Commuters’ choice-behavior with rewards for avoiding peak-hour driving

Eran Ben-Elia, Dick Ettema
Urban and Regional Research Center
Faculty of Geosciences
Utrecht University
P.O. Box 80115
3508 TC, Utrecht, The Netherlands
d.ettema@geo.uu.nl, e.benelia@geo.uu.nl

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Abstract
This paper’s focus is on the behavioral impacts of rewards for avoiding rush-hour driving during the course of the ‘Spitsmijden’ project, a 13 week field study conducted in the Netherlands. Discrete choice models for departure time and mode choice were estimated using panel mixed logit suitable for accommodating repeated responses. The results suggest that rewards can be an effective measure in changing commuting behavior. Specifically rewards reduce the shares of rush-hour driving, shift to earlier and later driving times and increase the shares of public transport, bike and working from home. However, other factors such as available information, experience, situational factors, supportive measures and even the weather can influence the behavioral impacts of the reward. These are important to account for during policy implementation.

1. Introduction
Congestion on urban roads throughout the European Union is increasing and is expected to worsen as the demand for travel increases and supply of road infrastructure remains limited (European Commission, 2006a, 2006b). Loading of excess demand on the Transportation System has considerable external costs such as pollution, noise and road user safety (Mayeres et al., 1996), as well as, increasing frequency of incidents, interrupted vehicle flow and uncertain travel times (Lomax & Schrank, 2003).

Transportation economists have been arguing for implementation of road pricing as a first-best solution to efficiently alleviate congestion externalities. A toll which reflects the true marginal cost of travel is implemented on congested facilities, resulting in a reduction in the number of travelers at peak periods and improving traffic flows (Nijkamp & Shefer, 1998; Rouwendal & Verhoef, 2006; Small & Verhoef, 2007). The bottleneck model (Vickrey, 1969) and its variants (Arnott et al., 1990, 1993) shows how a queue is formed from the departure time decisions of individual travelers and how a time-dependent toll could in theory dissolve it efficiently. Following Vickrey, the concept of schedule delay was introduced in travel decisions (Small, 1982) and
several empirical investigations applied it using specifications of discrete choice models (e.g., Bates et al., 2001; de Jong et al., 2003).

In practice, imposing road pricing is controversial and insight is lacking in key domains. First, as suggested initially by Vickrey, optimal pricing requires that tolls are designed to be variable making it quite complex for drivers comprehension (Bonsall et al., 2007; Verhoef, 2008). Second, it raises questions regarding social equity (Giuliano, 1994) and public acceptability in addition to economic efficiency (Banister, 1994; Viegas, 2001). Furthermore, perceptions of fairness seem to play a crucial role in public acceptability of pricing schemes (Eriksson et al., 2006). 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) and limit their effectiveness. Fourth, cognitive limitations and judgmental heuristics (e.g. Simon, 1982; Tversky & Kahneman, 1974) might play a role in travelers adaptation to pricing signals in variable conditions. All these can lead to different outcomes than those predicted by economic theory.

Second-best schemes have been suggested to circumvent the difficulties in implementing first-best solutions (Small & Verhoef, 2007). In this context, it has been asserted that an incentive for avoiding peak-hour travel can achieve a similar behavioral response to that of pricing (Ettema & Verhoef, 2006; Knockaert et al., 2007). The basic idea is to reward (or compensate) those travelers who are willing to shift to earlier or later departure times or to alternative travel modes. Thus, overall penalization of drivers through tolling is avoided and overall welfare is improved by reducing peak demand (see Figure 1). Research in behavioral psychology asserts the benefits of rewarding e.g. (Guyll et al., 2003; Sansgiry et al., 2006). Positive incentives promote learning and internalization (i.e. sustainable changes) whereas punishment induces compliant behavior but creates a negative learning effect associated with avoidance and aversion rather than internalization and understanding (Rescorla, 1987).

Commuter response to a possible reward is virtually unknown. Situational constraints such as household obligations or work time inflexibility could hamper the positive impact of the reward. Cognitive factors could also be critical in the manner which travelers will evaluate the cost-effectiveness of the reward. (Jou et al., 2008) provide evidence that Prospect Theory (Kahneman & Tversky, 1979) with its suggested asymmetry in the valuation of gains and losses can be of importance. In scheduling decisions. (de Borger & Fosgerau, 2008) suggest that loss aversion plays a key role in tradeoffs between time and money. Thus, values of time (VOT) are predicted to be non-linear depending on the reference state of the decision maker. To complicate things further, studies based on reinforced learning (Erev & Barron, 2005) reveal significant differences of behavior in static versus dynamic environments (Avineri & Prashker, 2003, 2006; Ben-Elia et al., 2008).

Despite of its potential as a congestion management tool, there is still lack of knowledge regarding the behavioral impacts of a reward. Consequently, ‘Spitsmijden’ (translated freely as peak avoidance) was organized in 2006 with the objective to investigate the potential impacts of rewards over commuters’ behavior. It was designed as an empirical field study i.e. revealed preference (RP) setting. In addition the impacts of providing real-time information in conjunction with the rewards were also specified as part of the project’s objectives.

Initial results show evidence of substantial behavior change in response to the rewards, with commuter shifting to earlier and later departure times and more use of public transport and alternative modes or working from home (Ettema et al., 2008). In this paper we significantly improve the understanding of commuter behavior during the course of the project by identifying what key factors influence the response to the...
It is speculated that both personal characteristics (i.e. socio-demographics) situational factors and cognitive factors (e.g. information acquisition, and experience) play a role in sustaining a behavior change in addition to the reward itself. The rest of the paper is organized in the following way: Section 2 describes the experiment design and the data collection. Section 3 explains the data analysis process and the choice models we applied specifically the Mixed Logit model for panel data. Section 4 presents the estimation results. Section 5, includes a discussion of the results and Section 6 some conclusions and policy implications.

2. Design & data collection

The Dutch 'Spitsmijden' experiment was conducted by a public-private partnership consisting of three universities, private firms and public institutions. With a budget of over 1 million Euros, its purpose was to collect a large sample of empirical or revealed preference (RP) data regarding the impact of rewards on behavior during the daily morning commute. During a period of 13 consecutive weeks in Autumn, 2006, 341 recruited volunteers (221 men and 120 woman) from the town of Zoetermeer, a satellite city of The Hague, participated in a scheme whereby they would receive daily rewards, either of money (between 3-7 Euros) or of credits to earn a 'Yeti' smartphone, if they avoided driving during the morning peak-hour. 232 participants chose to receive a monetary reward ('Money') and 109 the Yeti reward. Participants could avoid peak-hour travel (defined between 7:30-9:30 AM) either by shifting their departure times (earlier or later) or choosing other travel modes (like bike or public transport) or by working from home. Participants that opted for the Yeti option were also provided with real-time traffic information regarding travel times on the Zoetermeer – The Hague corridor (see Figure 2).

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, time-use constraints, and socio demographic characteristics. In the second stage which was an RP phase, detection equipment using in-vehicle installed transponders (onboard units and electronic vehicle identification) and road-side cameras was installed. In the first 2 weeks travel behavior data was collected without giving out rewards. Thus, although the design did not take account for a control group, before-after comparisons can still be made. 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 are 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 Yeti. In the last week travel behavior data was collected without rewards, however information was still available to Yeti users. In the third stage of the study, an evaluation survey was conducted regarding the experiences of the participants during the experiment. See (Knockaert et al., 2007) for further details.

Participants receiving money took part in 3 consecutive reward treatments (i.e. repeated treatments) a reward of 3€ (lasting 3 weeks) a reward of 7€ (lasting 4 weeks) and a mixed reward (lasting 3 weeks) which gave 3€ for avoiding the high peak (8:00-9:00) and 7€ for avoiding also the lower peak (7:30-8:00, 9:00-9:30). The order of the reward treatments (‘Schemes’) followed a block design with participants divided randomly to the 6 possible schemes. Some exceptions were applied to couples using the same vehicle. In retrospective, the scheme of treatments had no significant influence.

Yeti users were able to acquire credit during a period of 5 weeks. If they earned enough credit by avoiding peak-hour driving for sufficient number of days they could
keep the Yeti. The rest of the 5 weeks were unaccredited but participants could still have access to traffic information. Participants were divided between two schemes in relation to which of the first or second set of 5 weeks was attributed to the reward. Yeti users had access to real time traffic information 24 hours a day via the Yeti and traffic information availability was not dependent on the reward itself. The information consisted of a traffic map and online information on travel times on the main freeway between Zoetermeer’s exit and the western entrance to The Hague. In contrast, the money group had access to information available to all other drivers: pre trip through internet and other media and from VMS signs en-route.

Another important feature in the design was participants’ allocation to reward classes. This relates to the preliminary levels of commuting trips per week attributed to each participant which provided the base level for reduction of peak trips. The idea was to refrain from increasing the number of trips in off-peak periods that were not offset by existing peak hour trips. All in all participants were divided into 4 classes in each group. However, the majority of participants belonged to classes A and B which relate to 4-5 daily trips per week and the minority to classes C and D (1-2 daily trips per week).

Two surveys (one before and one after the trial) were conducted as part of the study. It is reasonable to hypothesize that factors influencing participants’ behavior during the RP phase are not limited only to the stimulus i.e. the rewards, and that other factors such as socio-demographic and personal characteristics, habits, constraints and even subjective experiences might also have a behavioral impact. Therefore, analysis of the surveys and especially the evaluation survey could provide valuable insights for behavioral analysis and modeling.

Socio-demographic and usual travel behavior patterns were investigated in the preliminary survey. The socio-demographic factors reveal a relatively homogenous population with high education levels (56%), moderate to high incomes and mostly families (81%). Travel characteristics reveal that commuting is routine and the most used mode of travel is the car (80%). Alternative modes are used by 20%, however, the stated average frequency of using non-auto modes is usually less than twice per week. Public transport is considered as a realistic alternative to driving for about a third of the sample while cycling is less attractive mainly due to distance.

Travel time characteristics show that the common time for commuting is the morning peak and that the usual travel time and arrival times are dependent on the congested travel times. Preferred arrival times are very close to the usual values. It is possible that preferred arrival times will affect change of behavior. Despite this apparent uniform behavior, a quarter of the sample can work from home as an alternative to driving and about half can either depart earlier or later (about 20-30 minutes delay on average). Almost 90% can start work earlier without difficulties or start preparations. Constraints for early departure involved mainly child care (30%) or dropping off kids at schools (20%).

Motivations and personal experiences were investigated in the evaluation survey. Getting rewarded for avoiding peak hour driving was the main motivator; however social contributions such as solving or gaining knowledge about congestion were also indicated. This result is inline with other studies that discussed road pricing acceptability and with a study of non-participants conducted as part of the project (Ben-Elia & Ettema, 2009a). Difficulty in changing behavior was stated by about half of the sample in terms of effort or expectations. The main difficulties encountered were mainly work-related (13%) or home-related (8%). Relatively few complained about lack of alternative modes, or weather. An interesting case was problems in the operation of the regional rail during the RP phase. 30% mentioned this caused difficulty and 20% mentioned they would have used public transit more often.
Supporting measures included mainly discussions with employer (40%), discussions with colleagues (25%), with family members (30%) and household task allocation arrangements (15%). Only few mentioned support measures relating to mode use or item purchases. One very interesting support measure was practicing behavior adjustment in the weeks before the trial (30%). Another interesting support measure was the increase in the usage of traffic information and especially public transport information during the course of the trial. 30% of all participants mentioned they sought information more often than before. 66% of Yeti users increased their use of information compared to only 13% of the Money group. In the Money group 78% stated they did not change their frequency of traffic information consulting. The mean weekly frequency of consulting pre trip traffic information (for work trips only) grew from 1.5 in the preliminary survey to 1.9 in the evaluation survey and this difference is significant (t=2.3, p<.05). The mean weekly frequency of consulting pre trip public transit information increased from .1 to .4 and this difference is also significant (t=4.1, p<.05). These differences were also significant for both groups separately. These results suggest that information is probably an important factor in promoting or discouraging a behavior change.

To conclude, posterior satisfaction from the trial was on average positive. 48% stated that they changed their driving times and would continue to do so in the future. 60% stated they consider the reward a good idea to encourage behavior change. In general 88% of participants stated they would choose to participate again if given the opportunity.

3. Data analysis and model specification

The total database collected during 13 weeks of ‘Spitsmijden’ consisted of 22,165 observation-days. For the sake of consistent behavior, only working days (including working from home) were accounted for in the analysis (16,725 observations). To simplify the analysis, we differentiated the response to a closed choice set of four discrete alternatives: peak-hour driving, driving earlier or later than the peak-hour and not-driving (all as entries in the personal daily logbook). Since each participant provides up to 65 consecutive daily responses, the data is constructed as a panel. Although each participant’s responses are independent of the other participants, within each participant’s responses, observations are dependent and hence correlated. Thus, the classic assumption of identically independent distributed (i.i.d) error terms is violated. Specifying panel effects can accommodate for this deficiency. In the context of discrete choice this can be accomplished using a mixed discrete choice model such as the Mixed Logit model.

Model specification

Mixed Logit (MXL and also referred to as Logit Kernel) is an advanced and highly flexible discrete choice model. MXL accommodates random taste variation, substitution patterns, and correlation in unobserved factors unrestricted over time (McFadden & Train, 2000). Unlike Probit models, it is not restricted to normal distributions, but can be derived under a variety of different specifications (Ben Akiva & Bolduc, 1996; Bhat, 1998; Hensher & Greene, 2001; Revel & Train, 2000). The MXL specification is easily generalized to allow for repeated choices i.e. panel (Bhat, 1999; Train, 1999). The simplest specification (1) treats the coefficients that enter utility as varying over individuals but being constant over responses for each person. Specifically, the utility from alternative \( i \) in response \( t \) by person \( n \) is:

\[
U_{int} = X_{int} \beta + \varepsilon_{int}, \quad \beta \sim f(\beta).
\]
Where: $X$ is a vector of explanatory factors, $\beta$ a vector of coefficients (with density $f$), and $\varepsilon$ is a vector of iid gumbel error terms.

When an MXL specification includes a panel the integrand involves a product of logits, one for each time period:

$$P_{ni} = \prod_{t=1}^{T} \frac{e^{X_{nt}^{\prime}\beta}}{\sum_{j=1}^{J} e^{X_{njt}^{\prime}\beta}} f(\beta)d\beta$$

where $P_{ni}$ is the probability that person $n$ chooses alternative $i$.

To simplify the need to specify each coefficient with its own density function, panel effects are usually accounted for using a general disturbance parameter ($u$) with 0 mean and an unknown variance parameter ($\theta$).

$$U_{int} = X_{int}^{\prime}\beta + \varepsilon_{int} + u_n, \quad u_n \sim iid(0,\theta_n), \quad \varepsilon \sim iid \text{ gumbel}$$

In most cases a normal distribution is assumed (see Greene, 2008). This is also referred to as the classic ‘random effects’ specification.

$$U_{int} = X_{int}^{\prime}\beta + \varepsilon_{int} + u_n, \quad u_n \sim N(0,\sigma_u^2)$$

Data analysis

The data analysis process included three stages. The first stage included extensive data screening. Multivariate analysis was conducted using ANOVA techniques for repeated measurements using aggregate data (at the treatment level). This enabled to identify the important factors that have an effect on the response. Several groups of factors were identified. The type and level of the rewards were the most important factors. However, other factors which were measured in the preliminary and posterior surveys were also found to be significant. These included information, experience, situational constraints and support measures and socio-demographic characteristics (Ben-Elia & Ettema, 2009b).

The second stage included aggregate choice modeling. MXL specification with panel effects (three random alternative specific coefficients) was estimated (using NLOGIT 4.0) based on the aggregate data (1532 observations). Instead of daily discrete choices we computed average treatment-level proportions. Thus, each participant provided 4 or 5 observations (depending on the group money or Yeti) instead of 65. This allowed a considerable amount of savings on estimation time (hours compared to days). The results of the estimation show which factors have a significant impact on the choice behavior. Non-significant factors were taken out of the model in a sequential trial and error method. Interaction effects were also tested but did not prove to be of real significance. Error components in the random effects specification also did not prove to be of additional value.

In the third stage we used the best specification obtained from the aggregate model and applied it to the daily (disaggregate) data. This model also contained daily factors which could not be included in the aggregate model like weather variables and travel time information provided by ATIS. The disaggregate models were estimated with BIOGEME version 1.8 (Bierlaire, 2003; Bierlaire, 2009). We also compared the goodness of fit of the model to simpler models one that contained only panel effects (a constants’ model) and one with only the treatment effect (restricted model) but without any other factor. However, comparing goodness of fit between aggregate and disaggregate models is invalid.
Simulated log likelihoods of all models were estimated with 1,000 Halton draws (Halton, 1960) which significantly reduce the number of draws required compared to pseudo-random draws (Bhat, 2003; Train, 2000). The models were estimated using 100, 500 draws and 1,000 draws. The differences between the last two sets were negligible. The results presented here are for the set of 1,000 draws. We also applied appropriate guidelines to assure proper identification (Walker et al., 2004).

4. Estimation results

The results of the estimation are presented separately for the aggregate (Table 1) and disaggregate models (Table 2). The utility functions are indicated and the definitions of the variables and the coefficients appear in the relevant tables.

Aggregate choice model

$U(\text{Ndrv}) = \beta^{N}_{v23}S1v23 + \beta^{N}_{v9}S1v9 + \beta^{N}_{ov}S3OV + \beta^{N}_{v6i}S3v6I$

$U(\text{Peak}) = \beta^{P}(\sigma^P) + \beta^{P}_{t2}t_{typ2} + \beta^{P}_{t3}t_{typ3} + \beta^{P}_{t4}t_{typ4} + \beta^{P}_{t5}t_{typ5} + \beta^{P}_{t6}t_{typ6} + \beta^{P}_{\text{grd}}\text{Gender} + \beta^{P}_{cm}\text{CABm} + \beta^{P}_{cy}\text{CABy} + \beta^{P}_{v6km}S3v6Km + \beta^{P}_{v6a}S3v6A + \beta^{P}_{v32c}S1v32Cm + \beta^{P}_{v281}S3v2Hm + \beta^{P}_{rr}\text{rdrail}$

$U(\text{Early}) = \beta^{E}(\sigma^E) + \beta^{E}_{v16}S1v16 + \beta^{E}_{\text{DP}}S1DP + \beta^{E}_{v27A}S1v27A$

$U(\text{Late}) = \beta^{L}(\sigma^L) + \beta^{L}_{v16}S1v16 + \beta^{L}_{v27A}S1v27A + \beta^{L}_{\text{Fll}}S3Fil + \beta^{L}_{EDHm}\text{EDHm} + \beta^{L}_{v281}S1v281$

The aggregate model shows that all reward treatments are significant ($p<.05$) and the sign of the coefficient is negative. The effects of the 7€ level (type 3) and the mixed reward (type 4) are quite similar. The effect of the Yeti credit (type 6) is similar to that of the 3€ level (type 2). Only the unaccredited Yeti (type 5) is not significant. These results suggest that on average the rewards had a significant impact on reducing peak-hour driving, corroborating our initial results. Another important factor relating to the experiment design is the participant's class association which relates to his or her pre-experiment frequency of commuting (days per week) and the number of possible rewards per week. The results show that Classes A and B (4-5 commutes per week) are significantly different than Classes C and D (1-2 commutes per week). Participants associated with classes A, B were more likely to continue driving in the peak and the model shows that for both groups the coefficients are positive. The coefficient for money is slightly larger than that of Yeti indicating the effect is slightly larger as well.

In addition to the reward and class, other variables also have a significant impact on the choice behavior. We divide these into 4 categories: personal characteristics, information factors, experience and habitual factors, and last situational factors. First, regarding personal characteristics variables: Gender seems to affect peak-hour driving, whereby women are more probable to continue driving in the peak compared to men. However, the significance is just at the 0.1 level. University level education (EDHm) has a significant and negative effect, for the group receiving money, on driving early. Thus, higher education seems to discourage change of behavior which is in compliance with the reward. It could be that education is masking a latent income effect.

Second, in terms of information, three variables had a significant behavioral impact. Weekly frequency of accessing pre-trip traffic information (Fil) had a positive effect on driving late. In addition, weekly frequency of accessing pre-trip public transport
information (OV) had a positive effect on not-driving. Searching for public transport connections (S3v6I), stated as one of the post-measurement support measures, also had a positive impact on not-driving. This suggests that on average access to information is important and can contribute to a wanted behavior change.

Third, habitual factors and experience had an important contribution as well. Factors relating to habitual time use include: the pre-experiment usual departure time (S1DP), preferred start of work time (S1v27A1) and number of days that late start of work is possible (S1V281). The usual departure time is negatively related to driving early i.e. the earlier the usual departure time is the more probable that driving early is chosen. The same effect is seen in the results of the preferred start of work time. In contrast the preferred start of work time had a positive effect on driving late. The number of days per week for starting work late also has a positive effect over driving later. Factors relating to modes include the belief in public transport (S1v16) / bike (S1v23) as realistic commuting alternatives and use of other modes apart from the car for commuting purposes (S1v9), which were also found to be significant. Belief in public transport as a viable alternative has a negative effect on both early and later driving options i.e. they reduce the attractiveness of driving. Use of other modes and belief in bike, on the other hand, have a positive effect on not-driving i.e. it encourages non-auto travel. Another factor related to public transport was the difficulty incurred by participants with the regional rail service. Knockaert et al., 2007, report that during the experiment, there were severe disruptions to the regional rail service with inadequate bus service replacements. In the model estimates it appears that stating that without these disruptions public transport would be used more often (rdrail) tended to increase peak-hour driving.

An factor relating to short run experience for the group receiving money is practicing behavioral changes before starting the experiment (S3V6Km). However, it is only significant at the 0.1 level. As reported by Knockaert et al., 2007, the starting shares of driving in the peak were already low compared to stated values (50% compared to 80%). The model estimates reveals that in the case of money, practicing has a negative effect on peak-hour driving. Related to retrospective experience - the ranking of behavior change difficulty in the case of money (S3v2Hm) shows that a high ranking of difficulty, has a positively effect on peak-hour driving, making it more attractive than changing behavior.

The last group relates to situational factors – constraints and support measures for behavioral changes. On one hand, a constraint for dropping off kids at school (S1v32C) increases the probability of continuing to driving in the peak. On the other hand, arrangements with the employer on flexible time-schedules (S3v6A), negatively affect peak-hour driving i.e. behavior changes are more likely.

The model has a final log likelihood of -1,651.35 and the rho-square is 0.22. A simple MNL model (without panel) has a log likelihood of -1,682.61. The log likelihood ratio test shows this difference is significant \( \chi^2 = 62.5, \text{df}=6, p<.05 \). Therefore, specifying the panel structure improved the model. Moreover, the three panel disturbances are all highly significant.

**Disaggregate choice model**

The disaggregate model estimation was based on the daily data. Due to missing values in the data, this included in the final results 14,750 observation for a panel of 335 participants (6 were excluded).

As a starting point for the disaggregate estimation, the final specification of the aggregate model was applied. However, after some trial and error attempts it was found that some factors that were previously significant turned out to be not
significant, whereas some factors that had no significance in the aggregate specification now became significant. In addition, we added daily factors like weather and travel time predictions.

\[
U(\text{Ndrv}) = \beta_{v23}^N \cdot S_{1v23} + \beta_{v9}^N \cdot S_{1v9} + \beta_{ov}^N \cdot S_{0v} + \beta_{v6i}^N \cdot S_{3v6i} + \beta_{v9}^N \cdot fg
\]

\[
U(\text{Peak}) = \beta_{t2}^P \cdot \sigma_{t2} + \beta_{t3}^P \cdot \text{typ}_3 + \beta_{t4}^P \cdot \text{typ}_4 + \beta_{t5}^P \cdot \text{typ}_5 + \beta_{t6}^P \cdot \text{typ}_6 + \beta_{\text{gender}}^P \cdot \text{Gender} + \beta_{\text{cab}}^P \cdot \text{CAB}_m + \beta_{\text{cy}}^P \cdot \text{CAB}_y + \beta_{v6km}^P \cdot S_{3v6km}
\]

\[
U(\text{Early}) = \beta_{v16}^E \cdot S_{1v16} + \beta_{DP}^E \cdot S_{1DP} + \beta_{v27a}^E \cdot S_{1v27a} + \beta_{T29}^E \cdot TT_{29}
\]

\[
U(\text{Late}) = \beta_{v16}^L \cdot S_{1v16} + \beta_{v27a}^L \cdot S_{1v27a} + \beta_{Fil}^L \cdot S_{3Fil} + \beta_{EDhm}^L \cdot EDhm + \beta_{T31}^L \cdot TT_{31}
\]

The results of the estimation for the disaggregate data do not show major differences compared to the aggregate model. The signs of the coefficients are similar and the sizes are comparable. However, three main changes can be noted. First, the significances levels of the different reward types and levels have increased. In terms of the t-statistics, the rewards are now the most important contributor in the model. In addition, the treatment of Yeti without credits is now significant, whereas in the aggregate model it was not. The probable reason for this difference is the increase in the sample size and the number of observations (treatments were conducted on a weekly basis). Although it is has the weakest effect amongst all the treatment levels, the results suggest that possession of the Yeti is contributing to a reduction in peak-hour driving. As no reward is attached to this period of treatment, the result asserts that the most probable effect to account for this behavior is available information.

A second change relates to the two situational factors – the constraint of dropping of kids at school and the support measure of discussions with the employer. These two are not significant any more. It seems that their effect has diminished within the day to day variation which is influenced by other factors. In addition, Gender, which was only significant at the 0.1 level in the aggregate model, is now very much significant. This strengthens previous results we obtained that women are less likely to change behavior compared to men.

The third change relates to additional factors at the daily level of measurement. Weather variables were tested including precipitation, temperature and wind speed. However, only wind was found significant and only for not-driving. This is quite logical as weather should not have a major impact on travelling by car (i.e. driving) whereas, not-driving, includes cycling which is used both quite extensively as an access and egress mode of public transport. The results suggest that strong winds reduce the attractiveness of not driving.

Two other factors were the predicted travel times from the traffic control systems. This includes the actual travel time (in seconds) to travel on the main freeway from Zoetermeer to The Hague. We received this data as quarter-hour averages. Thus for each day the quarter-hour average travel time is available. Given the known pattern of behavior, it was suggested that for driving early (i.e. before 7:30) the travel time at 7:15 (TT29) would be the most likely reference to decide whether to depart early. Conversely for driving late (i.e. after 9:30) the reference would be the travel time at
7:45 (TT31) as this was the average usual departure time indicated in the pre-measurement survey. The results show that both factors are significant. For early driving, the effect is positive, i.e. the higher the travel time at 7:15 is the more likely that early driving is chosen. This seems logical as it suggests that early congestion levels indicate that the peak hour will probably be much worse. However, it is worth noting that the effect is rather weak compared to other factors influencing early driving such as usual departure time and preferred arrival time. For late driving, the effect is also positive, suggesting a higher travel time at peak-hour times is more likely to lead to a later departure.

As mentioned earlier the goodness of fit of the final model was compared to two simplified models: The first with random constants only, the second with treatments (reward types and levels) but no other behavioral factor. The constants model with random coefficients had a log likelihood of -12,992.35. A log likelihood ratio test shows the final model has a better goodness of fit compared to the constants only model \(\chi^2 = 1938, \text{df}=25, p<.05\). The rewards-only model had a log likelihood of -12,209.32 and the log likelihood ratio test is significant \(\chi^2 = 36.37, \text{df}=19, p<.05\). Therefore, in both cases the final model is better than any restricted specification. This indicates that the reward is not the only significant factor influencing the behavioral response. Although a comparison between the aggregate and disaggregate models is statistically invalid, we note that the rho-square in the disaggregate model is almost twice that of the aggregate model.

5. Discussion

Congestion levels on major roads in the Netherlands are rising while alternative policies like road pricing are difficult to implement, in the short run, mainly due to lack of public support. Consequently, rewards have been suggested as a second-best strategy for managing congestion, since behavioral research asserts that rewards are more efficient in sustaining behavioral changes and promoting learning in the long run. The ‘Spitsmijden’ project was designed to empirically investigate the impact of rewards on travel behavior concerning commuting decisions. It is worth noting that we did not specifically design the aforementioned study, rather the collected data was provided and we worked on the data analysis with the best of what was available. In retrospect, a control group (with no rewards) would have provided a stronger comparison and test of validity to the presented results.

In this paper four alternative behavioral responses were considered – peak-hour driving, non-driving, and early / late departure. These responses form a closed choice set. Data was initially scrutinized with multivariate analysis (Ben-Elia & Ettema, 2009b) and subsequently panel-based discrete choice models were applied to investigate the behavioral response using aggregate and disaggregate data. The findings assert that commuter behavior during the course of Spitsmijden is dependent foremost on the type and level of the rewards. However, other factors have also been found to be of significance. In the following section we discuss five types of effects identified as key contributors to understand behavior changes – the reward, information availability, experience and beliefs, personal factors, situational factors and the weather.

The reward

Overall the results suggest that both the money reward and the Yeti reward had a considerable impact in promoting a shift in trip scheduling and mode choice. Peak-hour driving measures the level of non-shifters i.e. participants who did not change their behavior during the reward period. From the disaggregate model, it is evident that the reward was the most important factor influencing the level of the response.
The money reward significantly reduced the shares of peak driving with the 7€ level having the largest impact. The mixed reward was very similar and the 3€ level somewhat lower. Yeti credits are also quite effective in reducing peak-hour driving with the coefficient somewhat higher than the 3€ level. Moreover, in the disaggregated model Yeti without credits also appears to have a significant though weak impact on reducing peak-driving. These results assert that response to information provided by the Yeti device did in fact contribute to changing behavior. In addition as reported by (Ben-Elia & Ettema, 2009b; Knockaert et al., 2007), Yeti users were more likely to drive later compared to money receivers who tended to drive earlier.

**Information**

Information had an impact on the level of response of all the four response categories. First, as seen in the comparison between the pre-measurement and post-measurement surveys, there was a significant increase in the use and access of information both for traffic and for public transport as a result of the experience acquired in Spitsmijden. This result is valid for both Yeti and money groups. In terms of the model, the frequency of using pre-trip public transport information and accessing information on public transport connections (stated as a support measure), had a positive impact over not-driving. In the case of driving later, the frequency of access to traffic information had a positive impact.

Second, the travel time information provided by the traffic control systems also seems to have had an impact on the behavior. The travel time of 7:15, had a weak although significant effect on driving early, whereby the greater the travel time is, the more likely is that driving early is chosen given that the situation in the peak-hour itself will be considerably worse. Furthermore, the travel time of 7:45 (referring to the average peak-hour), had a positive impact on driving later, i.e. the greater the travel time in this period is, the more likely is that later driving is chosen.

Third, the significance of the treatment "unaccredited Yeti" in relation to the pre-reward period asserts that information alone can alter behavior, even without any substantial incentives. In the disaggregate model, the treatment had a weak but significant effect on reducing peak-hour driving. This suggests that information can influence and support a compliance with a wanted behavior change by itself but more strongly when an incentive is involved. Given that these results are based on a large extent on RP data compared to most of the previous studies which were based on stated preference experiments, further understanding of the connection between information and travel behavior has considerable implications for demand management schemes.

**Experience and beliefs**

As mentioned in the introduction, several studies in route-choice behavior (Avineri & Prashker, 2003, 2006, Ben-Elia et al, 2008) have identified the significance of past experience and learning on concurrent travel decisions. The current analysis allows us to conclude that experience has a major impact on the behavioral response to the reward. Experience can be identified in several stages: the effect of habits (long run), practicing for a behavioral change (short run), retrospective experience (subjective assessment of effort or difficulty) and beliefs which are not necessarily based on past experience.

Long run experience through habitual factors had a significant impact on commuters’ behavior. Habitual behavior can be attributed to factors such as the usual departure time, preferred start of work time and use of other modes. The usual departure time had a significant impact on driving earlier, whereby, the earlier one is used to travel to work; the more likely is that early driving is selected in response to the rewards.
The effect of preferred starting time of work had a similar impact on driving early. In the case of late driving, a later start of working time, contributes to driving later. In the case of not-driving, use of other modes for commuting purposes had a positive impact. These results assert that the closer the habitual behavior is to the behavioral change, the more likely is that the response will be exercised in the direction of the habitual behavior. If one is used to departing early (or late) relative to the time frames required to gain the reward or if one is accustomed to taking public transport to work, the less effort both physically and mentally is involved with the change and the more effective is the incentive in complying with wanted behavior. These results strengthen the convictions that habits have an important effect on any change to commuting behavior. It is also in line with the psychological literature which asserts the importance of the status quo reference and the bias it creates on evaluation of alternatives in decision making (Kahneman et al., 1990). Thus the higher this bias is the more effort is involved and the less likely is it that a decision maker will shift behavior away from the status quo.

The second type of experience is attributed to the short run. Practicing behavior change, before commencing the experiment, contributed to a reduction in peak-hour driving. The estimation verified this result is significant only for the group receiving money. The idea of practicing goes back to the law of effect (Thorndike, 1898) which asserts that the probability of repeating an action depends on the results of previous outcomes. Participants that engaged in practicing may have been more adaptive to the behavior change. Moreover, the effect of practicing is significant only for the money group which asserts that it could well have been a substitute for lack of information. Practice provides the participant with knowledge on how to improve his or her behavior. Conversely, Yeti users, who had access to online real-time information, had less dependence on practicing. Recent findings suggest that in route-choice decisions information expedites learning in the short-run whereas lack of information requires greater exploration and gradual learning (Ben-Elia et al., 2008). This may be similar to what the participants experienced as practicing in the short-run.

A third type of experience relates to retrospective evaluation. Ranking the effort of behavior change compared to prior expectations was found to have a positive and significant impact on peak-hour driving for the money group. Thus participants who, in retrospective evaluation, stated they experienced a high effort were less likely to change behavior. This measure indirectly indicates the level of stress participants were sensing during the course of the study. Stress related variables have not really received much attention in travel behavior research. This result is also in line with the psychological literature on learning behavior whereby difficulty reduces motivation to participate when the reward does not seem sufficiently attractive (Petty & Caciappo, 1986). The fact that the effect was not significant for Yeti users suggests that information might have helped to overcome some of these difficulties. This again provides evidence to the importance of information in the choice-making process.

Last, beliefs regarding the available alternative modes - public transport or bike, were found to have significant effects on the response of not-driving. This result has an added value for travel behavior modeling as it suggests that prior beliefs on available modes could have triggered a cognitive response congruent with these beliefs. Travel behavior studies tended to disregard such subjective taste variables. It is clear that this group of factors should receive more attention in a future behavioral modeling endeavor.

**Personal-related factors**

The fourth group of factors with significant impacts on behavior change is personal characteristics e.g. gender, education and the base level of commuting frequency.
(i.e. class association). Gender, in the case of peak-driving, suggests that men drove less in the peak compared to women. One idea that has been raised recently is time-poverty of women. It suggests that women are more constrained in time compared to men for various reasons but particularly household and child raising obligations. This is an interesting idea and deserves more attention to gender specific considerations in travel behavior research. In the case of driving later, higher education, for the group receiving money, had a negative effect. This seems to suggest a latent income effect (although income itself was not found to be significant) whereby a higher income reduces sensitivity to the reward – especially in the case of a small monetary gain relative to a high income and a major loss in terms of time related behavior changes.

The base level frequency of commuting (i.e. Class) is also an important factor. It is evident that there is a negative association between the base level– as attributed to the 'Class' variable and the rate of behavior change. Participants in class A and class B who make 4-5 daily commuting trips per week are more likely to continue driving during the peak compared to participants with lower commuting frequencies. A possible explanation is the ratio between the benefit (the reward) and the effort (in terms of the cost in changing behavior). In the case of a high commuting frequency this ratio is relatively low, making behavior change less attractive. In contrast, under low commuting frequencies the unrewarded option can be framed as a sure loss. According to the predictions of Prospect Theory (Kahneman & Tversky, 1979), risk seeking behavior in the domain of losses would imply that change of behavior away from peak driving is worthwhile.

**Situational factors**

As mentioned in the introduction, situational factors such as work restrictions or household obligations limit the ability to change behavior. In the aggregate model as well as the multivariate analysis we found that dropping of kids at schools – as a constraint on behavior change – contributed to more peak-hour driving. However, this effect lost its significance in the disaggregate model. The same happened to discussions with the employer over flexible working times – one of the stated support measures for the behavior change, which in the aggregate model had reduced peak-hour driving. In addition, many other constraints (in the preliminary survey) and support measures (in the post-measurement survey) were indicated including constraints on early/late departure, tele-working, child care etc; and support measures such as discussions with household members, work colleagues etc. However, none of these factors had a significant effect that we could identify. Thus the results do not elucidate if and when situational factors are important to discourage or encourage behavior changes. More research will be required to investigate them in the future. We do note however that the frequency of being able to start work late did contribute to driving later. This suggests that flexible working hours are important in order to contribute to the success of demand management schemes such as Spitsmijden.

**The Weather**

The only significant weather related factor in the disaggregate model was wind speed. Wind speed was negatively associated with not-driving. This probably relates to the use of the cycling/walking as a popular mode of access or egress when the main travel mode is public transport. Windy conditions which are prevalent in The Netherlands can sometimes make it dangerous and uncomfortable to cycle. Conversely, neither temperature nor precipitation had any major effect. These results suggest that weather conditions should be accounted for in situations where a demand management scheme is trying to encourage more use of non-motorized modes of travel.
6. Conclusions

This paper presented a comprehensive analysis of the results obtained from the Dutch Spitsmijden project – a novel approach to travel demand management based on incentives rather than penalties. The ideas of Spitsmijden are currently being extensively explored in larger catchment areas, over a longer periods of time and involving a considerably larger number of participants. Our analysis, based on state-of-the-art choice modeling, provides important insights elucidating which factors influence the behavioral response to incentives. Clearly, rewards do work and can bring about a change of behavior compliant with the reward. However, ample evidence showed the importance of other key factors such as availability of information, habits and previous experience, beliefs, gender and education, personal and situational factors and even the weather, all influencing the response triggered by the introduction of the reward. These findings are inline with previous behavioral research. Thus, although rewards are definitely a necessary condition to formulate behavioral changes, they are not always sufficient by themselves.

Traffic simulations based on Spitsmijden have revealed that the rate of response is critical to the success or failure of the whole incentive-based policy. To little and no major difference in traffic conditions will occur. To high and the result will be a worsening of congestion during the off peak hours (Bliemer & van Amelsfort, 2008). Evidently, a balanced measure is required to negotiate the response. The revelations of this paper provide some insights into managing the response and insuring a more successful policy implementation.

Acknowledgements

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Figure 1: The impact of the reward in the trip market

Point A is the user equilibrium with volume $V_0$ and cost $C_0$. T is the efficient equilibrium reached by putting a toll equal to TR (Volume is reduced to $V_1$). R is the user equilibrium with the reward for reducing peak-hour demand from $D_0$ to $D_1$. The result is saving of costs equal to $ARV_1 V_0$. Non-shifters ($D_1$) now enjoy lower costs of $C_1$ (and faster speeds) thus their welfare is improved. For shifters ($V_0 - V_1$) the loss in welfare is the area between the demand curve ($D_0$) or marginal benefits and user costs (AC) this is the triangle ART. The reward should be equal to this triangle. Naturally, this is a second based solution as in economic terms efficiency is maximized at point T.
Figure 2: Study area and main trajectory
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LL₀ | Initial log likelihood | -2,123.80 |
LL₉ | Final log likelihood | -1,651.35 |
ρ² | Rho square | 0.222 |
ρ²ₐ | Adjusted rho square | 0.206 |
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<td>$\beta^{Typ3}$</td>
<td>7€ reward</td>
<td>-2.35</td>
<td>0.0827</td>
<td>-28.36</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta^{Typ4}$</td>
<td>3-7€ reward</td>
<td>-2.37</td>
<td>0.0894</td>
<td>-26.47</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta^{Typ5}$</td>
<td>Yeti without credit reward</td>
<td>-0.637</td>
<td>0.104</td>
<td>-6.11</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta^{Typ6}$</td>
<td>Yeti with credit reward</td>
<td>-1.98</td>
<td>0.116</td>
<td>-16.98</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta^{S3v2Hm}$</td>
<td>High effort for behavior change (for money)</td>
<td>2.39</td>
<td>0.361</td>
<td>6.63</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta^{S3v6Km}$</td>
<td>Practice behavior change before starting experiment (for money)</td>
<td>-0.755</td>
<td>0.299</td>
<td>-2.53</td>
<td>0.01</td>
</tr>
<tr>
<td>$\sigma^E$</td>
<td>Random effect – driving early</td>
<td>2.97</td>
<td>0.133</td>
<td>22.37</td>
<td>0.00</td>
</tr>
<tr>
<td>$\sigma^L$</td>
<td>Random effect – driving late</td>
<td>2.10</td>
<td>0.0951</td>
<td>22.12</td>
<td>0.00</td>
</tr>
<tr>
<td>$\rho$</td>
<td>Random effect – peak-hour driving</td>
<td>1.98</td>
<td>0.0908</td>
<td>21.77</td>
<td>0.00</td>
</tr>
<tr>
<td>$\rho^2$</td>
<td>Adjusted rho square</td>
<td>0.412</td>
<td>0.410</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Values in italics not significant at 0.05 level