Temporal Effects in Adaptations of Daily Commuter Trip Choices in Response to Reward Scheme: A Panel Effects Mixed Logit Model Allowing for Covariance between Adaptation Strategies

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ABSTRACT

Several projects based on reward schemes have been implemented in the Netherlands stimulating car users to avoid using certain links of the network during peak hours. This paper reports the findings of a model, which was formulated to analyze temporal effects of the Dutch SpitsScoren reward scheme. On the one hand, one may expect that reward schemes lose their effectiveness over time as individuals tend to fall back in their old habits. On the other hand, by changing their routines, individuals may enjoy the new travel experience, leading to positive reinforcement and ultimately new habitual behavior. On balance, the impact of these opposite processes may work out differently for different segments of travelers. To disentangle these effects, a panel effects mixed logit model, predicting the probability of applying different adaptation strategies, including the option of no change, was estimated. As the various strategies may be correlated, the model also allows for covariance between the options. Results indicate that socio-economic and situational variables strongly affect travelers' adaptation strategies. The effectiveness of the reward scheme changes over time and affects the various options differently. The estimated model also shows evidence of significant covariances between adaptation strategies.

Keywords: reward scheme, pricing policy, long-term effect, Mixed Logit model

INTRODUCTION

Pricing policies aim at reducing congestion by encouraging use of other transportation modes such as transit, generating transportation revenue, and decreasing air pollution. Fuel tax, carbon tax, kilometer charge, parking, toll road and road pricing, sometimes called congestion pricing or value pricing, are the most commonly applied forms of pricing policies. These policies have been subject of travel behavior research during the last decade. The assumption underlying these policies is that travelers will adapt their current behavior when faced with increasing variable costs of car use. Even though, until now, examples of actual implications in the real world are limited, because of issues such as social equity, public acceptability and economic efficiency, many different pricing measures have been considered, both in the literature as well as in the political debate, in several countries. In The Netherlands, however, the vast public resistance against the implementation of road pricing has led to the implementation of alternative transportation management policies, different from pricing policies.

Prospect theory as a behavioral economic theory also states that people make decisions based on the potential value of losses and gains rather than their final outcome. Consequently, people react differently in response to financial gains versus losses (*1*). From a behavioral point of view, many psychological theories (*2, 3*), educational theories, socio-cognitive oriented theories (*4*), and various subjective utility theories (*5*) claim that rewards (financial and non-financial) are powerful instruments for influencing behavior. Although the arguments are compelling, the effects of reward schemes have not received much attention in the context of travel behavior and there is not much international experience about the effects of reward schemes on individuals' travel behavior.

Reward schemes mostly have been investigated in the context of safety. Some studies claimed that rewarding can be effective for accident-free driving (*6, 7, 8, 9*). Rewarding seatbelts and speeding behavior also has been studied in the literature (*8, 10, 11, 12, 13*). Results indicate a substantial change in behavior under reward. Temporary free bus tickets as a reward scheme have been investigated in a few short-term studies but without strong conclusions (*14, 15, 16, 17*).

In the Netherlands, the potential impacts of rewards on travel behavior for avoiding rush-hour trips has been explored by designing and conducting a pilot experiment called "Spitsmijden" or "peak-avoidance" in 2006. In the vicinity of The Hague in the west of The Netherlands, 340 participants were involved for 13 weeks. Participants could gain a reward in the form of money or credits to keep a Smartphone, by changing their departure time for their work trips outside the morning rush-hour, switching to another travel mode, and teleworking.

Various comprehensive research projects have been conducted based on this pilot experiment. Ettema and Verhoef (2006) reported the first results of this pilot project. Using a stated preference study they concluded that the project affected travellers' preferences, work and family constraints, current habitual pattern and also awareness of alternatives (*18*). Tillema et al., (2010) compared two congestion management schemes: road pricing (a time differentiated kilometer charge) and peak avoidance reward (Spitsmijden), and their impacts on changing commuter behavior based on two very different Dutch studies. Their results suggest that a reward scheme can be more effective than a pricing scheme and that both measures show the same influence regarding the alternatives chosen (*19*). Using the same pilot project, Ben-Elia and Ettema (2009, 2010, and 2011) identified the most important factors influencing travel behavior in response to reward stimuli. They concluded that the reward scheme is effective in the short-term. They also emphasized that although the reward results in changing travel behaviour, restricted avoiding peak trips is related to socio-economic characteristics and constraints (*20, 21, 22*).

Ben-Elia et al., (2011) address the process of behavioral change used qualitative research method. The existence of considerable heterogeneity in the process of behavioral change, they divided twelve participants of the Spitsmijden pilot project into four different categories: (i) stabilizers; (iii) flexible; (iii) relapsers; (iv) floaters. In addition they found that the reward system appears to trigger experimentation, resulting in updating beliefs, changing attitudes toward travel alternatives, and eventually behavioral change. Effort perception and habits also seem to play an important role in the travel decision making process (*23*). Bliemer and Amelsfort (2010), and Knockaert et al., (2012) are other two other examples of related studies (*24, 25*).

The studies seem to suggest that the reward schemes have been a useful solution in the short run especially in specific local situations. However, the long-term effects of such schemes are still uncertain. Do the reward schemes preserve behavioral changes in the long-term? One may argue that the reward schemes lose their effectiveness over time as individuals tend to fall back in their old habits. On the other hand, by changing their routines, individuals may enjoy the new travel experience, leading to positive reinforcement and ultimately new habitual behavior. What are the effects of effort perception, experiencing and learning, and fatigue or motivation in long-term on travellers' adaptive behavior?

To answer these questions, this paper investigates the impact of a reward scheme on travelers' behavior over time. The analysis is based on the Stated Intention (SI) data from the Dutch "SpitsScoren" reward scheme, another project in The Netherlands which has not been analyzed yet. It should be emphasized from the outset, that this data collected by a consultant was not gathered with academic research in mind. Consequently, as we will see later, the interpretation of the results may be subject to confounding.

The paper is organized as follows. First, the SpitsScoren project and the data are described in more detail. Changes in travel behavior over time are studied in the next section. Then, the modeling approach and estimated results are discussed. The paper is completed with an interpretation and conclusion.

SPITSSCOREN OR "PROFIT FROM THE PEAK" PROJECT AND DATA

Based on the results and success of the "Spitsmijden" pilot project, three real rewarding projects were designed and implemented, "SpitsScoren", "Spitsvrij", and more recently "Spitsmijden", in different provinces of The Netherlands. It should be noted that there are some differences in terms of design, implementation, used technologies, and the covered areas. The data used in this research were collected in the "SpitsScoren" or "profit from the peak" project. "SpitsScoren" is the first large-scale mobility project in operation with a total budget of approximately 9 million euro. The project started on October 26, 2009, and aimed at 5% reducing the congestion on the Dutch A15 motorway corridor during extensive construction works that started in 2011. In fact, this project was applied as a service to support participants in their daily mobility behavior by rewarding, monitoring, assisting, and keeping them involved. Thus, compared to other similar projects in The Netherlands, it has developed a different structure regarding performance and risks (*26*). Because of the considerable success, 7% reduction in morning peak trips, the project was extended until December 21, 2012.

Around two thousands regular users of the A15 motorway were identified by collecting license plate information to identify those vehicles that travelled at peak hours at least 5 times in four consecutive weeks. The drivers were then approached and invited to participate in the project. Similar to the other reward projects in The Netherlands, the basic idea was to pay participants not to drive on the mentioned corridor during morning (6-9 am) and afternoon (3-6 pm) rush-hours, thereby reducing their usual number of commuter trips during peak hours. During the project, which thus lasted for three years, the reward scheme was changed several times. It started with €5 for avoiding the morning peak in the direction of the harbor. From May 2011, participants could earn €1.5 for avoiding the afternoon peak in addition to the morning reward, from August 2012 to the end of the project, the reward level decreased to €3 for the morning peak and increased to €3.50 for the afternoon peak.

The participants received a smart phone to provide information on travel alternatives, and to keep track of their trips. They were supposed to indicate their daily decision for the next day using a special application on the smart phone. The possible alternatives were: driving to work before or after peak hours; using mass transportation; using slow mode; working from home (teleworking); carpooling; using alternative routes outside of the corridor; using group transport; special situation which indicates they are in holidays and don't travel to work; and other options. GPS signals from smart phones and camera detection were used to enforce and verify the participant stated intention. A fraud prevention protocol including a set of fraud detection and prevention measures was also drafted.

Three additional services called 'Value-Added-Service' were added to the phone to encourage and assist participants to choose the predefined alternatives and change their departure time and travel mode appropriately. The first one included a Web-based multi-modal trip planner to help participants in choosing relevant departure times and travel modes. Carpool planner was the second service and the third one concerned the provision of an office near the A15 corridor where participants could work during the peak hours and continue their working trip afterwards. These services make participants aware of different available alternatives to avoid travelling by car during peak hours (*26, 27*). Behavioral changes could not be identified as the number of participants using VAS services was too low.

The data is unique because of (i) the nature of the data -Stated Intention (SI)- collected in a real world project; (ii) the large geographical coverage; (iii) the large number of participants, and (iv) the duration (2010-2012). Unfortunately, it lacks sufficient variation in reward levels in each year and also in general. In addition, due to strict privacy issues, it does not come with much background information related to the activity program of participants and their residence. Another important limitation is that the participants in this project are not a representative sample of all travelers on the A15 corridor as they were selected according to the specific target of the project.

A total of 380 participants of the "SpitsScoren" project with socio-economic, situational, and reference information were selected for our analysis. To answer the question about the long-term impact of the reward scheme, three similar periods of four consecutive weeks from 2010-2012 were used to analyze in this research. Table 1 presents the socio-economic, reference and situational variables, and sample composition. In addition to these variables, weather information including weather type, wind speed and precipitation, was extracted for that area for different years.

TABLE 1 Variables and Sample Composition

Variable	Abbreviation	Description	Category	Percentage
Socio-economic	G	Gender	Male	85%
			Female	15%
	MS	Marital Status	Married	84.6%
			Single	15.4%
	HC	Having Children	Yes	51.8%
			No	48.2%
	NC	Number of cars in the household	One car	27.3%
			Two cars	38.5%
			More than two cars	34.1%
	IN	Income (per year, in €)	IN1= <30000;	5.7%
			IN2 = 30001-60000;	33.9%
			IN3 = 60001-90000;	18.2%
			IN4 => 90 001;	7.8%
			IN5 = I prefer not to answer	34.4%
	ED	Education	No schooling / education	0.8%
			LBO / VBO / VMBO	6.5%
			MBO	32.3%
			HAVO / VWO	9.9%
			HBO	31.5%
			WW (academic)	13.5%
	AG	Age	AG< 40	25.3%
			40<=AG<55	52.3%
			AG>=55	22.4%
Reference	PT	Number of morning peak trips in four consecutive weeks before start of the project	6<= MPT<10	12.2%
			10<= MPT<15	31.5%
			15<= MPT<=20	56.5%
Situational	PH	Possibility of working at home (teleworking)	Yes	47.4%
			Yes, but in practice it never happens	7.3%
			yes but my activities will not allow it	3.9%
			No	27.6%
			No, but in practice it is possible	13.8%
	FH	Flexibility of working hours	every day same start time	28.1%
			shift with fixed times	7.3%
			can decide myself on start and end times	14.3%
			can decide myself on start and end times but within certain time window	47.1%
			Other	3.1%

As Table 1 shows, most of the sample are men and car owners. Interestingly, 34% have more than 2 cars in their household. This can be explained as a proxy of income level of the household or can reflect having children older than 18 in the household. Almost 85% of the sample is married and half of them have children, although information about number and age of the children is not available. Regarding education level, 45% of the participants are highly educated and 42% of them are in the middle level of education. The average age is 46, the youngest 26 and the oldest 66. As mentioned before, participants' current travel behavior in terms of number of morning peak trips in four consecutive weeks, called reference number, was recorded before the start of the project using camera detection on the A15 corridor. According to Table 1, more than half of the sample makes between 15-20 morning peak trips in the four consecutive weeks. Also, almost half of the participants have the possibility of teleworking and different variation can be seen in terms of flexible working hours.

CHANGES IN TRAVEL BEHAVIOR OVER TIME

As we are interested in long-term effects of the reward scheme, changes in participants' travel behavior over time, according to the observation, are explored in more detail in this section. There are three types of data in the "SpitsScoren" project, Stated Intention (SI) of the participants, GPS traces and camera detection data. Because of privacy issues, we only have access to the SI data. In this paper, we only consider participants' SI for the morning peak trips. Excluding holidays, there are 10 predefined alternatives (including driving during the peak that can be interpreted as "no change" or base alternative) to avoid morning peak trips.

Because of the low percentages of some alternatives, they were aggregated into five alternatives: (i) Driving off-peak or changing departure time; (ii) Changing route outside the corridor; (iii) teleworking of working from home; (iv) Other that includes slow modes, group transportation, carpooling, and public transportation, and (v) Driving during the peak or no change (base alternative). Figure 1 demonstrates the shares of these aggregated alternatives over the three years.

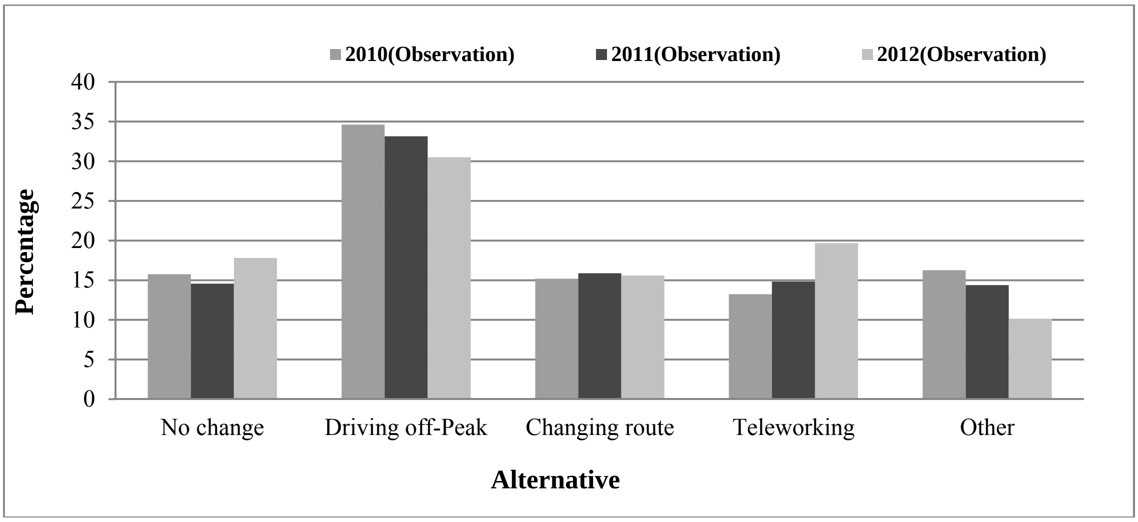

FIGURE 1 Observed travelers' behavior regarding alternative chosen over time

As can be seen from Figure 1, the most popular alternative for all three periods is "driving off-peak" or "changing the departure time of the trip", although its popularity decreases over time. An increase can be observed in the percentage of the "changing route" alternative from 2010 to 2011, with the same reward level. As the reward level decreased from €5 to €3 in the third period, the percentage of this option decreases, but it is still more than the first period. For "teleworking", the percentage increases from 2010 to 2012, although the reward level decreased in the last period. Participants have a higher tendency to change from 2010 to 2011, but this tendency decreases from 2011 to 2012 with a lower reward level. In addition, the tendency to shift to the "other" alternative decreases over the three periods.

Another interesting point concerns the number of alternatives that participants chose to avoid their morning rush-hour trips and gain the reward. Figure 2 shows the number of chosen alternative for three years.

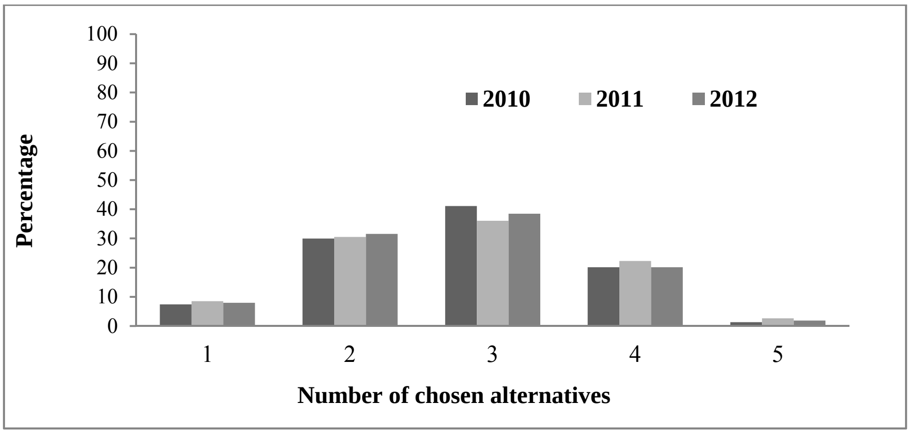

FIGURE 2 Number of chosen adaptation alternatives during three periods

According to the Figure 2, participants used multiple options, 2 options around 30%, 3 options around 40%, and 4 options around 20%, to avoid the peak. Palm et al. (2010) stated that most participants did not experience and used these adaptation alternatives before the project (*26*). Thus, the project increased their awareness of different travel options. Also, there seems to be no correlation with reward level in this regard.

MODEL ESTIMATION

In order to analysis the long-term effectiveness of reward, a two-stage data analysis was conducted. The analysis started with cross-sectional models, estimated from annual data, before any further and more complicated dynamic analysis conducted. Since each participant indicated his intention for the next working days in the four consecutive weeks (up to 20 working days), the data was constructed as a panel. The number of working days can be different for each participant. Thus, the panel is not balanced. A Mixed Logit (ML) formulation was used to estimate cross-sectional models. The same model structure was assumed for all three years to compare the results and study the effectiveness of explanatory variables. The parameters of the utility function were estimated using Nlogit 5.0 (*28*). Using a normal distribution, alternative-specific constants for “changing route” and “other” alternatives provided the best results and were therefore used to capture significant unobserved heterogeneity in the sample. The base utility of “driving during the peak” or “no change” was assumed to be 0. The numbers of Halton draws was set to 1000 to estimate the models.

Results indicate that respondents tended to change their decisions from “driving off-peak” to “teleworking” and “changing route” options. Income and number of peak trips for “no change”, household status and flexibility of working hours for “driving off-peak”, education for “changing route”, and possibility of teleworking for “teleworking” showed strong effects for all three years. However, their effect changed over time. It should be noted that we could not consider the effects of reward levels directly in this cross-section analysis as the project lacked variation in each year (for more detail see *29*).

In the second stage, the information of the three years was combined to estimate the effect of time (three periods: 2010, 2011, and 2012) and reward level (two levels: €5 and €3) directly and captures the dynamics in the utility function. Similar to the cross-section analysis, the data was constructed as a panel since each participant indicated his intention for the next working days in four consecutive weeks (up to 20 working days) for three years.
Equations 1, 2 and 3 show the formulated ML model:

$$U_{nit} = \alpha_{nit} + \beta_i X_{ni} + \varepsilon_{nit} \tag{1}$$

$$P_{nit} = \int L_{nit}\,(\beta) f(\beta) d\beta \tag{2}$$

where,

$$L_{nit}(\beta) = \frac{e^{\alpha_{nit}+\beta_i X_{ni}}}{\sum_{j=1}^{J} e^{\alpha_{njt}+\beta_i X_{nj}}} \tag{3}$$

U_{nit} is the utility of alternative i for individual n in time t and P_{nit} is the probability of individual n choosing alternative i at time t. α_{nit} represent the constant for alternative i in time t and varies across individuals (n) according to a normal distribution. X_{ni} represents the explanatory variables of alternative i for individual n and β_i is the coefficients of explanatory variables for alternative i to be estimated. ε_{nit} is the error term for alternative i in time t and varies across individuals (n). Normal distributions were used to specify the constants as random parameters in the utility function. Covariances between random parameters were also estimated.

Another important issue in the estimation of the mixed logit models is parameter stability. It depends on the choice of method and number of draws from the distributions of random parameters. Hensher and Greene (2001) stated that as the model specification becomes more complex in terms of the number of random parameters, a treatment of heterogeneity around the mean, and correlation of attributes and alternatives, the number of required draws increases (*30*). So far, the Halton-method has been the most intelligent draw method mostly used. However, studies reported by Train and Sandor (2004), and Bhat (2001) indicate the need for further research in this regard (*31, 32*). Considering the large sample size and number of observations for each individual, and a complex utility function in this research, the process of estimation is time consuming. The Halton draws was used with different numbers of draws. 100, 500, 1000, 1500, and 2000 draws were tested to secure a stable set of parameter estimates. Figure 3 presents the results for the random alternative-specific constants.

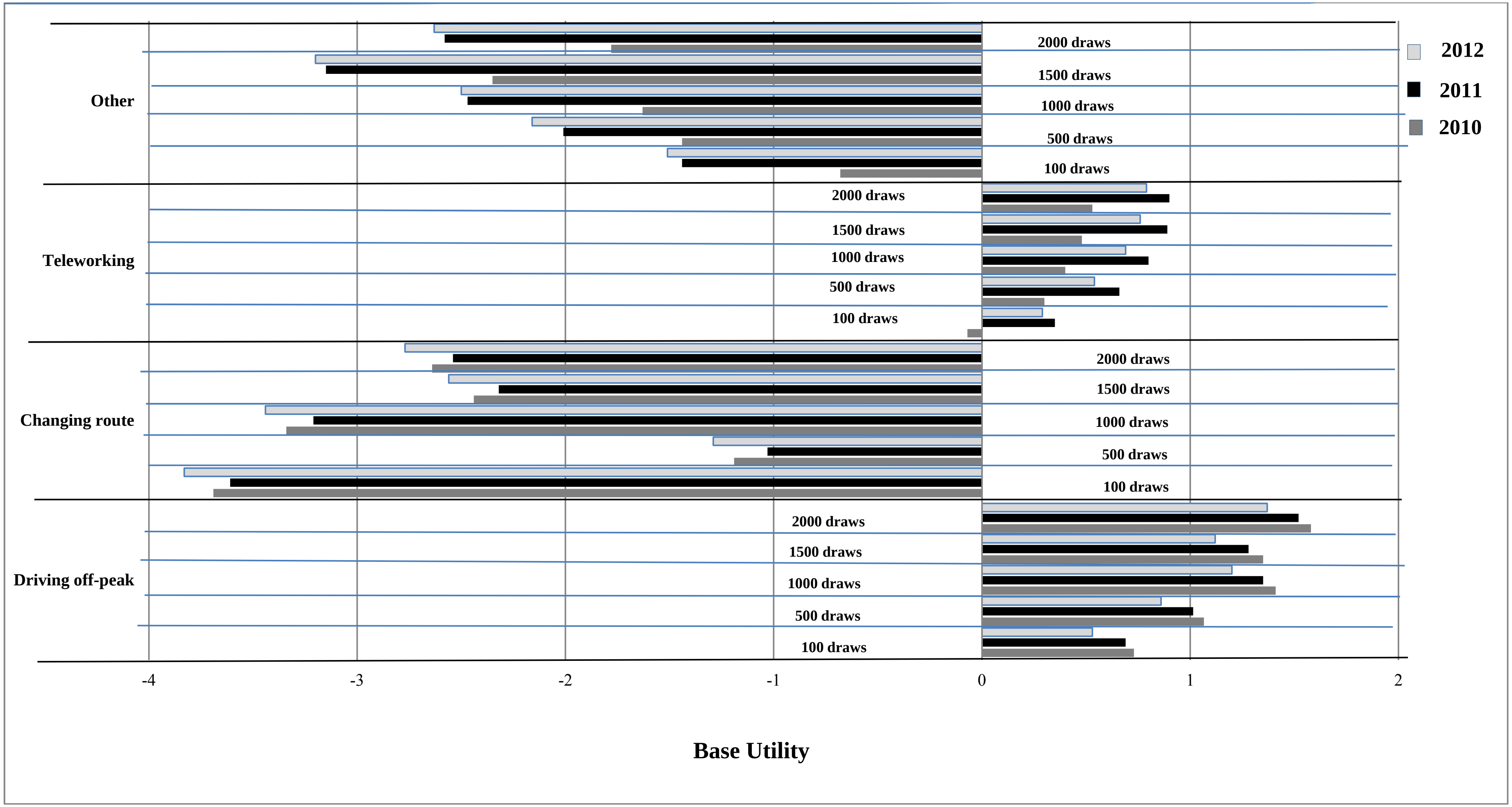

FIGURE 3 Estimated random alternative-specific constants for different number of Halton draws for three years

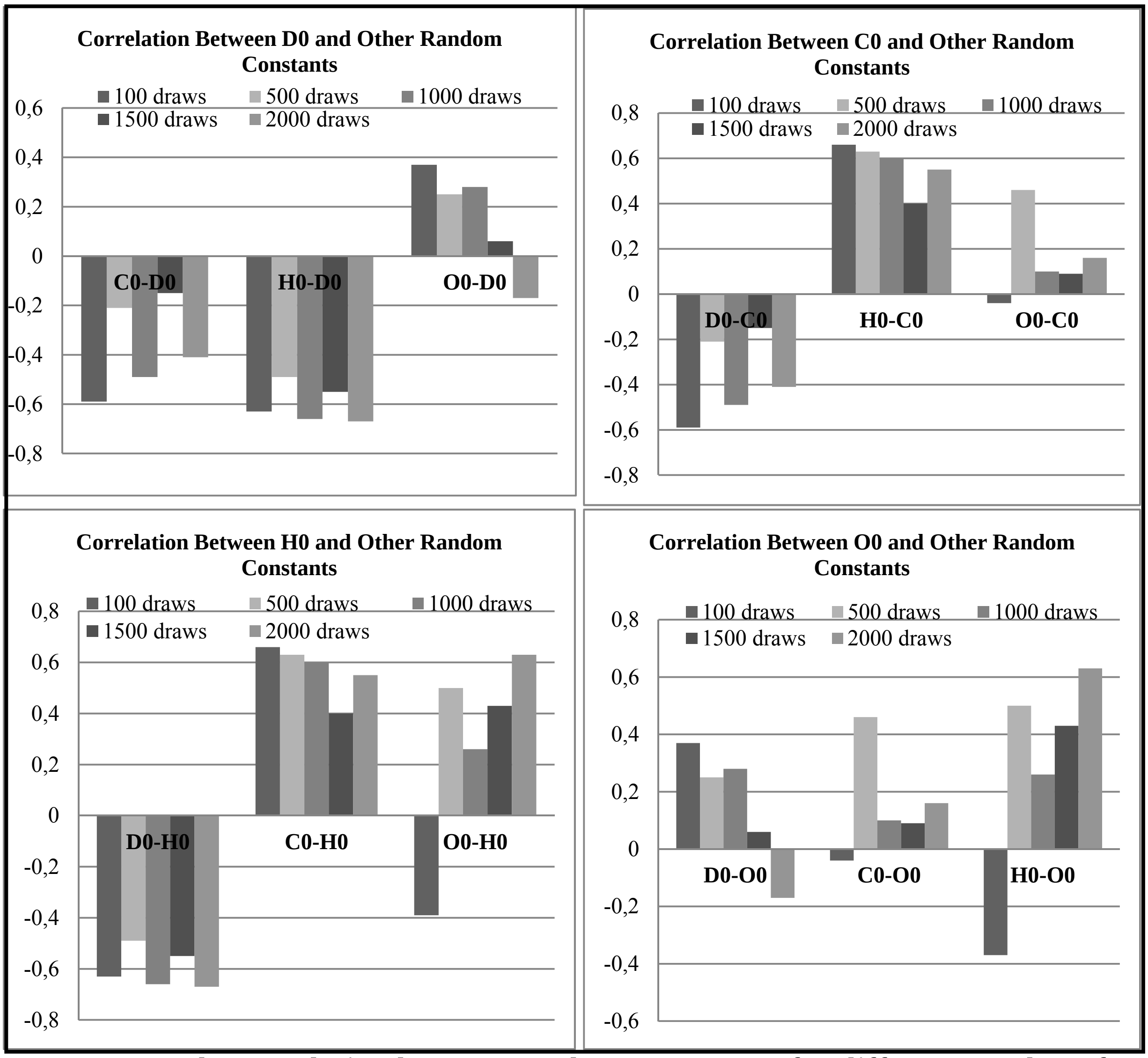

FIGURE 4 The correlation between random parameters for different number of draws

As Figure 3 shows, increasing the number of Halton draws does not result in stability of the random parameters. Although the dynamics of the base utility of different alternatives are the same over the years, the magnitudes are not stable by increasing the number of draws. We also take into account the covariances between the constants for different numbers of draws (see Figure 4).

Figure 4 provides the estimated covariances between random alternative-specific constants for different number of Halton draws. Because signs and significance of the estimated parameters with 1500 draws seem well interpretable while the goodness-of-fit of the model does not change between the different number of draws, the estimated model based on 1500 Halton draws is summarized in Table 2.

The goodness-of-fit of the model in terms of Rho-square relative to the null-model is 0.41. The *p*-value for all random parameters is less than alpha equal to 0.05. Thus, the mean of each random parameter is statically different from zero. Parameter estimates for the estimated standard deviations of the random parameters show the existence of significant unobserved heterogeneity in these parameters. High standard deviations of these parameters are also remarkable.

TABLE 2 The estimated utility function

Alt.	Variable	Description	β	P{|Z|>z}	St. dev.	P{|Z|>z}
No change (Driving during the peak)	*PT1*	Number of morning peak trip (first level)	-0.51	0.003		
	PT2	Number of morning peak trip (second level)	0.30	0.023		
	AG1	Age (first level)	0.13	0.321		
	AG2	Age (second level)	0.44	0.000		
Driving Off-Peak	*D0*	Constant	1.25	0.000	2.713	0.000
	t1	Time effect (first level=2012)	-0.13	0.001		
	t2	Time effect (second level=2011)	0.03	0.447		
	FH1	Flexibility of working hours (first level=no)	-0.53	0.000		
	FH2	Flexibility of working hours (second level=yes)	0.48	0.000		
	HC	Having children	-0.14	0.046		
Changing Route	*Co*	Constant	-2.44	0.000	4.046	0.000
	t1	Time effect (first level=2012)	-0.12	0.014		
	t2	Time effect (second level=2011)	0.12	0.015		
	PT1	Number of morning peak trip (first level)	-0.50	0.001		
	PT2	Number of morning peak trip (second level)	1.02	0.000		
	ED1	Education (first level=low educated)	0.56	0.049		
	ED2	Education (second level= middle educated)	0.79	0.000		
	ED3	Education (third level= high educated)	2.24	0.000		
Teleworking	*Ho*	Constant	0.71	0.000	2.493	0.000
	t1	Time effect (first level=2012)	0.05	0.215		
	t2	Time effect (second level=2011)	0.18	0.000		
	PH	Possibility of teleworking	0.44	0.000		
	P	Precipitation (continuous)	0.03	0.000		
Other	*O0*	Constant	-2.90	0.000	4.255	0.000
	t1	Time effect (first level=2012)	-0.30	0.000		
	t2	Time effect (second level=2011)	-0.25	0.000		
Log-likelihood=-20353.53879, ρ^2 =0.4096 , ρ^2 Adj=0.4094						

Time-dependent dynamics were captured for all alternatives, except the “no change” alternative. However, the second level of time (2011) for “driving off-peak” alternative and the first level of that (2012) for “teleworking” do not meet the significance level of 95%. It should be noted that we could not estimate any significant effect of reward level (€5 and €3) nor any interaction between time and reward variables.

The number of morning peak trips plays an important role in the participants’ decision to change their current pattern. We also found the effect of age on this alternative, but the first level that reflects the youngest age group (younger than 40) is not significantly different from zero. For "driving off-peak" or "changing departure time", having children and flexibility of working hours show significant effects. This adaptation option is more chosen by travelers who have more flexible working hours and do not have children. The number of morning peak trips or reference number and education levels influences participants' choice of changing route. The possibility of teleworking and precipitation affect the "teleworking" alternative to avoid rush-hour trips. For the last option, that represents the aggregation of other mentioned options, the mean parameter is the lowest and the heterogeneity is the highest across all alternative-specific constants.

INTERPRETATION

In this section, the effects of different variables used in the utility function are described and interpreted in more detail.

Dynamics of Adaptation Behavior over the Study Period

As mentioned before, the project lasted three years which is quite unique compared to the "Spitsmijden" project lasted for only 13 weeks. This provides the chance of capturing time-dependent dynamics of behavioral change over a long period. Figure 5 shows the time-dependent dynamics of the base utility of different alternatives compared to the base utility of "no change" that was assumed to be zero. According to Figure 5, in all three periods, "driving off-peak" and "teleworking" alternatives have a positive base utility compared to the "no change" alternative. Conversely, "changing route" and "other" alternatives have a negative base utility compared to the "no change" alternative.

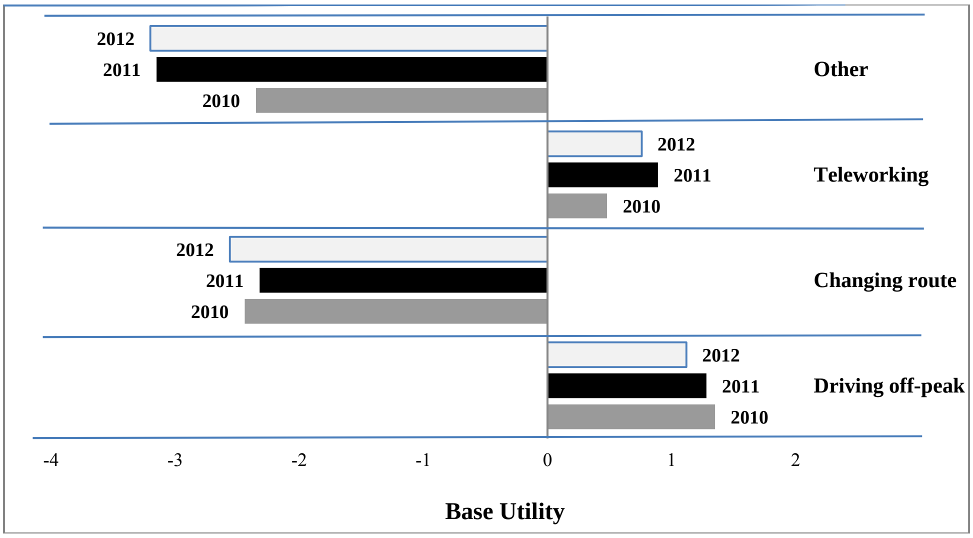

FIGURE 5 The time-dependent dynamics of the base utility of different alternatives compared to the base utility of no change

Not surprisingly, in all three periods "driving off-peak" and "teleworking" have a positive base utility compared to the "no change" option. These options are relatively easy to implement. On the contrary, the "changing route" alternative and "other" which mostly reflect a shift to other transportation modes, have a negative utility compared to the "no change" alternative. Difficulties in finding alternative routes outside the Spitscoren corridor, lack of good public transport towards the harbor, and long travel distance for slow modes increase the effort needed to adapt in case of these alternatives.

In 2010, after one year experiencing the benefits of reward and exploring the different alternatives, “driving off-peak” is the most and the “changing route” alternative is the least popular options.

In the second period (2011), however, the base utilities of “driving off-peak” and “other” alternatives decrease but the base utility of “changing route” and “teleworking” alternatives increase. Considering that the reward level is the same (€5) in these two periods, these changes can be interpreted to reflect the time effect. Ben-Elia et al. (2011), state that reward raises individuals’ awareness about their flexibility to use different adaptation options (*23*). Our findings are in line with this statement. Shifting from “driving off-peak” which is a first and the simplest way of adaptation, to “teleworking” and “changing route” alternatives after two years experiencing and learning process implies that participants became more aware of their possibility of “teleworking” and also learned about the possible alternative routes outside the corridor.

After three years experiencing and exploring the different alternatives in 2012, the base utilities of “driving off-peak” and “other” alternatives still show a decreasing pattern. Note that all base utilities decreased in 2012 compared to 2011, implying that “no change” becomes more popular. To emphasize, these dynamics may be associated to time, but the reduction of reward level may be effective as well. Fatigue and changing attitude because of three years experiencing and learning, and less motivation because of reward reduction may explain the decreasing pattern.

Choice of Adaptation Alternatives

Prior studies concluded that other variables can influence the choice for an alternative except the rewards. Especially, Tillema et al. (2010) and Ben-Elia and Ettema (2010) asserted that rewards can decrease the number of peak trips but that socio-economic variables, situational factors such as household and work constraints, habitual behavior and experience, beliefs, attitude and perceptions, travel information and weather may be effective variables as well (*19, 21*). The effect of such variables was tested in our study as well.

Effect of Usual Travel Behaviour or Reference Travel Behavior

Participants are car users who travel at least 5 times in the four consecutive weeks for their work activity in morning rush-hours. In order to study the effect of number of morning peak trips on participants’ decisions regarding “no change” and “changing route” alternatives, this variable was classified into three categories: (i) between 6 to 10 peak trips, (ii) between 10 to 15, and (iii) between 15 to 20 morning peak trips. The first category is assumed to have the highest and the last one the lowest flexibility.

Regarding the “no change” alternative, participants in the first category have a higher tendency to change while this tendency decreases for the second and third category with higher number of peak trips. Interestingly, participants with 10 to 15 peak trips are less likely to change their usual travel behavior compared to the last category. Gärling et al. (2004) and Cao and Mokhtarian (2005) found travelers preference of low effort responses over high effort responses (*33, 34*). As higher frequency requires more effort, fewer changes can be expected. It means the rewards cannot overcome the disutility of effort. Ben-Elia et al. (2011) also referred to the idea of satisfying behavior as another reason of this effect (*23*). They state that “the extra rewards gained by high frequency drivers will have a lower impact on behavior”.

For “changing route”, the first and the last category show a negative utility to choose this option while the second group shows a positive tendency to that. Participants with the lowest frequency have more flexibility and as a result prefer to choose other alternatives compared to changing route. The issue of effort also can be a reason of lower utility of this option for participants with highest frequency.

Effect of Socio-Economic Variables

Age, education and having children show significant effects on participants' decision. Figure 6 represents the effects of age and education on "no change" and "changing route" alternatives respectively. Three categories were considered for age. As can be seen in Figure 6, the young age (26-40) and middle age (40-55) groups are not inclined to change their current travel behaviour but participants who are older than 55 are more willing to change. This result may come from the fact that older participants face less constrained compared to two other categories. Thus, the required effort is less and probability of change is higher.

Education plays an important role in participants' decision to change route. The utility of choosing this option increases as the education level increases. It may demonstrate that high-educated people have a higher ability to search a new route through internet or other navigation devices. From another point of view, education is considered as a proxy for income. In this case, results indicate that as income increases the utility of the "changing route" alternative increases. According to previous studies, higher education shows a lower tendency of behavior change in case of reward. The "changing route" alternative has not been investigated in the "Spitsmijden" project. Therefore, higher educated participants might find changing routes more attractive as they are less sensitive to the extra travel costs cause by changing their usual route.

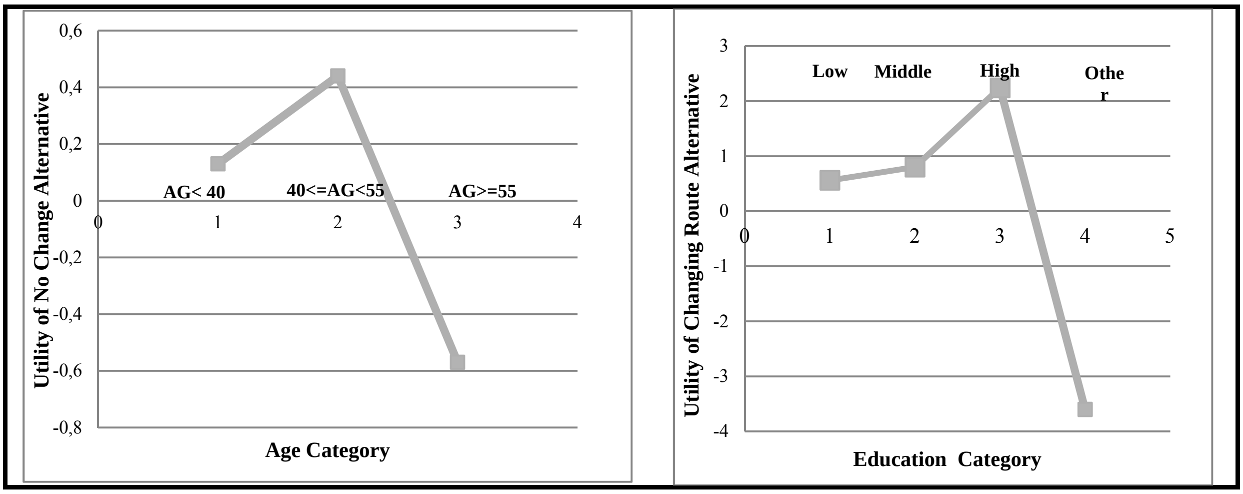

FIGURE 6 The effect of age and education on no change and changing route alternatives

Effects of Constraints and Flexibility in Work and Family Schedule

According to Table 1, 85% of the participants are married and 52% of them have children. Having children restricts the choice of "driving off-peak". Consequently, as expected, "driving off-peak" is less chosen by participants who have children. In contrast, participants without children tend to choose this option more often.

Flexibility of working hours strongly influences the "driving off-peak" decision. This variable was aggregated into three categories: participants who have flexibility, those who do not have, and the group who prefers not to answer. The utility of this alternative is negative for participants without flexibility and positive for flexible participants.

As expected, the possibility of "teleworking" has a significant effect on participants' decision regarding this alternative. This effect is positive for participants' who have this possibility and is negative for the other group.

Weather Effect

Precipitation affects the choice of "teleworking". In contrast to other explanatory variables, precipitation is not constant over the studied period. The average amount of precipitation across the period (September to October) was 1.63, 0.85, and 1.57 mm in 2010, 2011, and 2012, respectively. As expected the utility of "teleworking" increases with higher precipitation. According to the observations (Figure 1), the highest percentage of choosing teleworking is related to 2012. Figure 5 shows that the base utility of this alternative did not increase from 2011 to 2012. This means that precipitation could capture part of the dynamics of the utility of the teleworking alternative over time.

CONCLUSION

Several fascinating reward projects have been suggested and implemented in The Netherlands because of massive public resistance against the implementation of road pricing. Based on Stated Intention data from the Dutch "SpitsScoren" reward scheme, we studied the long-term effectiveness of reward scheme as an alternative to pricing policy. A panel effects mixed logit model that allows for covariance between the adaptation options, was used to capture the temporal effects of the reward scheme. The estimated model showed evidence of covariances between adaptation strategies.

Results indicated that from 2010 to 2012, "driving off-peak" and "teleworking" alternatives have the higher and "changing route" and "other" alternatives, have the lower base utilities compared to the "no change" alternative. However the effectiveness of the reward scheme changes over time and affects the various adaptation options differently. The number of peak trips, socio-economic and situational variables and weather conditions affect travelers' adaptation strategies.

Results of this study show that reward scheme lose its effectiveness over time. As Figure 1 demonstrates, in 2012, three years after start of the project, the percentage of "no change" increases implying that people stop adapting and fall back in their old habits under the scheme after three years. However, still no strong conclusion can be made about long-term effects and feasibility of large scale, region or even country-wide applications. The effects of effort, experiencing and learning, and fatigue or motivation in long-term on travellers' adaptive behavior, also cannot be neglected. Although, their long-term influences need to be more specifically explored. Our findings indicate that long-term reward scheme results in awareness of people about their possible adaptation options which lead to new habitual behavior.

Finally, we emphasize that considering the success of the Dutch reward projects, the effectiveness of such schemes relies on the design of the scheme such as scale, target group, feedback, available or provided supply especially in terms of public transport, carpooling, feedback, combination with other schemes and type of reward. The combination of charging and rewarding simultaneously is also an open discussion in The Netherlands now.

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