

A choice model of participation in a reward-based congestion management scheme

Eran Ben-Elia*, Dick Ettema

Urban and Regional Research Centre Utrecht (URU)
Faculty of Geosciences
Utrecht University
P.O. Box 80115
3508 TC Utrecht, The Netherlands

* (author of correspondence) e.benelia@geo.uu.nl

Key Words:

Congestion, incentives, motivations, Ordered Logit, participation, pricing, rewards, traffic management.

Abstract

This paper deals with analysis of potential participation in a reward scheme to avoid peak hour driving as part of an overall congestion management strategy in the Netherlands. Using rewards in the context of congestion management is novel compared to the great amount of attention road pricing has received so far. Psychological research emphasizes the importance of incentives such as rewards in promoting long term behavior changes and learning. In the Netherlands, reward schemes have been proposed and tested in the context of the 'Spitsmijden' project. Although reward schemes are effective in reducing peak hour driving of participants, a critical issue remains to what extent drivers will participate in such schemes. This study analyzes participation likelihood based on a survey of non-participants, conducted in the same catchment area. Since the response variable had 5 categories an Ordered Logit (OL) discrete choice model was estimated. A Mixed OL model with random parameters was also estimated. The results show that participation is linked to working time flexibility, constraints in the household and the workplace and especially to personal motivations. The most important motivator is the prospective earning of the reward. However, social benefits like finding solutions to congestion were also found significant. These results can provide further insights to understanding the importance of incorporating behavioral factors in choice modeling.

1. Background

This paper deals with an empirical analysis of car drivers' likelihood of participation in programs that apply rewards as a value added strategy in dealing with congestion in the Netherlands. In general the Dutch people have a negative public opinion regarding congestion pricing and tolls despite the government's wishes to implement pricing policy to tackle congestion and its related problems. To this end, the 'Spitsmijden' (translated freely as peak avoidance) project was organized to investigate the impact of rewards (as an alternative to pricing) on rush-hour travel behavior in an empirical setting (See detailed review in section 3). The impact of such alternative reward strategies on traffic conditions obviously depends on the participation rate among those invited. Therefore, as part of this study, data on participation likelihood was collected using a survey of non-participants i.e. respondents who were not invited for the reward study itself. Based on this data we estimated discrete choice models (with an Ordered Logit specification) in order to arrive at a possible description and explanation of motivations and dis-motivations associated with a plausible reward strategy. This analysis is complementary to the valuable data collected in the reward experiment itself, which is currently being in the process of publishing (Ben-Elia & Ettema, 2009). It is especially important in any policy decision on widening the scope of the project for adopting rewards as a nationwide strategy to deal with congestion.

The rest of the paper is organized as follows: Section 2 discusses theoretical concepts and the implications learned from behavioural research on congestion management and rewards; Section 3 describes the 'Spitsmijden' experiment in brief and the relevant data that was collected with emphasis on the non-participants' data; Section 4 describes the Ordered Logit model applied in our analysis; Section 5 presents the estimation results; Section 6 provides a discussion and conclusions.

2. The behavioral context of congestion

The issue of how best to tackle the growing problem of congestion has been preoccupying researchers and policy makers for many years. Congestion is a main negative externality and is a result of the 'public good' character of most road based transportation systems. Like the well-documented environmental 'tragedy of the commons' the lack of clear ownership on most public roads together with increasing car ownership and car use levels results in over use of the existing capacity - leading to excess demand on the system and increasing congestion. Congestion in it self has a negative impact on air quality, noise levels and road user safety (Mayeres et al., 1996). In addition to excess demand which is a recurring phenomena, the frequency of incidents and interrupted vehicle flow results in increasing non recurring congestion on major urban networks (Lomax & Schrank, 2003).

In 2001 the ECMT (in the European Commission's white paper on transport policy) estimated the annual congestion externalities cost at around 0.5% of European GDP. In 2006 this estimate increased to 1% of its annual GDP – around €100 billion – each year. At present, there are around 300 million drivers in the EU, while in the past 30 years the distance traveled by road has tripled and is set to increase further (European Commission, 2006a, 2006b). Although cleaner vehicles might be able to cut down on emission levels, thus improving air quality, other congestion externalities like road safety and increasing travel times will persist and grow in magnitude. Construction of new untolled capacity (new roads or expansion of existing ones) is hardly an efficient solution in the long run as free road capacity is rapidly used up, public transportation ridership falls and free land in crowded urban areas is growing scarcer and costlier.

The solutions offered to alleviate congestion range between system-based approaches (e.g. intelligent transport systems – ITS) to demand based ones (e.g.

road pricing, promoting modal alternatives, parking policy and land use development policy). However, road pricing has been recommended by transport economists as the first best solution to efficiently alleviate congestion externalities. As outlined in the 1920's (Knight, 1924; Pigou, 1920), a toll which reflects the true marginal cost of travel is implemented on the congested facilities, resulting in a reduction in the number of travelers at peak periods and thus improved traffic flows. In theory, by internalizing the external cost, and assuming that toll revenues are returned in some way to the users, the total user welfare would increase resulting in a better off situation compared to the non-tolled one (Nijkamp & Shefer, 1998; Rouwendal & Verhoef, 2006; Small & Verhoef, 2007). Some of the main technical barriers for first best pricing have now been overcome as demonstrated by HOT lane projects in California and Singapore's Electronic Road Pricing Scheme (Chin, 2002).

In practice, imposing road pricing is controversial and insight is lacking in various domains. First, optimal pricing requires that tolls vary over locations, times and even by meteorological conditions, vehicle type and driving style, making it quite complex and difficult for the user to comprehend (Bonsall et al., 2007; Verhoef, 2008). Second, it involves social equity and political acceptability in addition to economic efficiency (Banister, 1994; Viegas, 2001). Subjective conceptions of fairness and freedom therefore play an important role in social acceptability of pricing schemes (Eriksson et al., 2006). For example, Bonsall et al. (2007), describe the magnitude of discontent of Parisian drivers to the imposition of a congestion charge scheme during weekend peaks. Third, Situational constraints such as household obligations (e.g. child care), work organization and availability of information may also affect individuals' responses to pricing schemes (Garling & Fuji, 2006). There is also a question of the roles that cognitive limitations and judgmental heuristics (e.g. (Simon, 1982; Tversky & Kahneman, 1974)) take when travellers try to adapt their decision making to pricing signals in variable conditions and their impact on the

overall social benefits of such a complex system. Fourth, there is a great deal of controversy about the long term impacts of the tolls which can include route switching, trip rescheduling and mode changes in the short run (Shifan & Golani, 2005). However, In the long run these may also include activity patterns and location choice changes of individuals and firms (Arentze & Timmermans, 2007; Ben-Elia et al., 2003).

The feasibility problems of first based solutions lead to alternative suggestions i.e. second best schemes (see review by Small & Verhoef, 2007). An additional idea that has recently been suggested is that providing users a reward for avoiding peak hour travel can achieve a similar behavioral change to that of pricing (Ettema & Verhoef, 2006; Knockaert et al., 2007). Psychological research on Operant Conditioning Theory found in many text books shows that in general rewards produce overall better outcomes than punishments. Rewards promote learning and Internalization (i.e. sustainable changes) whereas punishment succeeds in compliance and halting of unwanted behaviour but creates a problematic effect associated with unpleasant memories and avoidance (e.g. Rescorla, 1987). Review of the behavioral research suggests that positive incentives can be applied to stimulate a variety of behaviors, and also establish behavioral change (Smith et al., 2003). Although the first results reported from reward strategies are promising (see Ettema et al., 2008), concluding from current behavioral research on the values of rewards compared to tolls is premature especially due to some key aspects which characterize commuters' travel related choices: they are repeated over time and they are conducted in an uncertain environment regarding travel times. Prospect Theory (Kahneman & Tversky, 1979) and Reinforced Learning (Erev & Barron, 2005) probably have important insights in this case. However, this issue is much more complex and is too broad for the scope of this paper.

Another uncertain element in valuing reward strategies as a travel demand tool is that their impact on traffic conditions critically depends on the participation rate in the program. For example in a simulation study on the traffic impacts of rewards it was found that a participation rate of 10% was beneficial both to switchers (i.e. rewarded travelers) and no switchers. However, a participation rate of 50% was considerably worse resulting in an increase in over all travel time (Knockaert et al., 2007). Other than conventional travel demand measures, such as price measures, reward schemes are implemented on a voluntary basis, implying that the impacts of rewards found for participants cannot be generalized towards the whole population. Given the novelty of this type of travel demand measure, the knowledge on factors that influence participation is limited.

Psychological literature on voluntary behavior stresses incentives such as rewards or punishments as previously mentioned. However, great importance is also laid upon socialization factors (e.g. communication, influence, conformity, persuasion and identification). Cognitive response theory asserts that self persuasion to participate is prominent when individuals recognize they have personal stakes in the matter, information provided is precise and triggers concordant thinking (Petty & Cacioppo, 1986). Literature on voluntary travel behavior change has also identified that providing exact information on behavioral alternatives and household or work related situational constraints influence the probability of change (Ampt, 2003; Stopher, 2004). For example, Eriksson et al. (2008) and Jakobsson et al. (2002), note that habit, plan formation, normative and motivational issues but also economic (dis)incentives play a role in structural behavioural change.

Given the specific context of the reward strategy described in this study, in which the reward is made dependent on behaviour by time of day, we expect that household or work related constraints with respect to time shifts play an important role. However, the aforementioned studies have described the decision whether or

not to change behaviour rather than the decision to participate in voluntary travel change programmes. Therefore, additional research in this domain is necessary. This is especially relevant in the Netherlands, since in anticipation of a nationwide road-pricing scheme, mobility management programs, including reward strategies, are developed that are based on voluntary participation. Gaining insight in the factors that influence participation will be critical to assess the success of such programs.

In order to gain insight into the factors that influence participation in voluntary travel reduction programmes in general and in reward strategies in particular, this paper develops models of the likelihood of participation in the 'Spitsmijden' experiment as a function of socio-demographic, work related and attitudinal factors.

3. Data description

The Dutch Spitsmijden experiment was conducted by a public-private partnership consisting of Universities, private firms and public institutions. Its purpose was to collect a large sample of revealed preference (RP) data regarding the impact of rewards on daily commuting behavior during the morning rush-hour. During a period of 13 consecutive weeks in Autumn, 2006, 340 recruited volunteers all from the town of Zoetermeer, a satellite city of The Hague, and working in The Hague participated in a scheme whereby they would receive daily rewards, either of money (between 3-7 Euros) or of credits to earn a smartphone. Participants could avoid peak hour travel (defined between 7:30-9:30 AM) either by changing their departure times (earlier or later) or choosing other travel modes (like bike or transit) or by working from home. If a participant opted for the smartphone option, he or she was also provided with real-time traffic information regarding travel times on the Zoetermeer – The Hague corridor.

Data was collected during the 'Spitsmijden' experiment in several stages. Upon recruitment, participants filled a web-based survey about their home to work travel routines, their daily commutes, constraints, and socio demographic characteristics. In the second stage, detection equipment using in-vehicle installed transponders and road-side cameras was installed and for 2 weeks travel behavior data was collected without giving out rewards. A web-based personal travel log book was also applied to record reasons of non-detection and to check whether participants' self reports of their behavior as consistent with detections. The reward trial itself was carried out for a period of 10 weeks. Different reward schemes were assigned in different orders depending on the reward type (i.e. money or smartphone). For a detailed description of the experiment design see (Knockaert et al., 2007). In the last week travel behavior data was collected without rewards. In the third stage of the study, an evaluation survey was conducted regarding the experiences of the participants during the experiment.

In addition, and this is the concern of this paper, a non-participants survey was conducted from a random sample of 262 inhabitants of Zoetermeer. Note that the non-participant survey was independent of the rest of the project and involved a different group of people. The purpose of this survey was to understand what are the potential motivations and dis-motivations of participation in a reward scheme to avoid peak hour driving, similar to 'Spitsmijden' as well as constraints and trends for changing travel habits. The insights revealed from this survey could have important implications for future policy decision on widening the scope of the project and possibly together with the analysis of the participants' data for adopting rewards as a nationwide strategy to deal with congestion. Descriptive results of the non-participants survey are presented in the remainder of this section.

Socio-demographic characteristics of the sample

262 respondents (167 men and 95 woman) answered the full survey. 92 respondents also mentioned they had heard or read in the media of the 'Spitsmijden' project. The ages of the respondents were between 22 and 70 with the 1st quartile under 38, the 2nd quartile 38-45, the 3rd quartile 46-52, and the last quartile consists of ages beyond 53 years old. 53% of respondents hold a university or higher education institution (HBO) degree while the rest hold secondary education degrees. Very few respondents stated they have only primary schooling. Household status reported was 12% singles, 32% cohabiting without children, 26% cohabiting with children under age 12, 25% cohabiting with children over age 12, 3% were single parents. The median monthly income 5,000-6000 € with the 1st quartile under 4,000 € and the last quartile over 6,000 € (note: 24% refused to answer this question). As can be verified from these statistics the sample shows a relatively homogenous population characterized by high incomes and good education levels most of which are middle aged and cohabiting with partners and children.

Regarding the characteristics of the workplace, in terms of size of the workplace, the median of the number of employees in the respondent's work place was 188 people. However the 1st quartile was small workplaces of less than 4 people while the last quartile was noted for big enterprises comprising more than 1,500 employees. The economic sectors most noted were 22% in finance and services, 24% in the public sector and government, 13% in health and social services, 8% in education, 8% in transport and communications the rest were mostly in construction, industry, trading and hotel & catering.

Travel behavior aspects

All the respondents travel from home to the vicinity of The Hague at least three times a week and the vast majority actually work in The Hague. The main

purpose of travel is also work related. 75% of respondents in possession of a car also own it, the rest lease it from their employer. Only 17% take passengers on a regular basis, in most cases this would be their partner or a work colleague.

- The stated travel time median is 30 minutes (average of 32 minutes) with 25%-75% of respondents travelling between 20-40 minutes.
- The departure time from home median is 7:15 (average of 7:19), with 25%-75% departing between 6:45-7:50.
- The starting time at work median was 7:45 (average of 7:47) with 25%-75% starting between 7:30 – 8:30.
- The end of work time median was 17:00 (average of 16:15) with 25%-75% leaving work between 16:00-17:30.

81 respondents (31%) stated they occasionally use other transport modes for the commute trip. Of those a third uses their bike and almost 50% use commuter rail. However the frequency of using bike and public transport is usually less than twice per week. 23% and 11% stated they believe public transport / bike are realistic alternatives to car travel. 36% stated their employer permits working from home. 35% stated they could not actually work from home. For the rest the common frequency of tele-working was about once a week which was also the respective median.

Work schedule flexibility and constraints to behavior change

66% of the respondents stated that they cannot start their work later under any circumstances. This result implies that delaying start of work is not a realistic option to most people. Only, 16% stated they can start late every day of the week while the rest can start later between one to four times a week (average of 2.4). For those that can delay their start of work the acceptable median of delay was 60 minutes (average 86 minutes) with the 4th quartile standing at 120 minutes delay.

An interesting perspective was reported regarding constraints to starting work earlier. 67% stated they can start working immediately and another 12% stated they can start preparations. Only 16% stated they have to wait for a given time, wait for their colleagues or could not enter the building. This result implies that earlier start of work is a valid option. In terms of factors influencing departure time, 61% stated they have no constraints. For the rest the majority mentioned constraints as child care or dropping off their kids at schools. 27% also mentioned 'other' factors which influence their departure time from home. These other factors were predominantly related to congestion (avoiding congestion by later or earlier departure), parking (departing early to ensure a parking place), but also coordination with the partner and weather conditions were mentioned.

Taking these constraints into account almost 50% of respondents stated they could depart early from home with the reported median by 30 minutes earlier (average 37 minutes) with the 1st and last quartile standing at 15 and 60 minutes respectively. 37% of respondents stated they could depart later with the reported median of 60 minutes (average 57 minutes) with the 1st quartile at 30 minutes and that last at 70 minutes.

Motivations for participation

The main focus of the survey was the future likelihood of participating in reward schemes such as 'Spitsmijden' for avoiding peak hour driving. The respondents were asked to rank their preference on a scale of 1 to 5 with 1 being definitely participate and 5 definitely not participate. The distribution was as follows: 16% definitely yes, 13% probably yes, 12% indifferent, 16% probably not and 42% definitely not.

If respondents answered positively or indifferent they were asked to specify different motivations which to their belief contribute to their likeliness to participate.

33% mentioned the reward itself, 6% mentioned contribution to the acquisition of knowledge of congestion, 48% mentioned contribution to solving congestion, 10% mentioned self experimentation with one's behavior, and 'other' motivations were mentioned by 22%. The most important other reason appeared to be achieving a shorter commute time by avoiding congestion, but environmental concern was also mentioned. Only one respondent failed to answer.

Respondents whose choice was not likely to participate were asked to mention their reasons for not participating. 65% mentioned work time restrictions, 7% mentioned household obligations, 5% mentioned lack of alternative modes, only 3% mentioned the reward was not satisfactory and 1% mentioned that too much administration was involved. Interestingly, 10% of respondents mentioned lack of will to change one's habits as a reason not to participate. 19% mentioned 'other' reasons. Only one respondent failed to answer.

In sum it appears that the main motivations for participation are the reward itself and the social contribution to solving congestion problems. The main reasons not to participate stem mainly from household obligations and also refusal to consider behavior change.

4. The Ordered Logit (OL) and Mixed OL model

The main objective of this study is to estimate multivariate models explaining participation in Spitsmijden as a function of personal and situational factors. As mentioned the choice variable in the survey was the likelihood to participate in the reward scheme. The scale of the choice variable was ordinal with 5 categories as mentioned above. Therefore, the Ordered Logit (OL) model was used. A mixed variant of the model is also possible when random parameters are specified.

In the OL model the respondent (n) is assumed to have some level of utility or opinion associated with the object of question – in our case the choice to participate. His/her opinion is represented on a continuous scale (U_n) which is unknown. However in answering the survey the respondents have to express their opinion in one of five categories (q). Thus even though the respondent's opinion U_n can take many different levels the survey allows only specific categories. For each category there exists some cutoff or threshold (τ_q) which represents the level of U_n most suitable to the respondent (see Figure 1).

Since some factors (those that are included in the survey) are known while others remain unobservable, U is decomposed as usual into a known or explained part (V_n) and an error term (ε_n) which represents unexplained factors.

$$U_n = V_n + \varepsilon_n$$

In general terms we consider $Q \geq 2$ categories ordered such that category q corresponds to a stronger preference towards participation compared to category $q-1$ ($q=1, \dots, Q$). We define $Q+1$ parameters τ_q such that $\tau_0 = -\infty$, $\tau_Q = +\infty$, and $\tau_{q-1} \leq \tau_q$. Each category q is associated with the interval $[\tau_{q-1}, \tau_q]$. The probability that the respondent selects category q is:

$$\begin{aligned} P_n(q) &= \Pr(\tau_{q-1} < U_n < \tau_q) \\ &= \Pr(\tau_{q-1} < V_n + \varepsilon_n < \tau_q) \\ &= \Pr(V_n - \tau_q < \varepsilon_n < V_n - \tau_{q-1}) \\ &= F_{\varepsilon_n}(V_n - \tau_{q-1}) - F_{\varepsilon_n}(V_n - \tau_q) \end{aligned}$$

where F_{ε_n} is the CDF of ε_n .

The ordered response model was first suggested by Zavoina & McElvey (1975) with ε_n distributed as standard normal. However, if ε_n is

assumed to be distributed logistic we obtain the familiar OL model. Therefore:

$$P_n(q) = \Pr(\tau_{q-1} < U_n < \tau_q) = \frac{e^{\tau_{q-1} - \beta'x}}{1 + e^{\tau_{q-1} - \beta'x}} - \frac{e^{\tau_q - \beta'x}}{1 + e^{\tau_q - \beta'x}},$$

whereby $V_n = \beta'x$ is the observable part of the respondents utility, β' is a vector of coefficients and x is a vector of explanatory variables. The probabilities for the extreme categories are by definition:

$$P_n(1) = F_{\varepsilon_n}(V_n + \infty) - F_{\varepsilon_n}(V_n - \tau_1) = 1 - F_{\varepsilon_n}(V_n - \tau_1)$$

$$P_n(Q) = (V_n - \tau_{Q-1}) - F_{\varepsilon_n}(V_n - \infty) = F_{\varepsilon_n}(V_n - \tau_{Q-1})$$

For further discussion of the ordered response see (Greene, 2008; Train, 2002; Ben Akiva & Lerman, 1985).

If the model parameters vary randomly in the population, a mixed version of the model – Mixed OL – can be specified (e.g. Bhat, 1999). In this case the probability (P_n) can be expressed in the form:

$$P_n(q) = \Pr(\tau_{q-1} < U_n < \tau_q) = \int \left(\frac{e^{\tau_{q-1} - \beta'x}}{1 + e^{\tau_{q-1} - \beta'x}} - \frac{e^{\tau_q - \beta'x}}{1 + e^{\tau_q - \beta'x}} \right) f(\beta) d\beta$$

Thus the Mixed OL probability is a weighted average of the standard OL model evaluated at different values of β , with the weights given by its distribution $f(\beta)$. Since this integrand has no closed form, the values of β are drawn from a simulation which is repeated many times and the results are averaged. The simulated probabilities enter the likelihood function to give a maximum simulated log likelihood estimator. For further discussion of simulated log likelihood procedure see Train, (2002) and Bhat (2001).

The models were estimated with the BIOGEME software (Bierlaire, 2003), version 1.6 (2008) and applying the CFSQP algorithm (Lawrence et al., 1997) for the log-likelihood optimization. In addition the Mixed OL model was run with 500, 1,000 and 2,000 Halton draws in the simulated log likelihood estimation. Halton sequences

(Halton, 1960) or Halton draws are designed to cover the integration space in a more uniform way and unlike other methods, induce a negative correlation over observations which guarantee a lower variance and therefore can significantly reduce the number of draws required (Train, 2000; Bhat, 2003). We employ this approach for the empirical results presented In section 5.

Identification is a key issue with any discrete choice model. The issue of identification is determining the set of restrictions to impose in order to obtain a unique set of estimated parameters. Walker (2004), provides specific guidelines to safeguard the identification of the mixed MNL model (Mixed Logit). However, since to our best knowledge there are no specific guidelines to insure the identification of a Mixed OL model we compared the consistency for 500, 1,000 and 2,000 Halton draws. We observed that there were no significant differences in the estimation results. For accuracy purposes the results of the Mixed OL model are presented for 2,000 Halton draws.

5. Results

Model specifications

Two models were estimated. The first was a standard OL model, while the second model was a Mixed OL model which used a random parameter specification. The choice of explanatory variables was done sequentially by a trial and error basis. For the Mixed OL model random parameters were assigned with a normal distribution to three variables. The choice of these variables was concluded on a trial and error basis and in a sequential manner. An initial trial of specifying a generic random parameter neither provided significant results nor was better off in terms of the final log-likelihood.

The definitions of the explanatory variables and random parameters in the utility function appear in the tables of results. All variables in the utility function are

linear in the parameters. All models have 235 individuals' observations out of the 262 available observations. When observations had missing values or respondents refused to answer, the observation was excluded.

The thresholds for the ordered categories (tau's) were estimated according to the ranking in the survey: from 1 (definitely participate) to 5 (definitely not participate). Since we decided to estimate the first threshold τ_1 the constant in the utility function was set to 0.

OL model

The OL model was estimated in a sequential manner keeping significant variables in and excluding non-significant ones. The results presented in Table 1 show only the variables that were found to be significant at the end of this elimination process. The results show that the model and all the estimated coefficients are significant. The thresholds of the OL model (tau's) are also significant and well behaved. It is worth noting that as the proportion of respondents who chose to participate is much smaller than the non participants, thus the utility of "definitely participate" is lower and negative compared to "definitely not participate" and the thresholds reflect that. Utility is increasing in the same direction as the thresholds.

The variables that have a positive effect on participation include: The belief in bike as realistic alternative ($t=2.18$, $p<.05$), weekly frequency of late start of work ($t=2.66$, $p<.05$), earlier departure time in minutes ($t=2.01$, $p<.05$), possibility of late departure ($t=2.02$, $p<.05$), and economic sectors of hotel & catering ($t=3.14$, $p<.05$); health & social services ($t=3.73$, $p<.05$). The only variable that has a negative effect on participation is constraints on arriving at work ($t=-2.63$, $p<.05$).

It appears that the likeliness to participate in 'Spitsmijden' is greater when the traveler is open to change of mode and has more flexibility in his or her weekly working schedule. This seems also to be correlated with the economic sectors of

hotel and catering and health and social services. These sectors may have the possibility to work more flexibly (e.g. change shifts). In addition when departure time can be shifted either early or late the likeliness to participate will rise. However work related constraints hinder that possibility.

Mixed OL model

Following the findings from the OL model it was tested whether including random parameters would improve the estimation and GOF in terms of the final log-likelihood. The model was estimated in a sequential manner keeping significant variables in and excluding non significant ones. The results presented in Table 2 show only the variables that were found to be significant.

The results show the model and all the estimated coefficients are significant. The thresholds of the categories (tau's) are also significant and well behaved. The Mixed OL model has a better off GOF compared to the standard OL model and the difference is significant ($\chi^2 = 118.32$ $p < 0.05$).

There are three main differences between the OL model and the Mixed OL model. First, some variables lost their significance (being able to depart early or late, bike availability) and were excluded from the Mixed OL model. Second, some variables remain significant: frequency of late start of work ($t = 3.63$, $p < 0.05$); economic sectors – hotel & catering ($t = 2.30$, $p < 0.05$), health and social services ($t = 2.47$, $p < 0.05$); constraints on arrival at work ($t = -2.00$, $p < 0.05$). Third, some variables which were not significant in the OL model are significant in the Mixed OL model. For example the effect of constraints at home is negative and significant ($t = -2.44$, $p < 0.05$).

The main contribution of the Mixed OL model was the inclusion of the motivations to participation in the model. Naturally, the reasons why not to participate (or dis-motivations) are not appearing in the model as they were by default only relevant to the two negative choice categories. Four out of six listed motivations for

participation are significant and their standard deviations are significant (the sign is arbitrary). The motivations that appear significant are the reward ($t=5.50$, $p<.05$); the contribution to solving congestion ($t=6.26$, $p<.05$); self experimentation ($t=2.01$, $p<.05$); 'other' ($t=4.53$, $p<.05$). The strongest effect is that of the reward. It is also associated with the lowest standard deviation ($t=2.81$, $p<.05$). This implies that the reward seems to be a main and general motivator for participation in 'Spitsmijden'. The second effect is the social contribution to solving congestion. However, its random parameter was not significant and excluded from the final model. The third effect is 'other' and its standard deviation is also significant ($t=-3.59$, $p<.05$). Naturally the standard deviation of 'other' is greater than that of the reward. This variable basically captures unobserved motivations within the sample. The weakest effect is self experimentation. Its standard deviation is significant ($t=-2.50$, $p<.05$), but relative to the mean value the variance is large. This implies that there is a high degree of heterogeneity in the effect of this motivator in the sample.

6. Discussion

Congestion management is an ongoing enterprise in many metropolitan areas. Economists have been stressing the importance of pricing as the most efficient solution to accommodate congestion. However, as noted in the review, first-best solutions are at times unfeasible. Moreover, to be done in a proper manner variable pricing has to be implemented in a manner which is typically too complex for ordinary users to comprehend. For this reasons second best solutions are getting more attention in recent years. Psychological theory and cognitive research have been discussing the positive aspects of rewards for many years. It is suggested that rewards create a long term learning effect unlike tolling which to some degree can be regarded as punishment with all its problematic drawbacks (as seen in the examples

of public discontent when tolling is exercised in democratic societies). However, it is still unclear, in the case of rewards, what are the overall system benefits compared to tolls.

The Dutch 'Spitsmijden' (or peak avoidance) project reviewed earlier, is unique in its investigation under RP settings the impacts of rewards on daily travel behavior. In the course of this project a participation survey was conducted amongst the inhabitants of the study area whom did not take part in the reward scheme themselves. The main purpose was to identify in an analytic manner the motivations and constraints on participation in a future reward scheme. Albeit the latter, the project is now entering its second trial with an enlarged catchment area and a longer time frame for data collection.

The SP participation study was conducted amongst respondents living in The Hague's satellite city Zoetermeer. The socio demographic descriptives reveal a homogeneous population with the vast majority being well educated, middle age and middle class households. In addition there did not appear to be any real variability in stated travel behavior regarding mode choice, departure time and starting time of work. Although, later departure seemed to the majority of respondents a difficult option, most of them stated that earlier departure is a viable alternative. On average given household and working related constraints, earlier departure was possible for 50% of respondents with an average of 37 minutes. Only 37% included the possibility of late departure with an average of 57 minutes. Although at first glance the sample appears homogenous, these last results reveal a degree of flexibility in the daily schedules allowing for a potential to apply rewards to encourage shifting of departure times for commuting trips.

Most interesting were the provided motivations and dis-motivations to participation. Amongst those willing to participate or indifferent (41%), the main motivator was the reward itself and to lesser degree the contribution to solving

congestion and self experimentation. This result indicates that to more than a third of the respondents, the reward scheme appears attractive. Amongst those unwilling to participate (59%) the main difficulties reported were work related constraints and unwillingness to change behavior (these can be regarded as possible non-traders). In addition some 20% mentioned other unspecified reasons both as motivators and dis-motivators. This indicates a considerable degree of heterogeneity of perceptions in the sample.

Since the choice variable was ordinal with 5 categories of ordered preference, the Ordered Logit (OL) model was the natural choice for model specification. In addition, the degree of heterogeneity in the reported motivations, justified applying a mixed specification, in order to capture the variability concealed within the sample but not observable to the researcher. The choice of OL models was verified to be correct as the thresholds for the different categories (tau's) all came out well behaved and the models gave significant goodness of fits.

The results of the estimation process show that flexibility in starting work late as well as the economic sector to which the respondent's are assigned have an important effect on choosing to participate. Higher flexibility and belonging to the health & social services or the hotel & catering sectors tend to increase the willingness to participate. Also, as seen in the standard OL model, rescheduling departure times – both early and late, contributes to choosing to participate. On the other hand constraints such as team-work at work or child care and home reduce the propensity to choose to participate.

The importance of the motivations to the explanation of potential choice behavior was revealed in the Mixed OL model which is better off in its goodness of fit. As was suspected in the statistical description, the reward is the most important motivator and it had the least variance compared to other motivators. Thus it is clear that to be viable, the reward must be perceived as worthy to encourage a behavior

change. If the reward can be regarded as a selfish motivator, the strength of the contribution to solving congestion (almost as high as the reward itself) can be regarded as a social equity motivator. In addition other unspecified reasons have a strong positive impact on choice. This requires further research in the future and more detailed assignment of broader terms for possible motivators. Last, self experimentation also has a significant impact. However, its high variance indicates there is considerable variability in this effect in the sample. More research is necessary here to understand the meanings hidden under this variable.

In conclusion, our study presents interesting insights into the behavioral aspects involved in participation in a traffic management scheme. Clearly, more research is necessary with a larger sample and wider population in order to verify the latest findings. Notwithstanding, there appears to be an important contribution of objective factors like flexibility in work-related and home-related schedules and constraints. In addition subjective factors have an even higher impact as depicted in the model containing the motivators. Naturally subjective perceptions of rewards are the most important factor. However other reasons including social equity seem to have important implications for future success of implanting a reward scheme as a viable second-best solution to tackle congestion.

References

- Ampt, E. "Understanding voluntary travel behaviour change." paper presented at *26th Australasian Transport Research Forum*, Wellington.
- Arentze, T., Timmermans, H. (2007), "Congestion pricing scenarios and change of job or residential location: Results of a stated adaptation experiment." *Journal of Transport Geography*, 15 (1), 56-61.
- Banister, D. (1994), *Equity and Acceptability Questions in Internalising the Social Costs of Transport*, Internalising the Social Costs of Transport, OECD, Paris.
- Ben-Elia E., Ettema D. (2009), "Rewards to avoid rush-hour driving: Time-use impacts in the Dutch 'Spitsmijden' study", paper submitted to the *Time Use Observatory conference*, Santiago de Chile.

- Ben-Elia, E., Shefer, D., Shifan, Y. (2003), Transportation impact statement (TIS) - a new tool for transportation and land-use planning, *Environment & Planning A*, 35 (12), 2177– 2190.
- Bhat, C. (1999), 'An analysis of evening commute stop-making behavior using repeated choice observation from a multi-day survey', *Transportation Research B* 33, 495–510.
- Bhat, C. (2001), Quasi random maximum likelihood estimation of the mixed multinomial logit model, *Transportation Research B*, 35, 677-693.
- Bhat, C. (2003), Simulation estimation of mixed discrete choice models using randomized and scrambled Halton sequences, *Transportation Research B*, 37, 837-855.
- Ben Akiva, M., Bolduc, D. (1996), *Multinomial probit with a Logit kernel and a general parametric specification of the covariance structure*, working paper, Massachusetts Institute of Technology.
- Ben Akiva, M., Lerman, S. R. (1985), *Discrete Choice Analysis: Theory and Application in Travel Demand*, MIT Press, Cambridge, MA.
- Bierlaire, M. "BIOGEME: a free package for the estimation of discrete choice models." proceedings of the *3rd Swiss Transportation Research Conference*, Ascona, Switzerland.
- Bierlaire, M. (2008), *Estimation of discrete choice models with BIOGEME 1.6*, Transport and Mobility Laboratory, EPFL, Lausanne, Switzerland.
- Bonsall, P., Shires, J., Maule, J., Matthews, B., Beale, J. (2007), "Responses to complex pricing signals: Theory, evidence and implications for road pricing." *Transportation Research A*, 41 (7), 672-683.
- Chin, K. K. "Road Pricing Singapore's Experience." paper presented at *3rd Seminar of IMPRINT-Europe*.
- Eriksson, L., Garvill, J., 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.
- Eriksson, L., Garvill, J., Nordlund, A. M. (2008), "Interrupting habitual car use: The importance of car habit strength and moral motivation for personal car use reduction." *Transportation Research. F*, 11 (1), 10-23.
- Ettema, D., Knockaert, J., Verhoef, E. "Using Incentives as Traffic Management Tool: Empirical Results of the "Peak Avoidance" Experiment." paper presented at *87th Annual meeting of the Transportation Research Board*, Washington D.C.
- Ettema, D., Verhoef, E. "Using rewards as a traffic management tool: Behavioural effects of reward strategies." paper presented at *IATBR Kyoto*.
- 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.
- Garling, T., Fujii, S. "Travel behavior modification: Theories, methods and programs." paper presented at *11th IATBR conference*, Kyoto, Japan.

- Greene W. H. (2008), *Econometric Analysis 6th Edition*, Upper Saddle River, N.J : Pearson/Prentice Hall.
- Halton, J. (1960), " On the efficiency of evaluating certain quasi-random sequences of points in evaluating multi-dimensional integrals." *Numerische Mathematik*, 2, 84-90.
- Jakobsson, C., Fujii, S., Gärling, T. (2002), "Effects of economic disincentives on private car use." *Transportation*, 29 (4), 349-370.
- Knight, F. (1924), "Some fallacies in the interpretation of social cost." *Journal of Economics* 38, 582–606.
- Knockaert, J., Bliemer, M., Ettema, D., Joksimovic, D., Mulder, A., Rouwendal, J., van Amelsfort, D. (2007), *Experimental design and modelling Spitsmijden*, Bureau Spitsmijden, The Hague.
- Lawrence, C., Zhou, J., Tits, A. (1997), *User's guide for CFSQP version 2.5: A C code for solving (large scale) constrained nonlinear (minimax) optimization problems, generating iterates satisfying all inequality constraints*, Institute for Systems Research, University of Maryland.
- Lomax, T., Schrank, D. (2003), *2002 Urban Mobility Study*, Texas Transportation Institute.
- Mayeres, I., Ochelen, S., Proost, S. (1996), "Marginal and external costs of urban transport." *Transportation Research D*, 1 (2), 111-130.
- Nijkamp, P., Shefer, D. (1998), *Urban Transport Externalities and Pigouvian Taxes: A Network Approach*, Edward Elgar Publishing, Cheltenham.
- Petty, R. E., Cacioppo, J. T. (1986), "Elaboration likelihood model of persuasion." *Advances in experimental social psychology*, L. Berkovitz, ed., Academic Press. , New-York, 123-205.
- Pigou, A. C. (1920), *The Economics of Welfare*, Macmillan, London.
- Rescorla, R. A. (1987), "A Pavlovian analysis of goal-directed behavior." *American Psychologist*, 42, 119-129.
- Rouwendal, J., Verhoef, E. T. (2006), "Basic economic principles of road pricing: From theory to applications." *Transport Policy*, 13 (2), 106-114.
- Shiftan, Y., Golani, A. (2005), "Effect of Auto Restraint on Travel Behavior ", *Transportation Research Record*, 1932, 156-163.
- Simon, H. A. (1982), *Models of Bounded Rationality*, MIT Press, Cambridge MA.
- Small, K. A., Verhoef, E. T. (2007), *The Economics of Urban Transportation*, Routledge, London.
- Smith, E. E., Nolen-Hoeksema, S., Fredrickson, B., Loftus, G. (2003), *Atkinson and Hilgard's Introduction to Psychology*, Wadsworth/Thomson Learning, Belmont, CA.
- Stopher, P. R. (2004), "Reducing road congestion: a reality check." *Transport Policy*, 11 (2), 117-131.
- Train, K. (2002), *Discrete Choice Methods with Simulation*, Cambridge University Press, Cambridge, MA.
- Train, K. (2000), 'Halton sequences for mixed logit', Working Paper No. E00-278, Department of Economics, University of California, Berkeley.
- Tversky, A., Kahneman, D. (1974), "Judgment under uncertainty: heuristics and biases." *Science*, 185, 1124-1130.

- 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.
- Walker, J. L., Ben Akiva, M., Bolduc, D. (2004), *Identification of the Logit Kernel (or Mixed Logit) Model*, working paper, Massachusetts Institute of Technology.
- Zavoina, R. & W. McElvey (1975), statistical model for the analysis of ordinal level dependent variables', *Journal of Mathematical Sociology*, Summer, 103–120.

Figure 1: Hypothetical distribution of opinions for ordered response

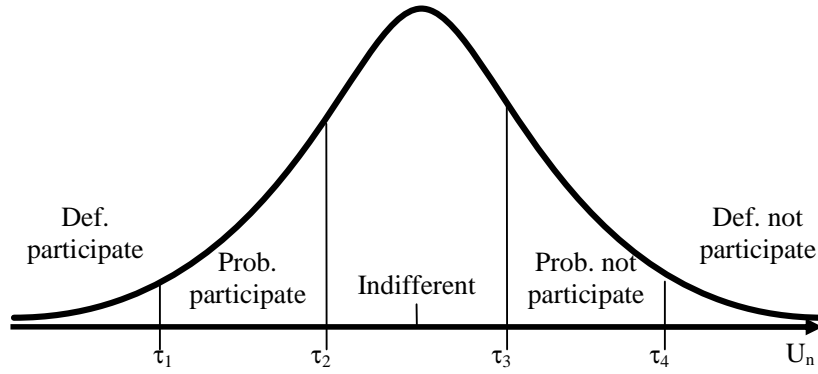


Table 1: Result of estimation of the OL model

Name	Definition	Value	Std err	t-test	p-value
β_{18}	Bike is a realistic alternative for commuting.	0.866	0.398	2.18	0.03
β_{20}	Weekly frequency of starting work late	0.182	0.0685	2.66	0.01
β_{22_3}	Situation upon arrival at work – I have to wait until a certain time.	-1.43	0.544	-2.63	0.01
β_{25m}	Earlier departure time (minutes)	0.00911	0.00453	2.01	0.04
β_{26}	Yes, I can depart later	0.566	0.280	2.02	0.04
β_{38_5}	Dummy for hotel and catering sector	2.90	0.925	3.14	0.00
β_{38_8}	Dummy for health and social services sector	1.37	0.367	3.73	0.00
τ_1	Threshold of Category 1: “definitely participate”	-2.80	0.280	-9.98	0.00
τ_2	Threshold of Category 2: “probably participate”	-1.90	0.243	-7.82	0.00
τ_3	Threshold of Category 3: “indifferent”	-1.28	0.225	-5.66	0.00
τ_4	Threshold of Category 4: “probably not participate”	-0.484	0.211	-2.30	0.02
	Number of estimated parameters	11			
	Number of observations	235			
	Number of individuals	235			
	Null log-likelihood	-378.218			
	Final log-likelihood	-315.630			
	Likelihood ratio test	125.176			
	ρ^2	0.165			
	Adjusted ρ^2	0.136			
	Final gradient norm	5.061e ⁻⁰⁰⁴			

Table 2: Result of estimation of the Mixed OL model

Name	Definition	Value	Std err	t-test	p-value
β_{20}	Weekly frequency of starting work late	0.303	0.0834	3.63	0.00
β_{22_3}	Situation upon arrival at work – I have to wait until a certain time.	-1.45	0.724	-2.00	0.05
β_{23_1}	Constraints on early departure – childcare	-1.17	0.479	-2.44	0.01
β_{30_1}	Motivation to participate – the reward	9.15	1.66	5.50	0.00
β_{30_3}	Motivation to participate – contribution to solving congestion	9.01	1.44	6.26	0.00
β_{30_4}	Motivation to participate – self behavior experimenting	7.13	3.54	2.01	0.04
β_{30_5}	Motivation to participate – other	8.37	1.85	4.53	0.00
β_{38_5}	Dummy for hotel and catering sector	3.54	1.54	2.30	0.02
β_{38_8}	Dummy for health and social services sector	1.17	0.475	2.47	0.01
σ_{30_1}	Standard deviation – v30_1	3.72	1.33	2.81	0.01
σ_{30_4}	Standard deviation – v30_4	-8.30	3.32	-2.50	0.01
σ_{30_5}	Standard deviation – v30_5	-5.02	1.40	-3.59	0.00
τ_1	Threshold of Category 1: “definitely participate”	-10.8	1.51	-7.18	0.00
τ_2	Threshold of Category 2: “probably participate”	-8.21	1.33	-6.16	0.00
τ_3	Threshold of Category 3: “indifferent”	-3.75	0.519	-7.21	0.00
τ_4	Threshold of Category 4: “probably not participate”	-1.01	0.242	-4.17	0.00
	Number of Halton draws	2,000			
	Number of estimated parameters	16			
	Number of observations	235			
	Number of individuals	235			
	Null log-likelihood	-378.218			
	Final log-likelihood	-197.313			
	Likelihood ratio test	361.811			
	ρ^2	0.478			
	Adjusted ρ^2	0.436			
	Final gradient norm	1.968e ⁻⁰⁰⁶			