EXAMINING TEMPORAL EFFECTS OF LIFECYCLE EVENTS 
ON TRANSPORT MODE CHOICE DECISIONS

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EXAMINING TEMPORAL EFFECTS OF LIFECYCLE EVENTS ON TRANSPORT MODE CHOICE DECISIONS

Abstract: This paper describes the first results of a study on the impact of events on transport mode choice decisions. An Internet-based survey was designed to collect data concerning seven structural lifecycle events. In addition, respondents answered questions about personal and household characteristics, possession and availability of transport modes and their current travel behaviour. In total, 710 respondents completed the online survey. The complexity of transport mode choice is modelled using a Bayesian Decision Network. This paper only focuses on the time influence of events on transport mode choice decisions. We assume that people change or at least reconsider their behaviour after a structural, lifecycle event, sometimes directly after experiencing a change and sometimes only after a while. We estimated a multinomial choice model to estimate the effect of these structural events, and in particular of the length of the time elapsed, on transport mode choice.

Keywords: transport mode choice, structural lifecycle events, time influence, dynamic behaviour, and learning and adaptation.

1 INTRODUCTION

Governments are trying using a variety of policies to decrease car use and stimulate other transport modes such as bike and public transport. Arguably, the effectiveness of such policies will improve as our understanding of the decision processes underlying transport mode choice improves.

Transport mode choice decisions are not made in isolation, different decisions are involved: route choice, the choice of the time of the day, the choice of activity, etc. In the past, different models of transport mode choice have been developed. Most traditional models have been kept quite simple; they typically predict the probability that an individual will choose a particular option as a function of attributes of the choice alternatives and a set of socio-demographics. The process of decision-making may be much more complex than these traditional models reflect. Choice behaviour is often context-dependent, implying that conditions beyond socio-demographics and attributes of the choice alternatives influence the outcome of the decision. Moreover, the dynamics of transport mode decisions are often (largely) ignored.

This paper is based on the fundamental assumption that important shifts in transport mode decisions are often triggered by events that occur during an individual’s and household’s life course. Events that one can think of are for example moving to a new residence, an increase in the number of persons in a household, changing job or job location, starting or ending an education, and a change in car availability. Some of these events imply changes in an individual’s choice set, which might either expand or become more constrained. Other events may imply that the utility of a particular transport mode may change, implying that if such a shift is dramatic enough, an individual may decide to choose a different transport mode. A basic assumption is that events not only change the (personal) conditions, but may also
trigger the adaptation and learning process. Behaviour is thus also influenced by

time.

In a previous paper (Verhoeven et al., 2005), we have argued that a Bayesian Belief
Network, or more precisely a Decision Network, may be used to model these direct
and indirect effects of lifecycle decisions on transport mode choice. However, the key
assumption of the existence of temporal effects on such lifecycle decisions on
transport mode choice has not been examined empirically. Before formulating and
calibrating a decision network model, in the present paper we will report the results of
a logit model, estimated to examine the temporal effects of these structural events on
transport mode choice.

The paper will first briefly discuss some existing models of transport mode choice.
This is followed by a discussion of the conceptual considerations underlying our
approach. Next, we will discuss the data and the results of the analysis. The paper
will be concluded by discussing the potential of the suggested approach and some
avenues of future research.

2 MODE CHOICE MODELLING

Many models of transport mode choice have been developed in the past; attitudinal
models (Fishbein and Ajzen, 1975), logit models (Ben-Akiva and Lerman, 1985) and
conjoint measurement models (Louviere, 1988) being the most commonly used
approaches. In these models, mode choice is typically conceptualized as a function
of the characteristics of alternative travel modes and a set of personal and household
characteristics. Previous studies, based on the latter two approaches, assumed that
these attributes generate some utility and that individuals maximize their utility when
choosing between alternative transport modes, subject to budget constraints.

Attitudinal models are an exception in that they do not involve maximizing utility, but
rather assume that transport mode choice is based on a set of attitudes. In this study,
a different perspective is explored in which the causal relation between events and
mode choice decisions is examined and modelled. A structural lifecycle event is
defined here as a major event in a person’s life such as a marriage or move that may
trigger a process of reconsideration of current behaviour. Some events, such as a
change in the place of residence, may dramatically change the space-time context
within which travel decisions have to be made. Other key events, such as a change
in car availability, may reduce constraints and expand an individual’s choice set.

Moving house implies a shift in characteristics such as; accessibility, distance/travel
time relationships and perhaps also the utility an individual derives from alternative
travel modes. An event such as changing jobs may also lead to changes in
characteristics of travel modes. A final example is the birth or adoption of a child,
which may induce new activities (e.g. day care) that are more difficult to complete
using the currently used travel mode.

Traditional models are static and estimate behaviour in an equilibrium situation. In
reality behaviour may not be static but always in motion toward an equilibrium
situation. Every time a person experiences an event, he is likely to reconsider his
behaviour as it may be out of balance, and his behaviour is moving towards a new
equilibrium situation. It takes time to get to the new equilibrium situation, meaning
that a person may continuously be engaged in an adaptation process. The aim of this
study is test the hypothesis that behaviour is not static but, even under constant conditions, changes over time.

3 CONCEPTUAL FRAMEWORK

The assumed effect of events on transport mode choice is inspired by the theory of learning and adaptation. According to this theory, individuals develop and continuously adapt choice rules while interacting with their environment. Transport systems, urban environments are highly dynamic, non-stationary and uncertain. People are also very dynamic; they adapt to all kind of changes (Arentze et al. 2003).

3.1 Conceptual Considerations

The reinforcement learning approach assumes that individual choices in complex environments are driven by rules that are formed and continuously adapted through learning while the individual is interacting with the environment. Through search an individual explores choice opportunities in his or her environment and keeps a memory record of the varying rewards associated with his actions. Actions that produce positive rewards are reinforced and have a higher probability of being repeated in future choice situations under similar conditions, while actions with negative outcomes tend to be avoided. In stationary environments, reinforcement learning implies that random behaviour will ultimately evolve into habitual behaviour.

In non-stationary environments, a gradually changing environment or discrepancies between the changing environments and changing personal or household circumstances may imply that the behaviour of interest is no longer adequate to cope with the new situation. An individual may then have to change one or more facets of his habitual behaviour. Key events may have a similar, but attenuated effect. A dilemma for any individual, who has limited knowledge about new circumstances, is the choice between exploration and exploiting current knowledge. Selecting actions that have not been tried before gives the opportunity of discovering new choices that may yield higher rewards than the currently best action. However, this comes with the risk of negative experiences. Individuals who wish to avoid such risks may stick to the currently best choice. Thresholds for reconsidering current choices and the thoroughness of search will vary depending on the individual’s tendency to take or avoid such risks.

If this reasoning is valid, we should find evidence of an effect not just of lifecycle events on the choice of interest but also of the time elapsed since the event was experienced.

3.2 Formalization

Figure 1 illustrates our assumption that behaviour is the result of the present state of a person and adaptation to a new state after a change caused by an event. An event, illustrated with E in Figure 1, affects behaviour (B) in two different ways, first through the change of the present state (from S₁ to S₂) and second through learning, illustrated with the evolution from B₂ to B₂’ to B₂” ending in the equilibrium situation indicated by B₂*.
Figure 1: assumed conceptual model of the influence of an event

(E is event, S is state and B is behaviour)

The present state is the actual environment or context of the person involved; including personal characteristics, possession and availability of transport, distances to different destinations and so on. This present state of a person influences his/her behaviour, indicated in the figure with the arrow between S and B. The figure illustrates that behaviour can change even though the state stays the same. Structural lifecycle events may change people’s values and judgements, and may result in new behaviour. However, this takes time and after a while behaviour is in equilibrium again, illustrated with an asterisk.

The assumed influence of time, the adaptation and learning process, is illustrated in the Figure 2. There is a visual break, which is the moment of an event (E). The new situation (S2), after the event, can result for example in less car use, new behaviour (B2). People need some time to adapt to the new circumstances, in Figure 2 this is illustrated with the time after the event until the equilibrium of the new behaviour (B2*). Demonstrating those trends and influences of time is the focus of the present research.

Figure 2: example of time influence on car use
3.3 Survey

In order to test this critical assumption of temporal effects underlying our approach, an Internet-based survey was administered. The survey consisted of the following components:

1. Household and personal characteristics;
2. Possession and availability of transport mode;
3. Event-related questions for seven different lifecycle events;

In particular, data was collected about seven structural events; change in residential location (1), change in household composition (2), change in work location (3), change in study location (4), change in car availability (5), change in public transport pass (6) and change in household income (7). The respondents answered questions about those events and filled out the event-matrix with information about date, month, and cause of every change. The respondents only had to remember events since a specific time.

For the purpose of this study, especially the event-history data were relevant. For the set of seven predefined events, respondents were requested to indicate whether they experienced the event, and, if so, to indicate how many times it took place, the timing of the event (month and year), what exactly changed by the event (before and after state) and the nature of the change that took place (cause).

4 DATA AND METHODS

To collect the required data a sample was drawn using an Internet-based survey. E-mail addresses were collected from a set of colleges and universities in the Netherlands. Approximately 2400 emails were sent with a request to participate and to send the mail to three other persons. In total, 939 persons agreed to participate and were emailed the address of the web-based survey. From this group of persons, 807 started and 710 finished the survey.

4.1 Data Collection

As for the sample composition, 59 percent were males, while 41 percent were females. This illustrates previous findings that Internet-based samples tend to be biased in the sense that males are overrepresented in the group of Internet users or more inclined to respond than females. In total 51.1 percent had a full time job (> 35 hours a week), 9.7 percent had no job, while the remainder had a part-time job. From all respondents 59.4 percent had no children, 6.8 percent had one, 23.1 percent had two children, while the remainder had more than 2 children. 59.9 percent of the respondents was married or lived together. Almost everybody owned a driver’s license, 93 percent and 78 percent of the respondents owned a car. The possession of a bike is also very high, 97.2 percent, and half the sample owned some kind of public transport pass. The sample is not completely representative for the Dutch population. The frequency of the personal characteristics age, education and household income differ from the Dutch standard. This sample contains more young people with a high education and a high income. There is also a slight difference in
possession of a car between the sample and the Dutch population, but that can be explained by the fact that car possession is increasing.

4.2 Multinomial Logit Model

To analyse the influence of time on mode choice, a multinomial logit model was estimated. The independent variables consisted of appropriately effect coded personal characteristics and availability and possession of transport modes (variables X), distances to different destinations (variables D), and especially the time elapsed since a person experienced an event and whether he or she experienced that event (variables Z). It is important to use the current state (variables X and Z) as independent variables, to avoid confounding the estimated parameters for time variables with the state-change effects of events. That is why we separated those two sets of variables. The variables X and D measure the influence of the change in state (from S₁ to S₂) and estimated parameters of Z variables represent the time influence, the adaptation process.

The independent variables X (personal characteristics and possession and availability of transport) that are included into the choice model are for example gender, age, education, income, number of household members, drivers licence, car possession, bike possession, public transport pass possession. In addition to these characteristics we also used the distance from home to work, study, stores, shopping mall and sport centre as independent variables (D). The respondents estimated the distance to those different locations in a matrix question. The time effects (variables Z) were operationalised in terms of the following equation:

$$Z = E \times \ln(T)$$

where E refers to the experience of a certain event. If someone experienced an event the value is 1 and if someone did not experience that event the value is 0. The variable T corresponds with the time elapsed (in months) since the last change. In other words, the number of months that have passed since a respondent experienced that event.

The dependent variable in the multinomial logit model is transport mode choice. This variable has three different choice options; car, slow transport and public transport. The respondents provided information with respect to their current mode choice behaviour for five different trip purposes. In particular, they indicated frequency, travel mode, alternative travel mode, destination, departure time at home, arrival time at home, estimated travel distance from their home to the destination and the estimated travel time. The total frequency that is the sum of the frequencies of using a particular transport mode across trips is used as the dependent variable in the logit model. Because respondents could indicate the frequency using their own ‘scale’ (day / week / month), all frequency data was rescaled into monthly frequency, which was the mostly used category.

4.3 Event history data

The third part of the survey provided us with the event-history data for this study. For the set of seven predefined events, respondents were requested to indicate whether they experienced the event, and, if so, to indicate how many times it took place, the timing of the event (month and year), what exactly changed by the event (before and after situation, for example 2 people and 3 people in the household) and the nature of
the change that took place (for example adoption or birth). Based on this information, the independent variable $Z$ was calculated according to equation 1. In order to give background information about the event-history data, Table 1 presents the percentage of respondents who recently experienced a structural event, the average number of months that has passed since they experienced the event most recently, the corresponding standard deviation, and the minimum and maximum number of months that have passed since the most recent occurrence of the event.

<table>
<thead>
<tr>
<th>Events</th>
<th>frequency</th>
<th>$\bar{T}_{\text{recent}}$</th>
<th>Std.</th>
<th>$\bar{T}_{\text{min}}$</th>
<th>$\bar{T}_{\text{max}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residential change</td>
<td>84.9 %</td>
<td>81</td>
<td>86.00</td>
<td>1</td>
<td>391</td>
</tr>
<tr>
<td>Household change</td>
<td>61.1 %</td>
<td>80</td>
<td>88.87</td>
<td>1</td>
<td>480</td>
</tr>
<tr>
<td>Work change</td>
<td>67.5 %</td>
<td>80</td>
<td>96.00</td>
<td>1</td>
<td>652</td>
</tr>
<tr>
<td>Study change</td>
<td>49.6 %</td>
<td>70</td>
<td>44.60</td>
<td>1</td>
<td>223</td>
</tr>
<tr>
<td>Car change</td>
<td>52.5 %</td>
<td>75</td>
<td>87.85</td>
<td>1</td>
<td>501</td>
</tr>
<tr>
<td>Public Transport change</td>
<td>58.7 %</td>
<td>67</td>
<td>59.81</td>
<td>1</td>
<td>359</td>
</tr>
<tr>
<td>Household income change</td>
<td>53.7 %</td>
<td>73</td>
<td>85.94</td>
<td>1</td>
<td>436</td>
</tr>
</tbody>
</table>

Almost every respondent experienced at least one of the events during his/her life, but some events happen more often. The average number of months ago varies from 67 – 81. Some respondents experienced the event shortly after filling out the survey while others experienced the event many years ago.

4.4 Transport mode choice data

The fourth part of the survey provided us with data about current transport mode choice behaviour of the respondents. As explained before respondents were requested to answer different questions about their current travel behaviour. Based on the information of the transport mode used and the trip frequency, the dependent variable $Y$ was calculated. The total frequency across different purposes was used as the dependent variable in the logit model. In order to give some insight in the transport mode choice of the respondent for the five different purposes, Table 2 presents the percentages for the different transport modes for the five purposes:

<table>
<thead>
<tr>
<th>Mode choice</th>
<th>Work</th>
<th>Study</th>
<th>Grocery</th>
<th>Shopping</th>
<th>Sport</th>
</tr>
</thead>
<tbody>
<tr>
<td>Car</td>
<td>45.2 %</td>
<td>19.9 %</td>
<td>47.5 %</td>
<td>42.4 %</td>
<td>41.8 %</td>
</tr>
<tr>
<td>Public Transport</td>
<td>19.3 %</td>
<td>25.3 %</td>
<td>0.6 %</td>
<td>8.1 %</td>
<td>2.6 %</td>
</tr>
<tr>
<td>Slow Transport</td>
<td>35.5 %</td>
<td>54.8 %</td>
<td>51.9 %</td>
<td>49.5 %</td>
<td>55.6 %</td>
</tr>
</tbody>
</table>
Overall, slow transport is mostly used, but for the work trip the car is most popular. Dutch people often ride their bike, supporting commonly held beliefs. Public transport is mostly used for work and study trips, which probably involve longer distances than the trips to the store or the sport centre.

5 RESULTS AND ANALYSIS

The multinomial logit model was estimated using LIMDEP (Econometric Software). The explanatory variables were effect-coded, while slow mode was used as the base mode for this logit model. Before discussing the temporal effects of the lifecycle events, we will first discuss the estimated effects for the remaining personal characteristics and distances.

5.1 Personal Characteristics and Distances

The model includes 76 variables and 709 observations. After 7 iterations, no further improvement in goodness-of-fit could be obtained. The log likelihood of the model is -188768.7 and the Rho Square is 0.487. Table 3 shows the estimated effects for the variables included in the model. Significant variables (alpha of 5%) are in bold and the calculated effects are in italic.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Car</th>
<th>Public Transport</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-2.3417</td>
<td>-2.2376</td>
</tr>
<tr>
<td>Males</td>
<td>0.0588</td>
<td>0.0412</td>
</tr>
<tr>
<td>Females</td>
<td>-0.0588</td>
<td>-0.0412</td>
</tr>
<tr>
<td>Age (17-24 years)</td>
<td>0.0491</td>
<td>-0.0003</td>
</tr>
<tr>
<td>Age (25-34 years)</td>
<td>0.0416</td>
<td>0.1732</td>
</tr>
<tr>
<td>Age (35-49 years)</td>
<td>0.0393</td>
<td>-0.1111</td>
</tr>
<tr>
<td>Age (50-79 years)</td>
<td>-0.1300</td>
<td>-0.0651</td>
</tr>
<tr>
<td>Education (high)</td>
<td>0.1761</td>
<td>0.2969</td>
</tr>
<tr>
<td>Education (low)</td>
<td>-0.1761</td>
<td>-0.2969</td>
</tr>
<tr>
<td>Alone, divorced, widow</td>
<td>-0.0562</td>
<td>-0.7331</td>
</tr>
<tr>
<td>Married/living together</td>
<td>0.0562</td>
<td>0.7331</td>
</tr>
<tr>
<td>Living on your own</td>
<td>0.3430</td>
<td>-0.4578</td>
</tr>
<tr>
<td>Living in student room</td>
<td>-0.5563</td>
<td>-0.7418</td>
</tr>
<tr>
<td>Living with parents</td>
<td>0.2133</td>
<td>1.1996</td>
</tr>
<tr>
<td>Household of 1 person</td>
<td>-0.0745</td>
<td>0.6532</td>
</tr>
<tr>
<td>Household of 2 persons</td>
<td>0.0103</td>
<td>-0.4198</td>
</tr>
<tr>
<td>Household of 3 persons or more</td>
<td>0.0642</td>
<td>-0.2334</td>
</tr>
<tr>
<td>No employed work</td>
<td>-0.1712</td>
<td>-0.0111</td>
</tr>
<tr>
<td>Part-time work</td>
<td>0.0173</td>
<td>-0.0257</td>
</tr>
<tr>
<td>Fulltime work</td>
<td>0.1539</td>
<td>0.0368</td>
</tr>
<tr>
<td>Income (medium)</td>
<td>-0.0773</td>
<td>-0.0799</td>
</tr>
<tr>
<td>Income (high)</td>
<td>0.0773</td>
<td>0.0799</td>
</tr>
<tr>
<td>Drivers license</td>
<td>0.5198</td>
<td>-0.3426</td>
</tr>
</tbody>
</table>
Table 4: Estimated Parameters of Variables D (Multinomial Logit Model)

<table>
<thead>
<tr>
<th></th>
<th>Car</th>
<th>Public Transport</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variable</strong></td>
<td><strong>Utility</strong></td>
<td><strong>Utility</strong></td>
</tr>
<tr>
<td>Distance to work</td>
<td>0.0170</td>
<td>0.0214</td>
</tr>
<tr>
<td>Distance to education</td>
<td>-0.0030</td>
<td>0.0107</td>
</tr>
<tr>
<td>Distance to the store</td>
<td>0.1834</td>
<td>0.1041</td>
</tr>
<tr>
<td>Distance to shopping area</td>
<td>0.0092</td>
<td>0.0011</td>
</tr>
<tr>
<td>Distance to sport centre</td>
<td>0.0032</td>
<td>-0.0009</td>
</tr>
</tbody>
</table>

The effects of the X and D variables are listed in Tables 3 and 4. Almost all variables are significant. Both constants, for car and public transport (PT), are negative, implying that in general the modes car and public transport are less attractive than the slow transport mode (ST). All estimated effects are all in anticipated direction. Table 3 shows that the utility of the car decreases very slowly with increasing age; above 50 years of age the utility for the car becomes negative relative to that of slow transport. Public transport has for people between 25 and 34 years old a positive utility compared with slow transport, which can be explained by the fact that Dutch students own a student PT pass allowing them free travel. After 34 years of age, the utility of PT decreases with increasing age. Figure 3 illustrates for example the utilities for the different transport modes for the variable age.
5.2 Event history effects

The events considered were defined as follows: a change in residential location means that the respondent moves to a different residential location; a change in household composition means in this case an increase in the number of household members, a change in work location only included respondents with a job; a change in study location included students who started a new education or changed school/university; a change in car availability is an increase of number of cars or decrease in car users; a change in PT pass possession included respondents who possess a PT pass and a change in household income is an increase in income. The results for the event variables (Z) are listed in Table 5.

Table 5: Parameters of Variables Z (Multinomial Logit Model)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Car</th>
<th>Public Transport</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change in residential location</td>
<td>-0.0427</td>
<td>-0.0415</td>
</tr>
<tr>
<td>Change in household composition</td>
<td>0.0331</td>
<td>-0.0586</td>
</tr>
<tr>
<td>Change in work location</td>
<td>0.0587</td>
<td>0.0801</td>
</tr>
<tr>
<td>Change in study location</td>
<td>0.0287</td>
<td>-0.0449</td>
</tr>
<tr>
<td>Change in car availability</td>
<td>-0.0232</td>
<td>0.0362</td>
</tr>
<tr>
<td>Change in PT pass possession</td>
<td>-0.0454</td>
<td>0.0962</td>
</tr>
<tr>
<td>Change in household income</td>
<td>-0.1230</td>
<td>-0.1129</td>
</tr>
</tbody>
</table>

The variables are all significant. Figures 4 – 10 illustrate the effects of the different events. Slow Transport (ST) is the base in this logit model and its utility is always zero. For interpretation of this graph, it is important to remember that a utility-line below the X-axis means that the more time elapsed since the most recent experience of the event $i$, the utility is lower than that of ST. Similarly, when the utility-line is above the X-axis, it means that an increase in elapsed time results in a positive utility compared to that of ST.
Figure 4: Change in residential location

Figure 5: Change in household composition

Figure 6: Change in work location

Figure 7: Change in study location
As mentioned before the variables X and D measure the influence of the change in state (from \(S_1\) to \(S_2\)) and estimated parameters of Z variables represent the time influence, the adaptation process. The result of experiencing the first structural lifecycle event, change in residential location, is a new residence in a new environment. This is the change in state and it affects behaviour of the person involved. Figure 4 represents the time influence of this change. The transport modes car and public transport (PT) both have a negative utility compared to slow transport (ST). A possible explanation for this effect can be the adaptation process; first a person takes the car to every destination and after a while he/she slowly learns about the new environment and probably knows where everything is in the direct environment. After that learning process he/she will adapt his or her behaviour to the
new circumstances and use slow transport more frequently. An increase in the number of household members results in a larger household. Again, the change in state is represented by the X variables (household of 1 person, household of 2 persons and household of 3 or more persons). Table 3 shows that an increase in household size results in an increase of utility for the car and a decrease (from 1 to 2 persons) or increase (from 2 to 3 or more persons) of utility for PT. The adaptation process for this change is shown in Figure 5. The utility of the car increases and the utility of PT decreases, when time since the experience of the event increases. This suggests that households only slowly change their behaviour towards the new equilibrium whereby the car is used more frequently compared to ST or PT. The time effect of a change in work locations is illustrated in Figure 6. The utility of the car and PT increases when time after experiencing a change in work location increases. Again, this suggests that people tend to stick to their (old) behaviour and only slowly adapt their behaviour to the new circumstances. When a change in study location occurred longer ago the utility of the car increases and the utility of PT decreases, as represented by Figure 7. A possible explanation is as follows: A student in the Netherlands receives a student PT pass to travel for free. After starting an education or change University, people may at first overreact to the change resulting in very frequent use of the PT. After a while they adapt and partly switch back to the use of the car. Figure 8 indicates that the utility-curve for the car is below the X-axis, meaning that an increase in time after experiencing a change in car availability results in a negative utility compared to that of ST. The utility-curve for PT is above the X-axis, which means a positive utility compared to ST. In this case a change in car availability means either an increase of the number of cars or a decrease of the number of car users. The effect of the change in state (number of cars or car users) on transport mode choice behaviour is given by the parameters of the X variables in Table 3. The graph of Figure 8 represents the time effect of this change. The negative effect of time after the event on car use may indicate that people overreact to the increase in car availability and, then, partly return back to slow mode as time passes. The adaptation process after a change in PT pass, in this case buying or receiving a Public Transport pass, is revealed in Figure 9. Time after the event has a positive effect on PT and a negative effect on the car compared to ST. The effect of the change in state (from no PT pass to student PT pass/PT subscription/benefit hour pass) on transport mode choice behaviour is given by the parameters of these X variables in Table 3. People possessing a PT pass use the PT more frequently and the car less frequently compared to ST. Thus, the time effect suggests that people only slowly adapt their behaviour to the new state. Figure 10 illustrates the adaptation process after experiencing an increase in household income. Time has a negative effect on both car and PT use. This suggests that people respond with an immediate big increase in car or PT use to the state change and after a while partly return to slow transport.

To conclude, all figures show significant temporal effects for the lifecycle events, after controlling for the other variables. This analysis suggests that there are two different ways in which people may react to a change: first people can overreact and after a while they (partially) return to their old behaviour and, second, the adaptation takes time and people slowly react on the change.
6 CONCLUSIONS AND DISCUSSION

The typical choice models capture statistical relationships between a dependent and a set of independent variables. As part of a wider study, which seeks to apply Bayesian decision networks in estimating direct and indirect effects of lifecycle events on transport mode choice, in this paper we have reported the results of a critical test of such an approach, which aimed at providing evidence that indeed temporal effects can be observed for such lifecycle events. The estimated parameters of a multinomial logit model support the suggested approach. All seven structural lifecycle events had significant temporal effects. Moreover, the effects are interpretable as particular patterns of adaptation. This provides evidence for the hypothesis that transport mode choice behaviour is dynamic.

These results imply that we will continue future research by estimating the Bayesian decision network. Although the current model was not meant as a model in its own right, it could be further elaborated. For example, we superimposed the log transformation in this application, but did not test whether this is actually the best transformation. In addition, we only took the most recent occurrence of events into account, but generalized event history models can be developed.

REFERENCES


