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Temporal Adaptation to Reward Schemes: Results of the SpitsScoren Project

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Abstract

Reducing congestion and improving the financial and environmental sustainability of urban transport represent new challenges for transportation planners. It requires a better understanding of the impact of various pricing policies on travel behavior. Most pricing policies have involved "push" measures. These measures involve extra charges to certain travel options and thus may lead to adaptation of individuals' behavior. Although push measures have been studied worldwide, examples of actual applications are still limited due to lack of social acceptability and political support. Public opposition to the implementation of national-wide road pricing in The Netherlands has triggered Dutch policy makers to design and implement an alternative transportation management policy, so-called "reward" measures. Several real projects have been implemented in The Netherlands, stimulating car drivers to avoid using certain links of the network or certain regions during peak hours. All these projects concluded that the "reward" measures are effective in the short-term. However, the long-term influence of such schemes is still uncertain. Using the data from the Dutch "SpitsScoren" reward project, this paper formulates a panel effects mixed logit model to explore individuals' adaptive behavior under a reward measure over time. The model is designed to account for correlations between choice options available to individuals in different time periods. Results indicate that except the "teleworking" option, the base utilities of other adaptation alternatives decrease over time, implying that effectiveness of the reward scheme decreases in the long-run. Socio-economic and situational variables seem to strongly affect travelers' choices of adaptation strategies. The estimated model also shows evidence of significant heterogeneity and covariances between individuals' choices of specific adaptation options over time.

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Keywords: Sustainable urban transportation; transportation pricing policies; reward measure; Mixed Logit model

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1. Background

Transportation pricing schemes aim at reducing congestion by increasing variable costs of car use. These "push" measures can be divided into financial instruments (e.g., higher fuel taxes, car parking charges and road tolls, etc.) and technical and regulatory constraints (e.g., traffic orders, removal of parking space and ban of vehicles). Thus "push" measures adapt individuals' travel behavior in such a way that their options are restricted to some extent since car use becomes less attractive. Other so-called "pull" measures policies are designed to discourage car use by making other alternatives more attractive. These measures generally increase individuals' choice options by improving existing choice alternatives or creating new alternatives. However, "pull" measures alone, are not always sufficient to trigger behavioral change. Social acceptability may, therefore, depend on whether the proposed strategy comprises "push" or "pull" measures. These policies in general and "push" measures in particular have been subject of travel behavior research during the last decade, even though, until now, examples of actual applications in the real world are limited, due to lack of social acceptability, equity, and economic efficiency. Many different "push" measures have been considered, both in the literature and in the political debate, in several countries. In The Netherlands, the vast public opposition against the implementation of national-wide road pricing has triggered Dutch policy makers to design and implement an alternative transportation management policy, based on the principle of "rewarding" desired behavior as opposed to punishing undesired behavior.

"Reward" schemes have been mostly investigated in the context of safety. Some studies claimed that rewarding can be effective for accident-free driving (Wilde, 1982; Janssen, 1990; Hagenzieker, 1999; Haworth et al., 2000). Rewarding seatbelts and speeding behavior has also been studied in the literature (Twilhaar et al., 2000; Mazureck & Hattem, 2006; Harms et al., 2008; Huang et al., 2005). 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 (Fujii et al., 2001; Fujii & Kitamura, 2003; Bamberg et al., 2003). In the Netherlands, the potential impact of rewards on travel behavior to avoid rush-hour trips has been explored in 2006 in the context of a pilot experiment, called "Spitsmijden" or "peak-avoidance". A total of 340 participants from the vicinity of The Hague in the west of The Netherlands were invited to participate in this pilot experiment. They could gain a reward in the form of money or credits to keep a Smartphone by changing their departure time of their work trips outside the morning rush-hour, switching to another travel mode, and teleworking. The pilot lasted for 13 weeks.

Various studies have evaluated this pilot experiment. Ettema and Verhoef (2006) reported the results of two analyses based on this pilot experiment. The authors used the SP experiment before the field experiment for their analysis. They concluded that the reward strategies (money or credits to keep a Smartphone) affected travelers' behavior. Changing the departure time of the trip and use of public transport were the most popular adaptation strategies. They also found a strong effect of work and family constraints, current habitual pattern and awareness of alternatives on participants' response to reward strategies (Ettema & Verhoef, 2006). 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. Road pricing analysis was carried out using a SP survey among 562 Dutch respondents. For the reward scheme, they used the RP data from "Spitsmijden" pilot experiment. 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.

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. Since 65 consecutive daily responses for each participant were available, the data was constructed as panel and the mixed logit model which allowed the correlation between alternatives, was used to analyze the data. Results demonstrated that the reward scheme is effective in the short-term. Moreover, the choice of adaptation strategy was found to be related to socio-economic characteristics, and family and work constraints. Bliemer and Amelsfort (2010), Ben-Elia et al. (2011), and Knockaert et al. (2012) are two other examples of similar studies.

The Mobility Credit system in Bologna, Italy is another recent example of a rewarding system. This project aims to stimulate individuals and companies to switch to more sustainable travel behavior. Changing mode from private car to bike, public transport and using carpooling/car sharing is rewarded by mobility credits, which can be used to get environmental/energy benefits, such as a free bus ticket. A pilot test called "MobiMart" includes four different projects of GHG (Greenhouse gas) reduction, was conducted. Two of these were finished and evaluated, while the other two are still ongoing. Ramazzotti et al. (2010), reporting the results of the pilot test, concluded that these projects have been successful, but that the effect could have been bigger should this rewarding system been augmented with some traffic restriction measures such as parking place reduction/ parking costs increase. Thus, the results of these studies on the effects of reward schemes on individuals' travel behavior suggest that these schemes look promising in the short run. However, the long-term effects of such schemes are still in doubt. On the one hand, one may expect that the effectiveness of reward measures decreases over time as individuals are reluctant to change their old habits or routines. On the other hand, by exploring new options, individuals may enjoy the new travel experience, which in turn may lead to positive reinforcement and ultimately to new habitual behavior. More studies are required to clarify the long-term effectiveness of reward measures on structural changes in individuals' travel behavior.

Using the data from the Dutch "SpitsScoren" reward project, this paper formulates a panel effects mixed logit model to explore individuals' adaptive behavior under a reward measure over time. The model is designed to account for correlations between choice options available to individuals in different time periods. The model predicts to what extent the probability of choosing an adaptation alternative in a certain period of time is affected by the probability of choosing the same option in another period.

The paper is organized as follows. First, the "SpitsScoren" project is described. This is followed by a discussion of sample composition. Then, the modelling approach and estimated results are presented. The paper is completed with a conclusion and discussion.

2. SpitsScoren or "Profit From the Peak" Project

Based on the results and success of the "Spitsmijden" pilot project, three new reward projects were designed and implemented, "SpitsScoren", "Spitsvrij", and more recently another "Spitsmijden" project, in different provinces of The Netherlands. It should be noted that these projects differ in terms of design, implementation and used technologies. The data used in the present study were collected as part of the "SpitsScoren" or "profit from the peak" project. "SpitsScoren" was 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 a 5% reduction of the congestion on the Dutch A15 motorway corridor during extensive construction works that started in 2011. The A15 corridor consists of the A15 motorway between Vaanplein and Rozenburg center (in both directions), the N492, the N218 (Hartel Bridge - crossing N57) and the road parallel to the A15 from Charlois to the Caland Bridge (Vondelingenweg, Old Maasweg, Botlekweg and Droespolderweg). In fact, this project was designed 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 developed a different performance and risks structure (Palm et al., 2010). 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 the 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 on holiday and do not 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. 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 do not constitute a representative sample of all travelers on the A15 corridor as they were selected according to the specific target of the project.

3. Sample Composition

A total of 380 participants of the "SpitsScoren" project with socio-economic, situational, and reference information was selected for our analysis. To answer the question about the long-term impact of the reward scheme, three similar periods of four consecutive weeks (September-October) in the years 2010-2012 were used. The September-October time period is more regular than other period because it has less holidays and days-off. Moreover, access to the full dataset was not provided. 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. As Table 1 shows, male car owners make up the majority of the sample. Interestingly, 34% have more than 2 cars in their household. Almost 85% of the sample is married and half of them have children. Information about the number and age of the children is not available. Regarding education level, 45% of the participants are highly educated and 42% have middle level education. The average age is 46, the lowest 26 and the highest 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. 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. Variation can be seen in terms of flexible work hours. 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") to avoid morning peak trips. Because of the low percentage of some alternatives, we aggregated the options into five alternatives: (i) Driving off-peak or changing departure time; (ii) Changing route outside the corridor; (iii) Teleworking; (iv) Other, including slow modes, group transportation, carpooling, and public transportation, and (v) Driving during the peak or no change.

4. Model Estimation and Results

A Mixed Logit (ML) model was used to analyze the long-term effects of the reward scheme. The model was designed to account for correlations between choices made by the same individual in different time periods. ML models can be specified in such a way that the error components in different choice situations from a given individual are correlated. Since each participant indicated his intention for the next working day across four consecutive weeks (up to 20 working days), panel effects were also estimated. Three years daily travel intention information was used to capture the dynamics in the utility function. Equations 1, 2 and 3 show the ML model:

$$U_{nit} = C_{ni1} * C_i T_1 + C_{ni2} * C_i T_2 + C_{ni3} * C_i T_3 + \sum_k \beta_{ik} X_{nkt} + \varepsilon_{nit} \tag{1}$$

$$P_{ni} = \int L_{ni}(C) f(C) dc \tag{2}$$

$$L_{ni} = \prod_t \frac{e^{C_{ni1}*C_iT_1 + C_{ni2}*C_iT_2 + C_{ni3}*C_iT_3 + \beta_{ik}X_{nkt}}}{\sum_{j=1}^{J} e^{C_{nj1}*C_jT_1 + C_{nj2}*C_jT_2 + C_{nj3}*C_jT_3 + \beta_{jk}X_{nkt}}} \tag{3}$$

U_{nit} is the utility of alternative i for individual n in choice situation t and P_{ni} and L_{ni} are the probability and logit probability of individual n choosing alternative i, respectively. t in the logit probability, L_{ni}, runs across days (up to 20 working days in each year). C_{ni1}, C_{ni2}, and C_{ni3} represent the time-dependent constants of alternative i for the first, second and third year that vary across individuals n. X_{nkt} represents explanatory variable k of individual n in choice situation t and β_{ik} is an alternative specific coefficient for variable k. ε_{nit} is the error term that is IID extreme value distributed. Normal distributions were used to represent the random constants.

Table 1. Variables and Sample Composition

Variable	Abbreviation	Description	Category	Percentage
Socio-economic	G	Gender	Male	85.0%
			Female	15.0%
	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%
			Preparatory vocational secondary education	6.5%
			Senior general secondary education / University preparatory education	9.9%
			Senior secondary vocational education and training	32.3%
			Master's degree	31.5%
			Doctor's degree	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<= PT<10	12.2%
			10<= PT<15	31.5%
			15<= PT<=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%

The covariance matrix was also estimated to explore to what extent the probability of choosing an adaptation alternative in a certain period of time is affected by the probability of choosing the same option in another period. Thus we allowed the covariance between the random constants, C_{ni1}, C_{ni2}, and C_{ni3} within each alternative and not between the alternatives. This imposed some restrictions on the covariance matrix. Time-dependent dynamics were captured by defining three dummy coded parameters, C_iT_1 , C_iT_2, and C_iT_3. C_iT_1 is one for alternative i in the first period (2010), and zero otherwise. Similarly, C_iT_2, and C_iT_3 are one for alternative i in the second (2011), and third period (2012) respectively, otherwise they are zero. Nlogit 5.0 was used to estimate the model. The number of Halton draws was set to 2000. The “no change” alternative was defined as the base alternative (constant=0 for each year). The first result demonstrated that there are no significant covariances between time-dependent random constants for “driving off-peak” and “teleworking” options. Therefore, the covariances were removed for these options in the final estimation. The final model is summarized in Table 2.

The model is statistically significant with a Chi-square value of 27755.55 with 42 degrees of freedom and a pseudo-R^2 value of 0.4026. The p-value for most non-random or fixed parameters is less than alpha equal to 0.05. Thus, these parameters are statistically different from zero. At the 95 per cent confidence level, the means of the second level of number of morning peaks trips (*PT2*), and the first level of marital status (*MC1*) that reflects the single group, are not statistically significant in this model. In addition, the mean of flexible working hours group (*FH2*) for the “driving off-peak” alternative and the middle educated group (*ED2*) for “changing route” alternative are not statistically different from zero.

Table 2. Final model estimation

Alt.	Variable	Description	β	Standard Error	P{|Z|>z}	St. dev.	P{|Z|>z}
No change	*PT1*	Number of morning peak trips (6<= PT<10)	-0.578	0.12252	0.0000		
	PT2	Number of morning peak trips (10<= PT<15)	0.056	0.09050	0.5362		
	MC1	Family status (Single)	0.027	0.13685	0.8452		
	MC2	Family status (Single parent)	0.692	0.26086	0.0080		
	MC3	Family status (Married without children)	-0.345	0.12234	0.0047		
Driving Off-Peak	*C21*	Constant for 2010	0.772	0.22407	0.0006	2.37977	0.0000
	C22	Constant for 2011	0.695	0.21565	0.0013	2.66301	0.0000
	C23	Constant for 2012	0.213	0.21114	0.3123	2.84496	0.0000
	FH1	Flexibility of working hours (first level=no)	-0.548	0.16379	0.0008		
	FH2	Flexibility of working hours (second level=yes)	0.050	0.16073	0.7578		
Changing Route	*C31*	Constant for 2010	-2.300	0.27560	0.0000	3.31495	0.0000
	C32	Constant for 2011	-1.845	0.25586	0.0000	3.24714	0.0000
	C33	Constant for 2012	-2.782	0.30258	0.0000	3.79403	0.0000
	ED1	Education (first level=low educated)	-1.030	0.25247	0.0000		
	ED2	Education (second level=middle educated)	0.199	0.18776	0.2891		
	ED3	Education (third level=high educated)	0.727	0.17225	0.0000		
Teleworking	*C41*	Constant for 2010	-0.583	0.15199	0.0001	1.77463	0.0000
	C42	Constant for 2011	-0.358	0.15519	0.0210	1.90594	0.0000
	C43	Constant for 2012	-0.293	0.19148	0.1256	2.31579	0.0000
	PH	Possibility of teleworking	0.678	0.07754	0.0000		
	P	Precipitation (continuous)	0.032	0.00784	0.0001		
Other	*C51*	Constant for 2010	-2.556	0.33701	0.0000	4.80287	0.0000
	C52	Constant for 2011	-2.612	0.36363	0.0000	4.15656	0.0000
	C53	Constant for 2012	-3.268	0.38579	0.0000	3.69306	0.0000

4.1. Random parameters

Examination of the spreads of each of the random parameters (alternative-specific time-dependent constants) around their respective means reveals that all alternatives exhibit preference heterogeneity. High standard deviations of these parameters are also remarkable. It should be noted that the constants of "driving off-peak" and "teleworking" alternatives in 2012 didn't meet the 95 per cent confidence level. Figure 1 shows the alternative-specific time-dependent constants or time-dependent base utility of the different alternatives. As mentioned before, the base utility of the "no change" option was set to zero. As Figure 1 demonstrates, in all periods, the "driving off-peak" alternative has a higher utility and the other options have a lower utility than the "no change" option. The lowest and highest negative utility can also be seen for "teleworking" and "other" options, respectively. Consistent with doughnut Figure1, the base utility of the most popular option, "driving off-peak", decreases between 2010 and 2012, and this reduction is more from 2011 to 2012 with the reduction of the reward level from €5 to €3.

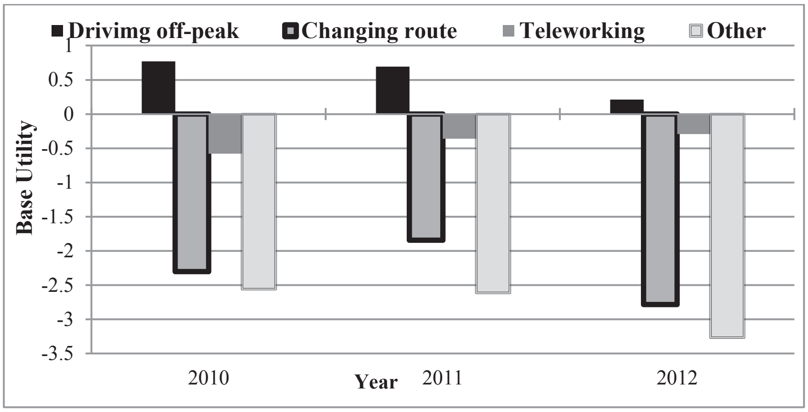

Fig. 1. The time-dependent base utility of the different alternatives

The base utility of the "changing route" alternative increases between 2010 and 2011 with the same reward level of €5, and then decreases with a decreasing reward level of €3. The base utility of the "teleworking" alternative, however, increases over the studied period, implying that the reduction in reward level in 2012 did not affect the utility of this option. In contrast, for the "other" option, a decreasing pattern can be seen. These findings reveal that during the studied period that lasted three years, the base utilities of all alternatives show a decreasing pattern, except for the "teleworking" option, implying that "no change" becomes more popular. It should be emphasized, however, that these dynamics may be associated with time, but may also be explained by the reduced reward level. Again the effect of other changes such as household and work constraints cannot be ruled out. Permitting correlated random parameters results in dependent standard deviations. To investigate this dependency, Cholesky decomposition was used to decompose the standard deviations into attribute-specific and attribute-interaction standard deviations. The diagonal values of the Cholesky matrix represent the amount of variance attributed to that random parameter when the covariance with other random parameters have been removed. The non-zero off-diagonal elements of this matrix carry the cross-parameter correlations. The Cholesky matrix is obtained from the variance-covariance matrix. To demonstrate, assume the variance-covariance matrix in which the variances are represented as the diagonal values a_{ij} where $i=j$ and the covariances are represented as the off-diagonal a_{ij} values where $i \neq j$. The Cholesky decomposition matrix is a matrix (b_{ij}) in which the upper off-diagonal values are all equal to zero, and other elements of the matrix are calculated as follows (e.g. Greene et al., 2005):

$$b_{ij} = \sqrt{a_{ij}} \qquad \text{for } i = j = 1 \text{ (the first diagonal element)else} \tag{4}$$

$$b_{ij} = \sqrt{a_{ij} - \sum_{i}^{i-1} bij^2} \qquad \text{if } i = j \neq 1 \text{ (all other diagonal elements)else} \tag{5}$$

$$b_{ij} = {a_{ij}}/{b_{ii}} \qquad \text{for } j = 1 \text{ and } i \neq j \text{ (lower off} - \text{diagonal elements in the first column)else} \tag{6}$$

$$b_{ij} = {(a_{ij} - \sum_{i}^{i-1} b_{jk} b_{ki})}/{b_{ii}} \qquad \text{for } j \neq 1 \; and \; i \neq j \text{ (lower off} - \text{diagonal elements not in the first column)} \tag{7}$$

As mentioned before, we are interested in exploring how the probability of choosing an adaptation alternative in a certain period of time is affected by the probability of choosing the same option in another period. Thus, we only allowed the correlation between alternative-specific time-dependent constants for each alternative. Because the correlation between "driving off-peak" and "teleworking" was not significant in the first run, correlations only concern the "changing route" (C3.) and "other" (C5.) options in the final estimation. Figures 2 shows the covariances between the random parameters for "changing route" and "other" alternatives.

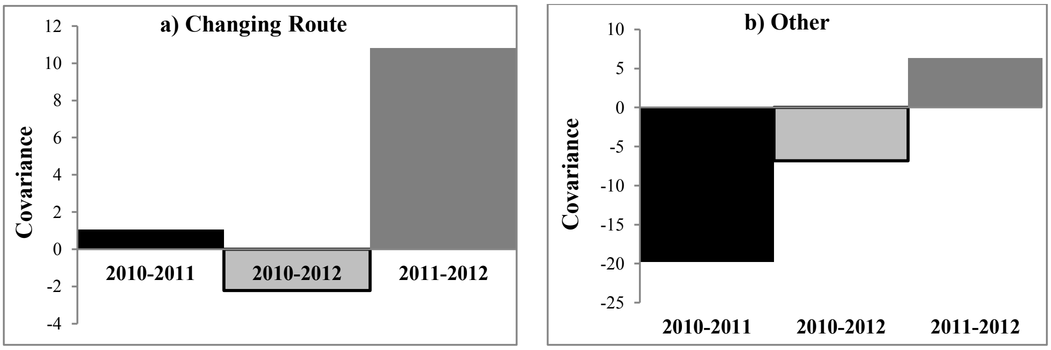

Fig. 2. (a)The covariances between base utilities of changing route ; (b) The covariances between base utilities of other alternatives

Because the alternative-specific time-dependent constants were specified as random parameters in the model, Figure 2 shows the covariances between the base utilities of the relevant alternatives in different years. Positive covariances between C31 and C32 and C32 and C33 suggest that participants who choose to change their route in 2010 are more likely to choose this option again in 2011, and those who choose this option in 2011 are more probably to choose it in 2012 as well. This probability is higher between 2011 and 2012. This relationship, however, is negative between 2010 and 2012 for this alternative. In the case of the "other" alternative, the probability of choosing this option in 2011 highly decreases, if participants choose it in 2010. The same relationship can be observed for 2010 and 2012, but the relation is not as strong as for 2010 and 2011. In contrast, the probability of choosing the "other" option in 2012 increases if this option is chosen in 2011.

4.2. Non-random or fixed parameters

The number of morning peak trips plays an important role in the participants' decision to change their current pattern. Participants in the first category (between 6 to 10 peak trips) have a higher tendency to change, while this tendency decreases for the second (between 10 to 15 peak trips) and third category (between 15 to 20 morning peak trips) with a higher number of peak trips. Gärling et al. (2004) and Cao and Mokhtarian (2005) found traveller's preference for low effort responses over high effort responses. As higher frequency requires more effort, fewer changes can be expected. It means that the rewards cannot overcome the disutility of high effort. We also found an effect of marital status on this alternative, but the effect for the first category (single group) is not significantly different from zero. The single parent group has the highest utility for the "no change" option that reveals their restrictions in changing their current work trip pattern. Married with and without children groups, in contrast, show more flexibility in changing their current trip pattern for work. For the “driving off-peak” alternative, flexibility of working hours shows significant effects. This variable was aggregated into three categories: participants who have flexibility, those who do not have, and the group who prefers not to answer. As expected, the utility of this alternative is negative for participants without flexibility and positive for flexible participants. Education levels influence participants’ choice of changing route. The utility of choosing this option increases as the education level increases. According to previous studies, higher education has a lower tendency of behavioural change in case of rewards (for example: Tillema et al. 2010). The possibility of teleworking and precipitation affect the “teleworking” alternative to avoid rush-hour trips. As expected, the effect of the possibility of teleworking is positive for participants who have this possibility and is negative for the other group. 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. The utility of “teleworking” increases linearly with higher precipitation.

5. Conclusion

The long-term effects of a “reward” scheme on individuals’ adaptive travel behavior was studied using the Dutch “SpitsScoren” reward project. Results of a panel effect ML model indicate decreasing patterns in the base utility of different adaptation alternatives, except “teleworking” over the studied period (2010-2012). It implies that the base utility of “no change” increases and participants tend to fall back into their habitual work-commute travel pattern. Accordingly, the “reward” scheme seems to loose its effectiveness over time. We also found evidence of significant covariances between the time-dependent base utilities of “changing route” and “other” alternatives. These covariances demonstrated that the probability of choosing these two options in one period depends on the probability of choosing them in other periods. Therefore, for choice situation like this study, the choice of one option made by an individual in one period is not always independent of the choice of that option by the same individual in other periods. In addition to these findings, we captured strong effects of socio-economic, situational, and family constraint variables on participants’ decision to change. This finding is in line with previous mentioned studies.

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