI is a good enough proxy for departure time from home. By convention, the time interval k starts $15k$ minutes after midnight and ends $15(k+1)$ minutes after midnight. We consider intervals 24 to 43, corresponding the period between 6:00 and 11:00. The morning 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 (reference relates to pre-test values i.e. the first two weeks without rewards).

- 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);
- $RFTIM_n$: reference detection time of individual n (in minutes after midnight, min: 421 (7:01), max: 592 (9:52), mean: 492 (8:12));
- $RFTRAV_n$: reference travel time of individual n (in seconds min: 173, max: 3069, mean: 411.68) adapted from the traffic information system;
- $PAT_n=RFTIM_n+RFTRAV_n/60$: reference arrival time of individual n (in minutes after midnight), used as a proxy for preferred arrival time;
- $XE_{kn}=\max(0,PAT_n-(15(k+1)+RFTRAV_n/60)$: early arrival, where $15(k+1)+RFTRAV_n/60$ is the latest possible arrival time when departing at time interval k,
- $XL_{kn}=\max(0,15k+RFTRAV_n/60-PAT$: late arrival, where $15k+RFTRAV_n/60$ is the earliest possible arrival time when departing at time interval k,
- EURO: reward in money (in Euros),
- CREDIT: reward in smartphone credits.

3.1 Multinomial 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:

$$V_k=A_k+BT\,TT_k+BE\,XE_{kn}+BL\,XL_{kn},$$

and the utility functions for time intervals of off peak hours (k=24,…,29 and k = 38,…,43) are defined as:

$$V_k=A_k+BT\,TT_k+BE\,XE_{kn}+BL\,XL_{kn}+BEUR\,EURO+BCR\,CREDIT.$$

Where: A is an alternative specific constant and BX variable X's parameter

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.

Parameter number	Name	Description	Coeff. estimate	std. error	*t*-stat	*p*-value
1	A25	06:15	-0.436	0.199	-2.19	0.03
2	A26	06:30	0.698	0.175	3.99	0.00
3	A27	06:45	0.649	0.190	3.41	0.00
4	A28	07:00	1.37	0.213	6.42	0.00
5	A29	07:15	1.94	0.242	8.04	0.00
6	A30	07:30	1.17	0.273	4.27	0.00
7	A31	07:45	0.823	0.304	2.71	0.01
8	A32	08:00	0.785	0.335	2.35	0.02
9	A33	08:15	0.954	0.369	2.58	0.01
10	A34	08:30	0.865	0.399	2.17	0.03
11	A35	08:45	0.869	0.435	2.00	0.05
12	A36	09:00	0.779	0.474	1.64	0.10
13	A37	09:15	0.782	0.511	1.53	0.13
14	A38	09:30	1.78	0.540	3.30	0.00
15	A39	09:45	1.53	0.578	2.65	0.01
16	A40	10:00	1.28	0.620	2.06	0.04
17	A41	10:15	1.43	0.661	2.16	0.03
18	A42	10:30	1.75	0.701	2.49	0.01
19	A43	10:45	1.89	0.747	2.53	0.01
20	BCR	Credit	1.31	0.0762	17.25	0.00
21	BE	Early arrival	-0.0278	0.00282	-9.87	0.00
22	BEU	Euro	0.196	0.00747	26.27	0.00
23	BL	Late arrival	-0.0355	0.00290	-12.25	0.00
24	BT	Travel time	-0.0116	0.00388	-3.00	0.00

Number of observations = 10,315

$L(0) = -30{,}900.978$
$L(c) = -26{,}328.662$
$L(\beta) = -22{,}518.767$
$\varrho^2 = 0.271$
$\bar{\varrho}^2 = 0.270$

Table 2: Estimated parameters for the multinomial logit model

Parameter number	Name	Description	Coeff. estimate	std. error	*t*-stat	*p*-value
1	A25	06:15	0.945	0.773	1.22	0.22
2	A26	06:30	3.18	0.915	3.47	0.00
3	A27	06:45	3.83	0.972	3.95	0.00
4	A28	07:00	4.84	1.03	4.69	0.00
5	A29	07:15	5.41	1.07	5.06	0.00
6	A30	07:30	5.17	1.12	4.62	0.00
7	A31	07:45	4.76	1.15	4.14	0.00
8	A32	08:00	4.66	1.19	3.93	0.00
9	A33	08:15	4.71	1.26	3.74	0.00
10	A34	08:30	4.55	1.31	3.48	0.00
11	A35	08:45	4.49	1.37	3.27	0.00
12	A36	09:00	4.37	1.44	3.03	0.00
13	A37	09:15	4.37	1.53	2.86	0.00
14	A38	09:30	5.36	1.63	3.29	0.00
15	A39	09:45	5.21	1.71	3.04	0.00
16	A40	10:00	4.97	1.83	2.72	0.01
17	A41	10:15	4.99	1.94	2.57	0.01
18	A42	10:30	5.06	2.06	2.45	0.01
19	A43	10:45	4.87	2.17	2.25	0.02
20	BCR	Credit	1.66	0.177	9.37	0.00
21	BE	Early arrival	-0.0715	0.0106	-6.76	0.00
22	S_BE	s.d Early arrival	0.0606	0.00615	9.85	0.00
23	BEU	Euro	0.308	0.0251	12.28	0.00
24	BL	Late arrival	-0.0405	0.00892	-4.54	0.00
25	S_BL	s.d late arrival	0.0438	0.00410	10.66	0.00
26	BT	Travel time	-0.0114	0.00494	-2.30	0.02
27	EC_EARLY	Error comp. Early dep.	1.53	0.180	8.49	0.00
28	EC_LATE	Error comp. Late dep.	2.02	0.332	6.10	0.00

Number of observations = 10,315

$$L(0) = -30{,}900.978$$
$$L(c) = -26{,}328.662$$
$$L(\beta) = -19{,}447.815$$
$$\rho^2 = 0.371$$
$$\bar{\rho}^2 = 0.370$$

Table 3: Estimated parameters for the mixture model

3.3 Latent class

A second type of improvement for the logit model is 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.

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 childcare responsibilities at home (coefficient: ClassChildCare),
- Dummy variable for arrangements with employer made prior to beginning the experiments to support flexible working times (coefficient: ClassFlexWorkTime).

The selection of these variables was based on the results of a COX-regression fitting the proxy PAT to different participants' characteristics and estimating a hazard model appropriately. The variables with the strongest effects were included.

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

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

The probability to belong to the second class is therefore

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

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

- Dummy variable for whether the participant is allocated to classes A or B (see Table 1) in the money group: alternatives 30 to 37. Coefficients: $BCABM_i$.
- Dummy variable for whether the participant is allocated to classes A or B (see Table 1) in the phone group: alternatives 30 to 37. Coefficients: $BCABP_i$.
- Gender of participant (1 if woman, 0 otherwise): alternatives 30 to 37 (peak intervals). Coefficients: BGN_i.
- Dummy variable for ranking the effort involved in behavioural change as high (inquired in the posterior survey): alternatives 30 to 37 (peak intervals). Coefficients: BEF_i.
- Number of days per week starting work late is possible: associated with after-peak departure time (alternatives 38 to 43). Coefficients: BDL_i.

- weekly frequency of consulting pre-trip of traffic information: associated with after-peak departure time (alternatives 38 to 43). Coefficients: BCI_i.

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

Name	Coeff. estimate	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	0.0
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	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

Number of observations = 10315

$$L(0) = -30900.978$$
$$L(\beta) = -21954.34$$
$$\rho^2 = 0.290$$
$$\bar{\rho}^2 = 0.287$$

Table 4: Estimation results for the latent class model (part 2)

The model has been estimated using a new version (1.9) of the software package Biogeme (Bierlaire & 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 5 reports the probability to belong to the class of individuals with a preferred arrival time for each segment of the population.

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 5: Latent class model: probability to have a preferred arrival time

Assuming that the sample is representative of the population under interest, we can compute aggregate quantities using sample enumeration based on the 10,315 observations. If $Pr(PAT|n)$ is the probability that individual n has a preferred arrival time, the share of such individuals in the population is given by

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

We are also interested in computing elasticities with respect to the rewards. Among the 10,315 observations, 5,443 are associated with a reward in cash, and 1,145 with a reward in Yeti credits (which leaves 3,727 without reward). We report here elasticities for time-interval 30 (7:30-7:45), which is the first interval of the morning peak period. The disaggregate elasticity for observation n is given by

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

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

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

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

where δ(*cash*,*n*) is 1 if observation *n* corresponds to a reward by cash, and 0 otherwise. δ(*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 only for relevant observations (i.e. where rewards were relevant):

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

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

Accounting only for the relevant observations, the estimated elasticity suggests that both types of reward are quite effective in decreasing peak-hour driving. In fact the elasticity of both reward measures is quite close to unity.

4. Discussion, conclusions and future work

This paper presents a model of departure time choice based on Spitsmijden's database regarding peak avoidance behaviour. 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 framework: 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 decreasing peak travel. This effect was evident in all three models estimated and the estimated elasticities. This result was expected and is in line with our previous findings. In addition, other factors some already discussed in previous research appear to have a significant influence on departure time choice (Table, **Error! Reference source not found.**). The significance of gender suggests that even when rewarded, women 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, seem to enocurage fixed schedules and hence a 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 in the reference period (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, asin previous findings, the importance of habitual behaviour in understanding travellers choices. Another important factor is that of effort involved in behaviour 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 significant and positive effects on departing after the peak. Heterogeneity in behaviour 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 5, that being a woman with child care responsibilities and no flexibility in working time, as could be expected, will lead to a greater association with a preferred arrival time. 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 commuter behaviour that involve modifications of daily schedules.

The richness of the Spitsmijden dataset is likely to reveal more details about the complex behaviour in terms of departure time choice. The main challenge is the estimation of 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 & 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 in the near future.

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