# THE IMPACTS OF AN INCENTIVE-BASED INTERVENTION ON PEAK PERIOD TRAFFIC: EXPERIENCE FROM THE NETHERLANDS

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**ABSTRACT**
Incentive-based travel demand management strategies are gaining increasing attention as they are generally considered more acceptable by the traveling public and policymakers. This paper presents a detailed analysis and modeling effort aimed at understanding how incentives affect traveler choices using data collected from a reward-based experiment conducted in 2006 in The Netherlands. The incentive-based scheme analyzed in this study included monetary rewards or credit towards obtaining a smartphone with a view to motivate commuters to change their departure time choice out of the peak period or shift mode of travel. The mixed panel multinomial logit modeling approach adopted in this paper is able to isolate the impacts of incentives on behavioral choices while accounting for variations in such impacts across socio-economic groups that may be due to unobserved individual preferences and constraints. The model also sheds light on the effects of behavioral inertia, where individuals are prone to continue their past behavior even when it is no longer optimal. Finally, the paper offers insights on the extent to which behavioral changes persist after the termination of the incentive period. In general, it is found that incentives are effective in changing behavior and can overcome inertial effects; however, individuals largely revert to their original behavior when the rewards are eliminated, thus suggesting that incentives need to be provided for a sustained period to bring about lasting change.

## 1. INTRODUCTION

Traffic congestion is an issue that metropolitan regions around the world seek to address through a variety of travel demand management (TDM) strategies. In the United States, it is estimated that Americans experienced a total delay of 5.5 billion hours in 2011 due to traffic congestion. This extra travel time contributed to an estimated additional 2.9 billion gallons of fuel consumption and an economic impact (loss) of $121 billion (*1*). In addition to delays and adverse economic consequences, traffic congestion leads to poorer air quality (*2*), substandard health among infants born to mothers living near congested corridors (*3*), and delays in evacuation and emergency response (*4*).

To address traffic congestion that largely occurs during peak periods in most metropolitan regions, planning agencies have been attempting to deploy travel demand management strategies that would help eliminate or temporally and spatially shift trips away from congested periods and corridors. Peak period congestion, which is often associated with the commuting hours of the morning and afternoon, is generally the target of such travel demand management strategies – although such strategies may also be applied in the context of travel to and from special events, around work zones, and around major tourist attractions and destinations. Travel demand management strategies may take the form of congestion pricing, incentives to shift travel to off-peak periods or alternative uncongested corridors, flexible work hours, telecommuting, transit subsidies, and ride-sharing programs (*5*).

A number of incentive-based schemes have been implemented in the transport sector around the world. Although there is some documented evidence on the impacts of such schemes, there exists a need for additional insights on the impacts of incentives on traveler behavior. The analysis in this paper utilizes data from an incentive-based scheme in The Netherlands to shed light on travelers' reactions to incentives both during and after the end of a reward scheme. The scheme considered in this paper is the *Spitsmijden* (Dutch for peak avoidance), which involved the use of incentives to shift commuters to alternative modes of travel or less congested periods of the day. Participants could choose a monetary incentive or credits towards obtaining a smartphone as a reward for altering their usual commuting behavior. This scheme is substantially different compared to other incentive-based studies in terms of project continuity and design. *Spitsmijden* is an initiative started by a consortium of Dutch businesses, universities, and government in 2006 for motiving frequent car users to avoid the peak period or change mode (*6*). The first experiment was performed over a 13 week period in 2006 on the A12 highway for commuters traveling from Hague-Zoetermeer, and it is data from this experimental period that is used for the modeling effort in this paper.

The modeling effort in this paper is aimed at understanding the role of various factors in explaining traveler response to incentive-based interventions. Commuters' usual trip characteristics, availability of alternative travel modes, work-related attributes (spatio-temporal flexibility in work arrangements), household constraints and characteristics, and vehicle availability constraints are all likely to affect departure time choice and mode choice. Including an array of explanatory variables in an appropriate model specification would help isolate the impacts of the incentive on traveler choices while controlling for other factors. In addition, as the goal of many incentive-based programs is to induce a sustained change in traveler behavior, it is necessary to examine commuter behavior in the post-reward period. Accounting for behavioral inertia (where individuals attempt to maintain the status quo in their travel choices) is important in the implementation of incentive-based strategies. Modeling efforts that can tease out such effects would help shed considerable light on this phenomenon that is not well understood.

Models of traveler choices should also attempt to account for behavioral heterogeneity, where the presence of unobserved factors contributes to variance in the effects of an observed variable on the dependent variable of interest. For this reason, the modeling effort in this paper – aimed at explaining how incentives affect departure time and mode choices – utilizes the random parameter panel mixed multinomial logit approach which is capable of accounting for repeated observations over time and population heterogeneity.

The remainder of this paper is organized as follows. The next section provides an overview of pricing and incentive-based strategies. The third section describes the incentive-based scheme, while the fourth section provides a brief overview of the data set used in the study. The fifth section presents the modeling methodology while the sixth section provides a discussion of model estimation results. Conclusions and implications of the findings are in the seventh and final section of the paper.

## 2. PRICING AND INCENTIVE-BASED STRATEGIES

Within the array of pricing-based policies, two broad possible approaches exist. In one approach, a congestion charge is levied to deter individuals from traveling in the peak period or along congested corridors. There are several real-world examples of such pricing-based schemes around the world, including the Singapore Central Business District congestion charge which reduced morning peak period traffic by 40 percent (*7*) and the Central London congestion charge which contributed to an automobile traffic decline of 20 percent (*8*). While congestion pricing is likely to be effective, there has been considerable resistance among the traveling public and policymakers to such schemes, particularly in the United States (*9*). Congestion pricing is viewed as having an adverse impact on low income segments of the population, and contributing to a fall in business activity, system inequities, and pricing inefficiency (*10*).

An alternative approach that has gained considerable attention is the incentive-based paradigm where individuals are not priced, but given incentives to travel in the off-peak periods or along uncongested corridors. There are a number of success stories of the use of incentives as interventions in areas such as smoking cessation (*11*), adoption of safe driving habits (*12*), and increased physical activity and exercise (*13*). In transportation, experiments in Melbourne (Australia), Kyoto (Japan) and Beijing (China) that offered reduced or free transit fares for travel outside the peak hours were found to be quite effective in reducing rush hour volumes (*14-16*). In the City of Bangalore, an experiment named INSTANT offered rewards to employees traveling in non-congested time periods; the number of individuals traveling in less congested periods nearly doubled as a result (*17*). The 2013 Smartrek initiative in Los Angeles (*18*) offered differing levels of reward depending on the time of departure and route used for travel in the region. It was found that, under the reward scheme, 60 percent of program participants altered their time of departure, and they could reduce their travel time by nearly 20 percent by doing so.

There is considerable literature that explains how and why incentive-based strategies influence behavior. Incentive-based interventions work in the form of a nudge or push and has been described by Thaler and Sunstein (*19*) as *an aspect of choice architecture that alters people's behavior in a predictable way without considerably compromising their economic pursuit*. Incentives are generally directed along three key dimensions – economic benefits, social benefits, and moral uprightness (*20*). In the context of travel behavior modification incentives, it is likely that individuals respond to the economic benefits that they may realize and the social benefits that may accrue to their community. These benefits may push people to direct their effort towards modifying behavior, adapting to a new routine, and developing a strategy for embracing change. One among many theories that has been proposed to explain the effects of incentives on personal effort and adaptation is goal setting theory. It identifies three possible ways in which monetary incentives can take effect: 1) They can induce people to set goals when they otherwise would not; 2) They may induce people to set more challenging goals (that require higher effort); and 3) They may contribute to greater goal commitment (*21*).

Although there is some experience with incentive-based schemes in the transportation demand management arena, there is a need for in-depth analysis of the impacts of such schemes. Prior research has been largely descriptive in nature (comparing before-and-after statistics, or comparing an experimental group and a control group) and has not exploited methodological tools and models capable of shedding deeper insights into the effects of incentives on traveler behavior. More importantly, previous research has rarely – if ever – analyzed the long-term (lasting) impacts of the incentives once they are eliminated; there is little knowledge of the extent to which individuals tend to switch back to their pre-incentive period behavior or continue to exhibit the desired change in behavior following the end of the reward or incentive period. In addition, it is important to consider pre-incentive period behavior as part of the impact analysis; traveler choices in the pre-incentive period are dependent (endogenous) variables and should not be treated as exogenous (independent explanatory) factors in an impact analysis.

## 3. THE INCENTIVE-BASED EXPERIMENT

The *Spitsmijden* is one of the largest reward based travel demand management (TDM) strategies that offers an opportunity to assess the effectiveness of incentives in reducing peak period vehicular traffic volumes. The program was initiated at the end of 2005 by a group of Dutch companies, government agencies, and universities in The Netherlands with the goal of developing an innovative mechanism to reduce traffic congestion on roadways. The pilot program, which is the focus of the current study, was launched in October 2006 on Dutch A12 motorway corridor. Morning commuters driving from Zoetermeer towards The Hague were eligible to participate in the program. A detailed explanation of the program is available in Knockaert et al (*6).*

Electronic vehicle identification cameras were used to identify vehicles that traversed the roadway of interest during the morning rush hours. Letters were sent to the households corresponding to these vehicles, and a total of 340 individuals consented to participate in the experiment. The participants completed an extensive questionnaire about their daily commute, socio-economic and demographic characteristics, and work schedules and arrangements. After the end of the program, the participants completed a post-Spitsmijden experience survey. The project focused on the reduction of morning peak period traffic volumes with the morning peak defined as 7:30-9:30 AM.

Participation in the pilot study required a 14-week commitment on the part of travelers. The first two weeks were devoted to collecting data about participants' pre-reward period travel choices. This was necessary because the reward made available to each individual was dependent on the level and frequency of peak period travel prior to the institution of the reward. The reward period was ten weeks long; during this period, participants could take advantage of rewards for avoiding peak period travel in the morning. The final week was a non-reward period; however, the travel behavior of participants was recorded in this final week to determine the extent to which participants reverted to their usual travel behavior upon the termination of the reward and the extent to which the reward mechanism may have brought about a longer-lasting change in traveler behavior.

Choices made by participants were registered using an On Board Unit (OBU) that was installed in their vehicles. Information on routes and time of travel collected by the OBU was transmitted automatically to a central database. Information on mode shifts (i.e., participants who chose to work from home or use public transit or non-motorized modes during the program period), was logged in a diary that had to be completed by every program participant at the end of each day of the program period.

Upon registration, participants were allowed to choose between two reward programs. The first was a monetary reward for avoiding the morning peak period. The second type of reward was the accumulation of credits that could be exchanged for a smartphone at the end of the program. Out of 340 participants, 232 participants chose the monetary reward scheme while the remainder chose the smartphone (a Yeti phone) reward. Individuals could avail the rewards only if they recorded a net change in behavior during the reward period. In other words, if an individual already avoided peak period commuting to a large extent in the pre-reward period, then the individual had to further cut his or her peak period commuting and record a net change in peak period travel to be eligible for the reward.

Each participant who chose the monetary reward scheme experienced three reward levels as follows: 1) €3 for avoiding the 7:30-9:30 AM period for three weeks; 2) €7 reward for avoiding the 7:30-9:30 AM period for four weeks; and 3) €3 reward for avoiding the 8:00-9:00 AM period that increased to €7 if the complete peak period of 7:30-9:30 AM was avoided, for three weeks. Participants of Yeti phone reward scheme received credits towards keeping the phone that was given to them at the beginning of the experiment. These participants were asked to use the Yeti smartphone for trip guidance and navigation as traffic information was relayed to them through the device. If the person with the phone avoided the morning peak period more than a predetermined number of days, then the participant was allowed to keep the phone; otherwise, the phone had to be returned at the end of the experiment. The threshold of the number of days that a participant had to avoid peak period travel was customized to ensure a significant net change in behavior between the pre-reward period and the reward period.

## 4. DATA DESCRIPTION

The data set included 13 weeks of observations, yielding a total of 22,165 participant-days of information. However, after removing records with missing data and no information about pre-reward period behavior, and in which the participants did not work during the program period, the data set included 16,015 participant-days of observations. The final sample includes 324 unique participants of which 208 were men and 116 were women. Table 1 provides a detailed description of the sample and the data used in this study. More than 85 percent of the sample is between the ages of 31 and 60 (the peak working years) and more than one-half of the sample has a professional and university degree education. Nearly 60 percent of the sample constitutes individuals living with a partner with children and just five percent constitute single parents. Given the nature of the program, all participants own at least one car; 47 percent own two cars, and just under four percent own three cars. Monthly personal income largely falls in the range of €1500 to €4500. Out of these 324 participants, 69 people did not wish to reveal their income. To account for missing income data and avoid loss of observations, missing income was imputed using a multivariate imputation by chained equation (MICE) methodology (*22*). Participant age, gender, education status, family composition, and vehicle ownership were used as independent variables for the income imputation exercise.

A large percent of the sample (41 percent) indicated that they had no flexibility for late arrival at work. However, more than 50 percent of the sample indicated that they could arrive late to work on more than one day per week, signifying a high level of flexibility among the commuters in the sample. Only 12 percent indicated that they had to wait for others before starting work in the event that they arrive early at work. Nearly three-quarters of the sample could not telework, while 20 percent of the sample could telework one day of the week. Among trip related characteristics, more than 50 percent of the sample indicated that they were constrained and could not depart to work early. The difference between congested and uncongested travel times was more than 30 minutes for 22.2 percent of the sample, indicating that a large percent of commuters could save substantial travel time by shifting to an uncongested travel period.

Two-thirds of the sample chose the monetary reward. In terms of reward class, 55 percent of the sample could collect a reward on all five days of the week (based on their pre-reward period behavior). Only 6.4 percent of the sample was limited to collecting the reward on one day of the week; these individuals presumably traveled four of the five days each week during the off-peak period in the pre-reward period. Thus, they were eligible for the reward on only one day of the week that would constitute a net change in behavior. Among participants who chose the Yeti smartphone, nearly 43 percent had to avoid morning rush hours on at least 15 days over a 5-week program period to keep the phone. About 8.5 percent of the Yeti phone sample had to avoid the peak period on all 25 days of the five-week period to retain the smartphone. These thresholds were set based on the usual behavior exhibited by the participants during the two-week pre-reward period.

Finally, the table shows the shares of alternatives in the data set that comprises 16,015 observation-days. In the pre-reward period, 23.4 percent of the participants drove before the rush hours, 46.8 percent traveled during rush hours, and 17.5 percent traveled after the rush hours. The remaining individuals used alternative modes or worked from home. The reward period shows considerable changes in travel behavior. During the reward period, 37 percent traveled before the peak period, only 20 percent (down from 46.8) traveled during the rush hours, and 18.7 percent traveled after the peak period. The percent of individuals using alternative modes or working from home increased from 16 percent in the pre-reward period to about 24 percent in the reward period. However, it appears that individuals quickly revert to their pre-reward period behavior after the incentives are eliminated. Behavior in the post-reward period largely mirrors the behavior in the pre-reward period, with a very modest drop in peak period travel (from 46.8 percent to 45.7 percent). The share of bicycle travel dropped from 4.5 percent to 1.5 percent, while the share of public transportation use climbed from 4.7 percent to 6.6 percent. There is therefore some indication of a sustained, albeit modest, change in behavior following the completion of the reward program.

## 5. METHODOLOGY

In this study, a random parameter panel mixed multinomial logit (MMNL) for departure time choice/mode choice analysis is adopted. Panel MMNL is used to accommodate heterogeneity across individuals due to both observed and unobserved attributes. For the discussion of the model structure, consider the indices $q\ (q = 1, 2, ..., Q)$ for individual decision makers, $i$ for the available alternative $(i = 1, 2,..., I)$ and $t$ for the choice occasion, with a maximum of 65 choice occasions available for 65 days[1], $(t = 1, 2,..., T)$.

Following the traditional utility maximizing models for choices analysis, the utility $U_{qit}$ that an individual $q$ associates with alternative $i$ on choice occasion $t$ may be written as follows:

$$U_{qit} = (\boldsymbol{\beta}' + \boldsymbol{v}'_q)\boldsymbol{x}_{qit} + \varepsilon_{it} \tag{1}$$

where $\boldsymbol{x}_{qit}$ is a $(M\times1)$-column vector of exogenous variables such as individual specific attributes and their trip characteristics, individuals' work-related attributes, and rewards for rush-hour avoidance, which affect the utility of alternative $i$ for individual $q$ at $t^{th}$ choice occasion. $\beta$ is a corresponding $(M\times1)$ column vector of mean effects of the coefficients of $\boldsymbol{x}_{qit}$ on alternative choice propensity, and $\boldsymbol{v}_q$ is $(M\times1)$ column vector with its $m^{th}$ element representing unobserved factors specific to individual $q$ and her/his trip-work related factors that control the influence of the corresponding $m^{th}$ element of the vector $\boldsymbol{x}_{qit}$. The elements of the $\boldsymbol{v}_q$ vector are assumed to be independently drawn from a normal distribution; $v_{qm} \sim N(0, \sigma_m^2)$. $\varepsilon_{it}$ represents a choice-occasion specific random error term assumed to be identically and independently standard Gumbel distributed across all individuals.

For a given value of the vector $\boldsymbol{v}_q$, the probability that individual $q$ will choose alternative $i$ at the $t^{th}$ choice occasion can be written in the usual multinomial logit form:

$$P_{qit} \mid \boldsymbol{v}_q = \frac{e^{\boldsymbol{\beta}'\boldsymbol{x}_{qit} + \boldsymbol{v}'_q\boldsymbol{x}_{qit}}}{\sum_{j=1}^{I} e^{\boldsymbol{\beta}'\boldsymbol{x}_{qjt} + \boldsymbol{v}'_q\boldsymbol{x}_{qjt}}} \tag{2}$$

The unconditional probability can then be computed as:

$$P_{qit} = \int_{v_q} (P_{qit} \mid \boldsymbol{v}_q) d\boldsymbol{F}(\boldsymbol{v}_q \mid \boldsymbol{\sigma}) \tag{3}$$

where $\boldsymbol{F}$ is the multivariate cumulative normal distribution and $\boldsymbol{\sigma}$ is a vector that stacks up the $\sigma_m$ elements across all $m$ (independence of the elements of $\boldsymbol{v}_q$ is assumed). The dimensionality in the integration above is dependent on the number of elements in the $\boldsymbol{v}_q$ vector.

The parameters to be estimated in the model of Equation (3) are the $\boldsymbol{\beta}$ and $\boldsymbol{\sigma}$ vectors. To develop the likelihood function for parameter estimation, the probability of each individual's observed choices across all time occasions is needed. Conditional on $\boldsymbol{v}_q$, the likelihood function for individual $q$*'s* observed sequence of choices may be formulated as:

$$L_q(\boldsymbol{\beta} \mid \boldsymbol{v}_q) = \prod_{t=1}^{T} \left[ \prod_{i=1}^{I} \left\{ P_{qit} \mid \boldsymbol{v}_q \right\}^{\delta_{qit}} \right], \tag{4}$$

where $\delta_{qit}$ is a dummy variable taking the value of '1' if the $q^{th}$ individual chooses the $i^{th}$ choice alternative on the $t^{th}$ occasion, and '0' otherwise. The unconditional likelihood function for individual $q$*'s* observed set of choices is:

[1] 65 observation days are not available for every participant as some participants were on leave or did not work during the experiment. But, for ease in presentation, we consider all participants to have the same number of observation days.

$$L_q(\boldsymbol{\beta},\boldsymbol{\sigma}) = \int_{v_q} L_q(\boldsymbol{\beta} \mid \boldsymbol{v}_q) d\boldsymbol{F}(\boldsymbol{v}_q \mid \boldsymbol{\sigma}) \tag{5}$$

The log-likelihood function is $L(\boldsymbol{\beta},\boldsymbol{\sigma}) = \sum_q \ln L_q(\boldsymbol{\beta},\boldsymbol{\sigma})$. We adopt a maximum simulated likelihood approach using Halton pseudo-random draws (250 draws were used per choice occasion) to estimate the model parameters. Details of the Halton sequence and the procedure to generate this sequence are available in Bhat (*23*, *24*, *25*).

## 6. MODEL ESTIMATION RESULTS

The variables selected for inclusion in the model specification are based on research reported in the literature and the behavioral intuitiveness of model coefficients. Dummy variables representing reward categories are included in the utility of all alternatives. The base alternative is taken to be *travel before peak period*. For the reward, five different dummy variables are defined representing €3, €7, €3-€7, credits for phone, and no credits-but with traffic information. These dummy variables assume the value of zero in pre- and post-reward periods and assume the value of one in the reward period. In this study, the data is modeled in a joint fashion, stacking the observations of the pre-reward period, reward period, and post-reward period, respectively, for each participant. Unobserved factors that affect pre-reward behavior also influence participants' reward period and post-reward behaviors, and the reward class (level) to which they belong.

For example, consider an individual who is very schedule oriented (independent of work time flexibility) compared to observationally equivalent peers, and strictly follows a regimen that is intrinsically aligned with usual workday timings. For this individual, this unobserved attribute may contribute to his or her traveling in the pre-reward period exclusively during the rush hours. As a result, this individual is eligible for the highest reward class. If the pre-reward choices are considered exogenous in the modeling of reward period choices, then individuals with a strong schedule orientation (which is unobserved) will be assigned to get a higher reward, while individuals with a relaxed schedule orientation (and do not travel exclusively in the rush hours in the pre-reward period) will be assigned to receive a lower reward. That is, individuals who are intrinsically unlikely to change schedules are presented with a high reward while individuals with a higher proclivity to change schedules are presented with a low reward. The net result, if the pre-reward choices are considered entirely exogenous in reward period choices, would be an underestimation of the effect of the reward on changing to off-peak period travel. The way to address this is to consider the pre-reward period choices as being endogenous to the reward period choices, and model the choices for these different periods jointly to accommodate the unobserved rigid (or flexible) schedule orientation of individuals. By controlling for this endogeneity, it is possible to obtain econometrically consistent estimates of the effect of the reward on the likelihood to shift to off-peak periods of travel. The same argument can be extended to other potential unobserved factors (e.g., sensitivity to travel time, constraints at home or work) that contribute to endogeneity of pre-reward choices.

To examine how the behavior of participants changed in response to the temporary availability of a reward, a dummy variable is added to the specification. This variable takes a value of zero for the pre-reward and reward periods, and a value of one in the post-reward period. To explore differential impacts of rewards across gender, income, and age, multiple interaction variables were included and tested for significance. The inertia effect was included in the utility equations for the choice occasion *t* for a person as $Inertia_{iq,t} = BRCR_{iq} \times d_t^{RPR}$, where

$BRCR_{iq}$ is the before reward-period choice ratio of individual $q$ for alternative $i$. The dummy variable $d_t^{RPR}$ takes the value of one if the choice occasion $t$ is in the reward or post-reward periods and zero otherwise. A positive sign is expected on the inertia variable for all alternatives.

Model estimation results are presented in Table 2. In light of the large number of parameters in the model, a brief overview of key findings is provided in this section. The constant term suggests that individuals are inclined to travel during the rush hour as evidenced by the positive coefficient, and to a lesser degree by public transportation and bicycle (where they can avail of the reward even when traveling during rush hours). The significant standard deviations on the random parameters (constants) for shared-ride and work from home suggest that there are unobserved factors contributing to preference heterogeneity for these alternatives. For example, gregarious individuals may be inclined to carpool; and individuals who are employed in specific occupation types may be inclined to work from home.

Among individual characteristics, females are less likely to travel after the rush hour or via carpool with family and friends. Those with lower levels of education are more likely to travel after the rush hours, possibly due to lower paying jobs that are part time or contractual in nature and afford schedule flexibility. They are also more likely to share a ride, presumably due to vehicle ownership constraints. On the other hand, they are less likely to use public transit; the significant standard deviations on these random parameters suggest the presence of unobserved factors affecting preference for transit. It is possible that these individuals live and work in locations that are not well served by transit. Somewhat consistent with these results is the finding that lower income individuals are more likely to share a ride and less likely to ride transit.

Individuals living in households without children appear to enjoy a less constrained lifestyle as they eschew driving in rush hour, sharing a ride with others, and using public transit. On the other hand, single parents – who may be very schedule constrained – drive in rush hours and after rush hours (perhaps after dropping off a child at school), and are more likely to use transit and bike modes. Single parents may also be more responsive to the reward scheme due to financial constraints, and are hence more likely to shift mode of transport in the reward and post-reward periods. However, there is considerable preference heterogeneity exhibited by single parents. Additionally, higher level of household car ownership is associated with a reduced proclivity for rush hour driving, propensity to share a ride, and use of public transit; the flexibility that higher car ownership levels afford explains these results, as also evidenced in many other studies (for example, Bhat and Sardesai (*26*)).

Those in the peak working age (30-60 years) are less likely to travel in rush hours, less likely to share a ride, and less likely to use public transit. However, there is significant preference heterogeneity when it comes to rush hour driving and use of public transportation, possibly due to spatial effects and household and work constraints.

Individuals with limited arrival time flexibility are more likely to travel before or during rush hours, as expected. They are also more likely to travel by shared ride, public transit, and bicycle – signifying their desire to arrive on time at work by any mode possible. Those who can start work even if they arrive early are more likely to drive in the rush hours or share a ride (and thus arrive early or on time). As expected, those who can telecommute are inclined to do so. Individuals who cannot depart early (due to home constraints) are likely to avoid the peak period and travel after the peak period.

It is interesting to note that individuals who have less than a 20 minute travel time differential between congested and uncongested periods are less likely to use alternative modes such as shared ride and public transit; this is consistent with expectations because driving is an acceptable proposition when congested conditions are not terribly worse than uncongested conditions. Such individuals are also more likely to travel in the after-rush hour period and use bicycle; these findings are not readily intuitive and are worthy of further exploration.

Inertial effects are strong and significant. As expected, all coefficients are positive – indicating the substantial presence of inertial effects that reinforce the continuation of past behavior as long as it is not disturbed. The one negative coefficient (albeit statistically insignificant) is associated with peak period driving; this coefficient is negative because the inertial effect is shaken by virtue of the multi-week reward period. In the reward period (that dominates the data set), many travelers were incentivized to shift their time or mode of travel; in other words, inertia – although clearly present – was overcome and had no impact during the reward period for this particular alternative as large number of program participants changed their behavior (from traveling in peak period by car).

The rewards contribute to a reduced proclivity to travel during the peak period as evidenced by the negative coefficients in the utility equation of that alternative. Provision of traffic information and the third monetary reward category contribute positively to public transit use, and negatively to bicycle use. The large monetary incentive of €7 also contributed negatively to working from home. It is likely that the shift from car to public transit is easier than a shift from car to bicycle or work from home. Interaction variables suggest that there is considerable variation in the effect of the reward across socio-economic groups. Those with high income respond to higher levels of monetary incentives (€7) compared to other incentive levels. The effects are more pronounced for individuals at lower income levels, suggesting that lower income individuals exhibit greater elasticity of behavior in response to reward incentives (as expected). Females are likely to shift to public transportation at high levels of monetary incentive (€7), but not likely to do so for credits towards a phone. On the other hand, they appear more inclined to work from home when provided with traffic information.

The variable "post reward behavior" signifies the extent to which participants continued their reward-period behavior after the termination of the reward. There is a strong proclivity to resume rush hour driving after the termination of the reward period. It is possible that the reward was sufficient for many to consider a temporary disruption in their schedule and household logistics, but the alternative travel choices were not considered superior to driving during rush hours in the absence of the reward. As seen earlier in Table 1, modest changes persisted beyond the life of the reward scheme; some participants shifted to public transportation and some bicycle riders shifted to off-peak driving. These changes, although modest, are worthy of further exploration with a view to better understand the factors that contribute to lasting changes in behavior.

The model shows a strong goodness of fit. A simple multinomial logit model (MNL) with constants-only had a mean log-likelihood value of -23471 while the simple multinomial logit model with variables had a log-likelihood value of -18593.9, indicating a significant improvement in fit attributable to the explanatory variables. However, the mixed panel multinomial logit model (MMNL) presented in Table 2 has a log-likelihood value of -18442.16, which is a further significant improvement over the simple multinomial logit model. A useful goodness-of-fit statistic is:

$$\bar{\rho}_c^2 = 1 - \frac{-18442.16 - 87}{-23471 - 6},$$

which is 0.2107, a value that is consistent with disaggregate choice models of this nature. The likelihood ratio test between the restricted MNL and non-restricted MMNL models is: $-2[-18593.9-(-18442.16)]=303.48$.

The value of 303.48 is far greater than the critical $\chi^2$ value of 18.48 with seven degrees of freedom at a 99 percent confidence level. This suggests that there is significant preference heterogeneity due to unobserved factors in how individuals of different socio-economic characteristics respond to rewards aimed at managing peak period vehicular travel demand.

## 7. CONCLUSIONS

Incentive-based schemes are being increasingly considered around the world to help manage travel demand, particularly during peak periods, and bring about changes in traveler choices towards more sustainable modes of transport, less congested times of travel, and less congested corridors. Although there is some descriptive information on the impacts of incentive-based travel demand management strategies, there is a need for additional evidence on the impacts of such schemes on traveler behavior. It is necessary to be able to isolate the effects of reward-based strategies on traveler behavior while controlling for other explanatory factors, account for variations in effects across socio-economic groups, and accommodate the presence of individual taste heterogeneity due to unobserved attributes. There is a paucity of modeling efforts that can provide deep and rich insights into these aspects of the impacts of reward-based travel demand management strategies.

This paper aims to fill this need by offering a mixed panel multinomial logit model of the effects of a reward based scheme on peak period vehicular travel. The study utilizes data collected in the *Spitsmijden* (Dutch for peak period avoidance) program conducted in The Netherlands. Travel behavior data of 324 participants from the initial experiment (conducted in 2006) is used in this study. Participants' travel behavior was measured during a pre-reward period of two weeks, a reward period of 10 weeks, and a post-reward period of one week. About two-thirds of the participants opted for monetary cash-based incentives while one-third chose a smartphone credit- or traffic-information based incentive. The modeling methodology treats the pre-reward traveler choices as endogenous to reward-period travel choices, thus recognizing that the level of reward that an individual can attain is dependent on their usual (pre-reward) travel behavior.

The mixed multinomial logit model offers deep insights into the effects of various factors on traveler behavior in response to rewards. As expected, socio-economic factors, work attributes, and trip characteristics (degree of flexibility) affect traveler response to incentives. The level of incentive is also quite significant in explaining the choice of alternative, with higher levels of incentive more likely to induce a desirable change in behavior. It is found that inertia plays a significant role in human travel behavior; in general, participants exhibited a high degree of inertia where they tended to continue exercising the same travel choices despite the presence of an incentive to change behavior. However, for a significant number of program participants, the incentive was large enough to overcome the inertia associated with traveling in the peak period. Also, it is found that the incentive based scheme was not sufficient to bring about lasting changes in behavior. Within just one week of the termination of the reward program, travelers reverted largely to their pre-reward period behavior – particularly with respect to driving in the rush hours. It is clear that many individuals travel during the rush hours because that routine fits within the overall schedule of their household and work life; while the incentive motivated individuals to disturb that equilibrium and accept an alternate routine for a temporary period (when they reaped the rewards), the inconvenience of changing behavior was substantial enough to induce them to largely return to their usual pre-reward period behavior.

The moral of the story is that a temporary incentive may not be effective in bringing about a sustained long term change in traveler behavior. Clearly the monetary incentives are effective, because behavior changed significantly during the reward period. The question is: how can this change be sustained over time after the reward systems are removed? The answer to this question merits considerable additional research; focus group sessions and post-experiment surveys that collect data on why individuals revert to their original behavior would provide valuable insights to answer this question. Incentives may have to be provided for a longer (to be determined) period of time so that individuals get used to a new routine and home/work life arrangement; once they fall into a new (presumably satisfactory) routine, then it is likely that the changes will stick because of new inertia effects and because the cost to change routine once again would be greater than the value of the incentive that is being eliminated.

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## REFERENCES

1. Schrank, D., B. Eisele, and T. Lomax. *TTI's 2012 Urban Mobility Report*. Texas A&M Transportation Institute, The Texas A&M University System, December 2012. https://assets.documentcloud.org/documents/566377/2012-urban-mobility-report.pdf. Accessed July. 29, 2015.
2. Shefer, D. Congestion, Air Pollution, and Road Fatalities in Urban Areas. *Accident Analysis & Prevention*, Vol. 26, No. 4, 1994, pp. 501-509.
3. Currie, J., and W.R. Walker. Traffic Congestion and Infant Health: Evidence from E-ZPass. *American Economic Journal: Applied Economics*, Vol. 3, No. 1, 2009, pp. 65-90.
4. Litman, T. Lessons from Katrina and Rita: What Major Disasters can Teach Transportation Planners. *Journal of Transportation Engineering*, Vol. 132, No. 1, 2006, pp. 11-18.
5. Litman, T. The Online TDM Encyclopedia: Mobility Management Information Gateway. *Transport Policy*, Vol. 10, No. 3, 2003, pp. 245-249.
6. Knockaert, J., M. Bliemer, D. Ettema, D. Joksimovic, A. Mulder, J. Rouwendal, and D. Van Amelsfort. Experimental Design and Modelling Spitsmijden. *Utrecht, Consortium Spitsmijden*, 2007.
7. Phang, S.Y., and R.S. Toh. From Manual to Electronic Road Congestion Pricing: The Singapore Experience and Experiment. *Transportation Research Part E*, Vol. 33, No. 2, 1997, pp. 97-106.
8. Litman, T. London Congestion Pricing: Implications for Other Cities. *Victoria Transport Policy Institute*, 10, 2006. http://core.ac.uk/download/pdf/6630967.pdf. Accessed July 29, 2015.

9. Schaller, B. New York City's Congestion Pricing Experience and Implications for Road Pricing Acceptance in the United States. *Transport Policy*, Vol. 17, No. 4, 2010, pp. 266-273.
10. Gneezy, U., and A. Rustichini. A Fine is a Price. *The Journal of Legal Studies*, Vol. 29, No. 1, 2000, pp. 1-17.
11. Volpp, K.G., A.B. Troxel, M.V. Pauly, H.A. Glick, A. Puig, D.A. Asch, R. Galvin, J. Zhu, F. Wan, J. DeGuzman, E. Corbett, J. Weiner, and J. Audrain-McGovern. A Randomized, Controlled Trial of Financial Incentives for Smoking Cessation. *New England Journal of Medicine*, Vol. 360, No. 7, 2009, pp. 699-709.
12. Dionne, G., J. Pinquet, M. Maurice, and C. Vanasse. Incentive Mechanisms for Safe Driving: A Comparative Analysis with Dynamic Data. *The Review of Economics and Statistics*, Vol. 93, No. 1, 2011, pp. 218-227.
13. Charness, G., and U. Gneezy. Incentives to Exercise. *Econometrica*, Vol. 77, No. 3, 2009, pp. 909-931.
14. Currie, G. Quick and Effective Solution to Rail Overcrowding: Free Early Bird Ticket Experience in Melbourne, Australia. In *Transportation Research Record: Journal of the Transportation Research Board*, *No. 2146*, Transportation Research Board of the National Academies, Washington, D.C., 2010, pp. 35-42.
15. Fuji, S., and R. Kitamura. What Does a One-Month Free Bus Ticket Do to Habitual Drivers. *Transportation*, Vol. 30, 2003, pp. 81-95.
16. Zhang, Z., H. Fujii, and S. Managi. How Does Commuting Behavior Change Due to Incentives? An Empirical Study of the Beijing Subway System.*Transportation Research Part F*, Vol. 24, 2014, pp. 17-26.
17. Merugu, D., B.S. Prabhakar, and N. Rama. An Incentive Mechanism for Decongesting the Roads: A Pilot Program in Bangalore. In *Proceedings of ACM NetEcon Workshop*, 2009. http://web.stanford.edu/~balaji/papers/NetEcon_final.pdf. Accessed July. 29, 2015.
18. Hu, X., Y.C. Chiu, S. Delgado, L. Zhu, R. Luo, P. Hoffer, and S. Byeon. Behavior Insights for an Incentive-Based Active Demand Management Platform. In *Proceedings of the 93rd Annual Meeting of the Transportation Research Board*, 2014, Washington, D.C.
19. Thaler, R.H., and C.R. Sunstein. *Nudge: Improving Decisions about Health, Wealth, and Happiness*. Yale University Press, 2008.
20. Levitt, S.D., and S.J. Dubner. *Freakonomics*. HarperCollins Publishers, New York, 2010.
21. Locke, E.A., K.N. Shaw, L.M. Saari, and G.P. Latham. Goal Setting and Task Performance: 1969–1980. *Psychological Bulletin*, 90, No. 1, 1981, p. 125.
22. Buuren, S., and K. Groothuis-Oudshoorn. MICE: Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software*, Vol. 45, No. 3, 2011, pp.1-67.
23. Bhat, C.R. A Multi-Level Cross-Classified Model for Discrete Response Variables. *Transportation Research Part B*, Vol. 34, No. 7, 2000, pp. 567-582.
24. Bhat, C.R. Quasi-Random Maximum Simulated Likelihood Estimation of the Mixed Multinomial Logit Model. *Transportation Research Part B*, Vol. 35, No. 7, 2001, pp. 677-693.
25. Bhat, C.R. Simulation Estimation of Mixed Discrete Choice Models Using Randomized and Scrambled Halton Sequences. *Transportation Research Part B*, Vol. 37, No. 9, 2003, pp. 837-855.
26. Bhat, C.R., and R. Sardesai. The Impact of Stop-Making and Travel Time Reliability on Commute Mode Choice. *Transportation Research Part B*, Vol. 40, No. 9, 2006, pp. 709-730.

**LIST OF TABLES**

**TABLE 1 Sample Description**

| Variables | Share % | Variables | Share % |
|---|---|---|---|
| **Individual and Household Characteristics** | | **Work Related Characteristics** | |
| *Gender* | | *Number of days allowed for late arrival* | |
| Male | 64.2 | Zero | 41.0 |
| Female | 38.8 | One | 5.2 |
| *Age* | | More than one | 53.8 |
| 20 – 30 | 11.4 | *Amount of time allowed for late arrival* | |
| 31 – 45 | 46.6 | Less than 20 minutes | 43.8 |
| 46 – 60 | 40.1 | Between 20 and 45 minutes | 13.3 |
| More than 60 | 1.9 | More than 45 minutes | 42.9 |
| *Level of education* | | *Office situation - if early arrived* | |
| Pre-vocational secondary education | 10.2 | Can start work and make preparation | 88.0 |
| Lower vocational education | 4.3 | Can't start work/wait for other | 12.0 |
| Upper secondary vocational education | 29.0 | *Number of days allowed for teleworking* | |
| Higher professional /university degree | 56.5 | Zero | 74.1 |
| *Marital status* | | One | 20.4 |
| Single | 13.3 | More than one | 5.5 |
| Living with partner without children | 22.5 | | |
| Living with partner with children | 57.4 | | |
| Single parent | 4.9 | | |
| Other | 1.9 | **Reward Distribution** | |
| *Number of cars* | | *Reward type* | |
| One | 49.1 | Monetary | 67.3 |
| Two | 47.2 | Smartphone | 32.7 |
| Three | 3.7 | *1. Reward class(Monetary)* | |
| *Monthly personal income level* | | A [5]* | 55.4 |
| Less than 1,500€ | 6.5 | B [4] | 27.5 |
| Between 1500€ to 3000€ | 51.2 | C [2] | 10.5 |
| Between 3000€ to 4500€ | 37.4 | D [1] | 6.4 |
| More than 4500€ | 4.9 | * maximum number of reward-days per week | |
| **Trip Related Characteristics** | | | |
| *Early departure constraint from home* | | *2. Reward class (Smartphone)* | |
| Can depart early | 46.1 | A [15]** | 42.5 |
| Cannot depart early | 53.9 | B [20] | 29.4 |
| *Travel time diff (congested and uncongested)* | | C [23] | 19.9 |
| Less than 20 minutes | 38.8 | D [25] | 8.6 |
| Between 20 minutes and 30 minutes | 38.8 | ** minimum number of days must avoid peak hours in 5-week period | |
| More than 30 minutes | 22.2 | | |

**Share of Alternatives for Observation-Days (%)**

| *Alternatives* | *Total* | *Pre-reward period* | *Reward period* | *Post-reward period* |
|---|---|---|---|---|
| Driving before rush hour (Base) | 34.2 | 23.4 | 37.2 | 24.9 |
| Driving during rush hour | 25.9 | 46.8 | 20.0 | 45.7 |
| Driving after rush hour | 17.5 | 13.3 | 18.7 | 13.9 |
| Using carpool/ family-friend carshare | 5.3 | 4.4 | 5.5 | 4.4 |
| Avoiding rush hour by using public transportation | 10.3 | 4.7 | 11.7 | 6.6 |
| Avoiding rush hour by using bike | 3.0 | 4.5 | 2.9 | 1.5 |
| Working from home | 3.8 | 2.9 | 4.0 | 3.0 |

**TABLE 2 Model Estimation Results**

| | Rush Hour Driving | | After Rush Hour Driving | | Family-friend cars/carpools | | Public Transportation | | Bike | | Work From Home | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variables | Estimate | t-stat | Estimate | t-stat | Estimate | t-stat | Estimate | t-stat | Estimate | t-stat | Estimate | t-stat |
| Constant | 0.9264 | 7.19 | -0.3466 | -3.42 | -7.6790 | -7.29 | 0.3850 | 1.12 | 0.3165 | 1.87 | -15.1605 | -5.72 |
| Constant (std dev) | | | | | 3.0497 | 6.90 | | | | | 7.8293 | 6.04 |
| **Individual and Hhold Characteristics** | | | | | | | | | | | | |
| *Gender (Male is base)* | | | | | | | | | | | | |
| Female | | | -0.4292 | -7.22 | -1.1258 | -4.96 | | | | | | |
| *Education (University degree is base)* | | | | | | | | | | | | |
| Secondary education | | | 0.6478 | 8.16 | 0.7675 | 3.14 | -0.5788 | -2.80 | -0.5339 | -2.75 | | |
| Secondary education (std dev) | | | | | | | 3.6050 | 8.01 | | | | |
| Lower vocational education | | | 0.6478 | 8.16 | 0.7675 | 3.14 | -0.5788 | -2.80 | -0.5339 | -2.75 | | |
| Lower vocational education (std dev) | | | | | | | 3.6050 | 8.01 | | | | |
| Secondary vocation education | | | 0.4950 | 8.43 | | | -0.5788 | -2.80 | | | | |
| Secondary vocation education (std dev) | | | | | | | 3.6050 | 8.01 | | | | |
| *Monthly Income (Between €1500-€3000 is base)* | | | | | | | | | | | | |
| Less than €1500 | | | | | 0.8580 | 1.72 | -3.167 | -4.61 | | | | |
| Less than €1500 (std dev) | | | | | 2.5063 | 3.87 | | | | | | |
| *Family Composition (Living with partner and children is base)* | | | | | | | | | | | | |
| Single | | | | | | | | | | | | |
| Living with partner without children | -0.4311 | -8.21 | | | -0.4311 | -8.21 | -0.5379 | -3.51 | | | | |
| Single parent | 0.8276 | 6.24 | 1.4298 | 7.90 | | | 1.4298 | 7.90 | 1.5241 | 4.45 | | |
| Single parent (std dev) | | | 0.4939 | 2.63 | | | 0.4939 | 2.63 | | | | |
| Number of cars (count (1-3)) | -0.0447 | -1.17 | | | -1.0443 | -5.59 | -0.2255 | -1.86 | | | | |
| *Age of the individuals (Between 20-30 years is base)* | | | | | | | | | | | | |
| 30-45 year | -0.4661 | -6.92 | | | -0.5149 | -2.51 | -0.7523 | -3.50 | | | | |
| 30-45 year (std dev) | 0.0744 | 2.18 | | | | | 1.5581 | 4.96 | | | | |
| 45-60 year | -0.4661 | -6.92 | | | -0.5149 | -2.51 | -0.7523 | -3.50 | -1.1307 | -6.56 | | |
| 45-60 year (std dev) | 0.0744 | 2.18 | | | | | 1.5581 | 4.96 | | | | |
| **Work Related Characteristics** | | | | | | | | | | | | |
| *Late arrival time allowed (more than 20 minutes is base)* | | | | | | | | | | | | |
| Less than 20 minutes | | | -0.9995 | -16.93 | 0.8083 | 8.28 | 0.8083 | 8.28 | 0.8083 | 8.28 | | |
| *Office situation – if early arrived (cannot start early/waiting is base)* | | | | | | | | | | | | |
| Can start work | 0.4355 | 5.07 | -0.2355 | -2.83 | 1.5681 | 4.56 | -0.6347 | -2.59 | | | | |
| *Number of Teleworking days (zero is the base)* | | | | | | | | | | | | |
| One | | | | | | | | | | | 4.7080 | 5.95 |
| More than one | | | | | | | | | | | 8.9533 | 6.65 |

**TABLE 2 Model Estimation Results (continued)**

| | Rush Hour Driving | | After Rush Hour Driving | | Family-friend cars/carpools | | Public Transportation | | Bike | | Work From Home | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variables | Estimate | t-stat | Estimate | t-stat | Estimate | t-stat | Estimate | t-stat | Estimate | t-stat | Estimate | t-stat |
| *Early departure from home constraints (can depart early is base)* | | | | | | | | | | | | |
| Cannot depart early | -0.3819 | -8.14 | 0.1368 | 2.44 | | | | | | | | |
| *Travel time difference between congested and non-congested trip (more than 20 minutes is base)* | | | | | | | | | | | | |
| Less than 20 minutes | | | 0.1945 | 3.63 | -0.9171 | -4.59 | -0.3903 | -2.87 | 0.2742 | 2.10 | | |
| **Inertia** | -0.0268 | -0.45 | 3.5068 | 29.02 | 11.5141 | 9.08 | 4.6193 | 8.88 | 3.1802 | 8.03 | 9.7472 | 4.44 |
| Inertia for before rush hour driving as this is alternative specific Estimate: 2.9405 t-stat: 40.39 | | | | | | | | | | | | |
| **Reward** | | | | | | | | | | | | |
| *Monetary and Smartphone (€3 is base)* | | | | | | | | | | | | |
| €7 | -0.7477 | -11.89 | | | | | | | -0.8533 | -5.56 | -0.8681 | -1.97 |
| €3-€7 where €7 is for peak of the peak | -0.7377 | -10.57 | | | | | 0.3786 | 2.29 | -0.7148 | -3.96 | | |
| Smartphone credits | | | | | | | | | | | | |
| No credits (Traffic information) | -0.6178 | -7.78 | | | | | 0.6753 | 4.10 | -0.4554 | -1.54 | | |
| Interaction (Reward * inc >€4500) | | | | | | | | | | | | |
| *€3,smartphone,no credit is the base* | | | | | | | | | | | | |
| €7 | -0.5672 | -2.08 | | | -1.2710 | -1.42 | 0.9963 | 3.18 | | | | |
| €3-€7 where €7 for peak of the peak | -0.5874 | -1.75 | | | | | 0.9963 | 3.18 | | | | |
| Interaction (Reward * inc >€1500) | | | | | | | | | | | | |
| *€3,smartphone, no credit is the base* | | | | | | | | | | | | |
| €7 | -1.0702 | -3.19 | | | | | 3.3008 | 3.46 | | | | |
| €3-€7 where €7 for peak of the peak | -1.1627 | -2.82 | | | | | 3.2718 | 3.51 | | | | |
| Interaction (Reward * Female) | | | | | | | | | | | | |
| *€3, smartphone, no credit is the base* | | | | | | | | | | | | |
| €7 | | | | | | | 0.9711 | 4.19 | | | | |
| €3-€7 where €7 for peak of the peak | | | | | | | | | | | | |
| Smartphone credits | | | | | | | -2.1745 | -3.92 | | | | |
| No credits (Traffic information) | | | | | | | | | | | 2.3975 | 2.73 |
| **Post reward behavior** | 0.8939 | 11.91 | | | | | | | -0.9122 | -2.85 | | |
| *Interactions* | | | | | | | | | | | | |
| Female * inertia | | | | | -2.1523 | -5.47 | -2.3138 | -5.07 | -2.1523 | -5.47 | 5.2292 | 2.28 |
| Age (>45years) * inertia | | | -0.5740 | -3.57 | | | 3.4704 | 6.75 | -2.7548 | -5.89 | | |