

# **Carrots versus sticks: Rewarding commuters for avoiding the rush-hour—a study of willingness to participate**

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## **Key Words:**

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## **Abstract**

This paper deals with the potential participation in a reward scheme to avoid peak hour driving. Using rewards in the context of congestion is novel compared to the attention received by road pricing. Psychological research emphasizes the importance of incentives such as rewards in promoting long term behavior changes. In the Netherlands, reward schemes have been tested through the 'Spitsmijden' project. This study analyses participation based on a survey of non-participants. Ordered Logit (OL) and mixed OL discrete choice models were specified. The results show that participation is linked to working time flexibility, constraints in the household and the workplace and especially to personal motivations. These results provide behavioral insights to formulating a coherent and flexible policy to implement rewards on larger scales as serious tool in the transportation demand management kit.

# 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 participants in 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 will be published in the near future. 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 of the results whereas section 7 addresses policy implications of the suggested approach.

## **2. The behavioral context of congestion**

The issue of how best to tackle the growing problem of both recurring and non-recurring congestion and related externalities like deteriorating air quality have been preoccupying researchers and policy makers for many years (Mayeres et al, 1996). In 2006 the the European Commission's white paper on transport policy estimated the annual congestion externalities cost at around 1% of European GDP.– around €100 billion – each year. (European Commission, 2006a, 2006b).

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. 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). Technical barriers for first best pricing have now been mostly overcome as demonstrated by HOT lane projects in California and Singapore's Electronic Road Pricing Scheme (Chin, 2002). However, as initially suggested by Vickrey (1969) optimal tolling requires that tolls vary over locations and times (Arnott et al., 1990, 1993) and if environmental conditions are to be taken in account also by meteorological conditions, vehicle type and even driving style (Bonsall et al., 2007).

All these make first best pricing solutions considerably complex to implement and difficult for the user to comprehend.

In practice, imposing an efficient tolling scheme is controversial and involves social equity and political acceptability in addition to economic efficiency (Banister, 1994; Viegas, 2001). Furthermore, subjective conceptions of fairness and freedom 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. The travelers' voluntary behavioral responses to the tolls can include in the short run route switching, trip rescheduling and mode changes (Shiftan & Golani, 2005). 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). 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.

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. The 'Spitsmijden' Data**

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 if they avoided driving during the peak hours (defined between 7:30-9:30 AM). Participants could avoid peak hour travel either by changing their departure times (earlier or later) or choosing other travel modes (like bike or public transport) or by working from home. The rewards, set according to the participant's preference, were either of money (between 3-7 Euros) or of credits to earn a smartphone.. Each day a participant did not drive during the peak period he or she received a reward which was delivered at the end of each week. In the smartphone variant, if participants acquired a minimum amount of credits they could keep the device as a gift at the end of the experiment. In addition the smartphone also provided real-time traffic information regarding travel times on the Zoetermeer – The Hague corridor. The value of the smartphone was more or less equivalent to the expected amount of money each participant could earn in the money variant (about 300 Euros).

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. If a participant in the survey was also by chance a participant in Spitsmijden, the interview was discontinued and the observation was not included in the final sample. 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 women) 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 1<sup>st</sup> quartile under 38, the 2<sup>nd</sup> quartile 38-45, the 3<sup>rd</sup> 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 1<sup>st</sup> 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 population characterized by high incomes and good education levels most of which are middle aged and cohabiting with partners and children. These descriptives were also found in the analysis of the actual participants in Spitsmijden and are apparently typical for the middle-class suburban population of Zoetermeer.

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 1<sup>st</sup> 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 4<sup>th</sup> 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 1<sup>st</sup> 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 1<sup>st</sup> quartile at 30 minutes and that last at 70 minutes.

## **Choice and 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. It should be noted that in this situation the reward was just stated verbally as a motivation without any monetary or other definition.

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 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 ( $\tau_q$ ) 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,  $U_n$  is decomposed as usual into a known or explained part ( $V_n$ ) and an error term ( $\varepsilon_n$ ) 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  $\tau_q$  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  $F_{\varepsilon_n}$  is the CDF of  $\varepsilon_n$ .

The ordered response model was first suggested by Zavoina & McElvey (1975) with  $\varepsilon_n$  distributed as standard normal. However, if  $\varepsilon_n$  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,  $\beta'$  is a vector of coefficients and  $x$  is a vector of explanatory variables. The probabilities for the extreme categories are by definition:

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

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

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  $\beta$ , with the weights given by its distribution  $f(\beta)$ . Since this integrand has no closed form, the values of  $\beta$  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 OL model and the Mixed OL model were estimated separately with sequential trial and error basis, resulting in a different set of significant explanatory variables for each model. For the Mixed OL model random parameters were assigned with a normal distribution. The choice of these variables was also concluded on a trial and error basis and in a sequential manner. An initial trial of specifying a generic random parameter (i.e. random effects) 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 chose to estimate the first threshold  $\tau_1$  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 participation is lower and negative 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. It is interesting that household constraints such as childcare and dropping off at school did not come out significant. This was against our expectation. A possible explanation is that household constraints have an impact on the early/late departure variables and the latter resulted in better fitting since most of them are continuous and not nominal.

### **Mixed OL model**

Following the findings from the OL model it was tested whether including random parameters would improve the estimation and GOF. The model was estimated separately and independently from the OL model 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 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 ( $t=2.30$ ,  $p<.05$ ), health and social services ( $t=2.47$ ,  $p<.05$ ); constraints on arrival at work ( $t=-2.00$ ,  $p<.05$ ). 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 ( $t=-2.44$ ,  $p<.05$ ). The reason for this behavior of the estimation can be attributed to the independent estimation of the mixed OL model leading to a different set of variables that maximize the log-likelihood function.

The most notable change compared to the OL model is the addition of the motivations for participation as explanatory variables. Motivations which are subjective in nature have no real meaning if they are not treated as random. Note, that the only significant random variables were those of the motivations while for all the rest of the variables in the mixed OL the random specification was not significant. 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. This results in the dis-motivations being perfect choice predictors for non-participation categories. We note that this is a drawback to the results. However, given that the survey design was conducted externally we made the best of the data that was available.

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 for '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 for many modern cities. Economists stress 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 understand. For this reasons second best solutions are getting more attention in recent years. Psychological theory and research have for many years been discussing the positive aspects of rewards. 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 a spearhead in investigating 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 non-participation study was conducted amongst respondents living in The Hague's satellite city Zoetermeer. The socio demographic descriptives revealed 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 fit.

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 and social services or the hotel and 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 had a better 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.

To summarize, our study presents interesting insights into the psychology involved in participation in a reward 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.

## **7. Policy implications**

This paper has outlined the factors that influence commuters' willingness to participate in a reward program involving financial incentives to avoid car trips in the morning peak. The results suggest that willingness to participate is primarily determined by variables related to work and household organization, subjective motivations, and to a much lesser extent by socio-demographic characteristics. From a policy point of view various implications can be drawn from this study.

With respect to the effectiveness of the approach it is noted that the net effect (in terms of congestion and impacts on traffic flows) of an incentive-based approach depends on the participation rate as well as on the behavior of those participating. A study by Bliemer & van Amelsfort (2008), indicates that an optimum exists in this respect. If rewards are too low, few people will be willing to participate resulting in hardly any change of behavior. If rewards are too high, too many will participate and avoid the peak frequently, leading to rising congestion in the initially congestion free

periods before and after the original peak. Thus, an optimum needs to be found with respect to participation rate and behavioral response. This is important since research in the road pricing arena (Gärling et al., 2008; Schuitema et al., 2008) suggests that perceived effectiveness is a critical factor for public acceptance of policies.

This study suggests that policy makers have various handles to influence effectiveness of Spitsmijden. First, as already mentioned, the height of the reward will play a central role. In addition, however, organizational factors, such as work time flexibility, telecommuting and providing public transport alternatives can be actively used by policy makers to work toward an optimal solution. An implication of this is that employers will have an impact on the effect of Spitsmijden to the extent that they allow employees to divert from their original work hours or work from home. This implies a change away from conventional traffic policies in the Netherlands, in which the government has typically implemented policies in a top down way. Spitsmijden, in contrast, requires a more active participation from employers. Currently, Spitsmijden is tested in pilot projects in the Netherlands, also involving various large employers in test regions. These tests reveal that employers are willing to discuss their role in Spitsmijden for two reasons. First, they feel that reducing congestions and keeping their region accessible is in their own interest. Second, they consider more flexible work arrangement that facilitates Spitsmijden as a service that may attract and keep employees.

A second implication concerns equity in the Spitsmijden approach. A typical concern raised against road pricing is that road users with different values of time (VOT) will experience different utilities. Those with a low VOT are forced to divert from their preferred departure time, implying a lower utility. Commuters with a higher VOT will pay the toll, but this is offset by the travel time gain resulting from improved accessibility. In this respect it is noted that reward schemes such as Spitsmijden are

fundamentally different. First, participation is voluntary, implying that no one is forced to accept options with negative implications. If someone changes departure time, this will be because the advantage of the reward outweighs the disadvantage of a departure time shift. Likewise, if someone shifts to public transport or working from home, this will be because the net effect (changed behavior plus reward) is positive. In addition, non-participants who travel in the peak will benefit from increased accessibility during the peak hour. The only group who might suffer from Spitsmijden is car commuters who already drive before or after the peak. However, this is a relative minority in the total number of commuters. As indicated above, large-scale peak avoidance might increase congestion during their original travel hours. However, careful implementation and optimization should be able to avoid this. Nevertheless, the issue remains that not everyone can benefit to the same extent. First, those already travelling outside the peak or by non-auto modes will not be able to earn the reward, whereas those who shift to these travel options are rewarded. Second, those with less flexibility in terms of work or household organization or mode availability have fewer options to optimize their outcomes. Although the second issue can be addressed by active policies, the first remains an issue of concern. An important point to make, though, is that decisions to participate are, according to our model, not made along lines of income and spending power, suggesting that equity concerns along that dimension do not occur, as would be the case with road pricing.

A final policy implication concerns the financial impacts of the approach. The counter side of avoiding losses amongst road users is that reward measures such as Spitsmijden require net input of taxpayers' money. Studies on road pricing have revealed that acceptability of such policies depends on how benefits are spent and invested (Schuitema et al., 2008). Likewise, it can be argued that Spitsmijden raises the issue where the money to implement the measure would come from. We would argue that, as for any other transport policy, the costs and societal benefits of



Spitsmijden should be balanced against each other. This issue is related to the way in which Spitsmijden is applied. If it is applied as a permanent measure, the costs of rewarding road users should be treated no different than the costs of building extra infrastructure to accommodate excess demand on the road networks capacity.

Another option would be to apply Spitsmijden as a temporary measure during road construction works. In that case, the costs of the measure could be balanced against the expected congestion and travel time delays due to temporary reduction of road capacity. It should be noted, though, that the concept of Spitsmijden allows for fine-tuning by setting the exact reward levels in a relatively similar manner to dynamic road pricing. In this way, not only traffic flow and congestion effects can be optimized, but also the balance of societal costs and benefits.

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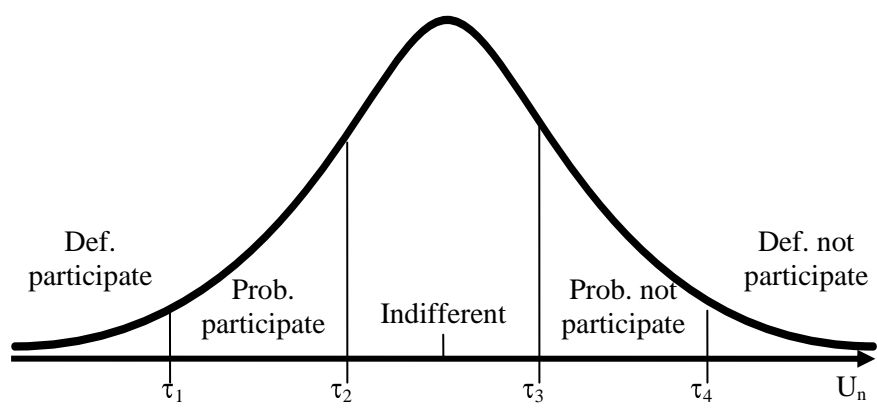
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**Figure 1: Hypothetical distribution of opinions for ordered response**



**Table 1: Result of estimation of the OL model**

Name	Definition	Value	Std err	t-test	p-value
$\beta_{18}$	Bike is a realistic alternative for commuting.	0.866	0.398	2.18	0.03
$\beta_{20}$	Weekly frequency of starting work late	0.182	0.0685	2.66	0.01
$\beta_{22\_3}$	Situation upon arrival at work – I have to wait until a certain time.	-1.43	0.544	-2.63	0.01
$\beta_{25m}$	Earlier departure time (minutes)	0.00911	0.00453	2.01	0.04
$\beta_{26}$	Yes, I can depart later	0.566	0.280	2.02	0.04
$\beta_{38\_5}$	Dummy for hotel and catering sector	2.90	0.925	3.14	0.00
$\beta_{38\_8}$	Dummy for health and social services sector	1.37	0.367	3.73	0.00
$\tau_1$	Threshold of Category 1: “definitely participate”	-2.80	0.280	-9.98	0.00
$\tau_2$	Threshold of Category 2: “probably participate”	-1.90	0.243	-7.82	0.00
$\tau_3$	Threshold of Category 3: “indifferent”	-1.28	0.225	-5.66	0.00
$\tau_4$	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			
	$\rho^2$	0.165			
	Adjusted $\rho^2$	0.136			
	Final gradient norm	5.061e <sup>-004</sup>			

**Table 2: Result of estimation of the Mixed OL model**

Name	Definition	Value	Std err	t-test	p-value
$\beta_{20}$	Weekly frequency of starting work late	0.303	0.0834	3.63	0.00
$\beta_{22\_3}$	Situation upon arrival at work – I have to wait until a certain time.	-1.45	0.724	-2.00	0.05
$\beta_{23\_1}$	Constraints on early departure – childcare	-1.17	0.479	-2.44	0.01
$\beta_{30\_1}$	Motivation to participate – the reward	9.15	1.66	5.50	0.00
$\beta_{30\_3}$	Motivation to participate – contribution to solving congestion	9.01	1.44	6.26	0.00
$\beta_{30\_4}$	Motivation to participate – self behavior experimenting	7.13	3.54	2.01	0.04
$\beta_{30\_5}$	Motivation to participate – other	8.37	1.85	4.53	0.00
$\beta_{38\_5}$	Dummy for hotel and catering sector	3.54	1.54	2.30	0.02
$\beta_{38\_8}$	Dummy for health and social services sector	1.17	0.475	2.47	0.01
$\sigma_{30\_1}$	Standard deviation – v30_1	3.72	1.33	2.81	0.01
$\sigma_{30\_4}$	Standard deviation – v30_4	-8.30	3.32	-2.50	0.01
$\sigma_{30\_5}$	Standard deviation – v30_5	-5.02	1.40	-3.59	0.00
$\tau_1$	Threshold of Category 1: “definitely participate”	-10.8	1.51	-7.18	0.00
$\tau_2$	Threshold of Category 2: “probably participate”	-8.21	1.33	-6.16	0.00
$\tau_3$	Threshold of Category 3: “indifferent”	-3.75	0.519	-7.21	0.00
$\tau_4$	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			
	$\rho^2$	0.478			
	Adjusted $\rho^2$	0.436			
	Final gradient norm	1.968e <sup>-006</sup>			