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# Modeling the behavioral determinants of travel behavior: An application of latent transition analysis

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ABSTRACT

This paper applies the relatively new method of latent class transition analysis to explore the notion that qualitative differences in travel behavior patterns are substantively meaningful and therefore relevant from explanatory point of view. For example, because the bicycle may function as an important access and egress mode, a car user who also (occasionally) uses the bicycle may be more likely to switch to a public transit profile than someone who only uses the car. Data from the Dutch mobility panel are used to inductively reveal travel behavior patterns and model transitions in these patterns over time. Additionally, the effects of seven exogenous variables, including two important life events (i.e. moving house and changing jobs), on cluster membership and the transition probabilities are assessed. The results show that multiple-mode users compared to single-mode users are more likely to switch from one behavioral profile to another. In addition, age, the residential environment, moving house and changing jobs have strong influences on the transition probabilities between the revealed behavioral patterns over time.



## 1. Introduction

A fruitful way to improve the predictive power of travel behavior models and to increase our general understanding of travel behavior lies in the use of panel data (repeated measures from the same individuals). Whereas cross-sectional data can only reveal inter-individual differences at one moment in time, panel data can reveal intra-individual changes over time. In effect, panel data are generally better suited to understand and predict (changes in) travel behavior.

In the transport domain (at least) two approaches to handling panel data can be discerned. Within the first, the variables under investigation are directly related over time. Typically, this involves the specification of a structural equation model with lagged stability relationships (between the same variables over time) and cross-lagged relationships (between different variables over time), see e.g. Golob and Meurs (1987); Golob (1990a). An overview of such studies can be found in a review paper of Golob (2003). While focused on different substantive questions, a general conclusion of this line of research is that past travel behavior is highly predictive of future travel behavior. Hence, travel behavior is found to be strongly inert.

The second and less adopted approach is based on the idea that, at each point in time, a finite set of clusters underlies the associations between the variables of interest and that change over time can be captured by modeling people's transitions between these clusters. Hence, in contrast to the first approach, no direct (lagged) relationships are estimated between the variables over time. Instead, (any) effects over time are assumed to be mediated by the relationship between the latent cluster variables, which are defined by the (same set of) observed variables at each point in time.

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In several papers Ma and Goulias (Ma and Goulias, 1997; Goulias, 1999) applied this approach to data from the Puget Sound transportation panel. Using cluster analysis in combination with a mixed Markov latent class analysis, Goulias (1999) identified various activity and travel behavior clusters and examined the cross-sectional and over-time relationships between them. The notion that travel behavior is strongly inert was confirmed by this line of research, as many people were observed to remain in their initial cluster. However, a substantial proportion was also observed to transition between (very) different activity/travel patterns over time, indicating that, from one year to the next, many people renegotiated their activity/travel patterns.

While this second approach to handling panel data can be extended in many interesting ways, these have, as far as the author is aware, not been explored in any follow-up study. Focusing on travel behavior, this paper aims to further explore the potential of this alternative approach and thereby illustrate its value to practitioners and researchers alike. Its specific contributions are threefold.

The first and main contribution of the present research lies in the recognition that qualitative differences between travel behavior patterns are substantively meaningful and therefore relevant from explanatory point of view. For example, it may be expected that a car user who also (occasionally) uses the bicycle is more likely to switch to a public transit profile than someone who only uses the car (because the bicycle may function as an important access and egress mode). Hence, being member of a particular travel behavior cluster not only increases the probability of remaining in the same cluster, but may also be associated with particular probabilities of moving to another cluster (different from other clusters). Several other mechanisms (discussed in the next section) may be identified why the probabilities of remaining in the same cluster or transitioning to another over time may be differently affected by initial cluster membership.

As a second contribution, this study explores the effects of several exogenous variables and events on both initial cluster membership and the transition probabilities. More specifically, this study will examine the role of several personal characteristics (gender, age, education level, employment status) and whether a person lives in an environment which is conducive of a car-, cycling- and/or public transport or not. These variables may be expected to influence the probabilities of belonging to a particular cluster (at one point in time) as well as the probabilities of remaining in the same cluster or transitioning to another cluster over time. The effects of two life events, namely moving house or changing jobs, will also be assessed. Such events represent possible 'windows of opportunity' to change one's travel routines (Bamberg, 2006) and may therefore also be assumed to influence the transition probabilities.

The third and final contribution of the present research is that it introduces latent class transition analysis to inductively reveal travel behavior patterns and model transitions in these patterns over time (Collins and Lanza, 2009). Cluster research in the transport domain generally relies on the ad-hoc and deterministic classification method of cluster analysis to identify homogenous clusters. Latent class analysis, on the other hand, is a model-based clustering technique which probabilistically assigns individuals to classes/clusters. This reduces misclassification biases. Additional benefits over cluster analysis are that statistical criteria can be used to judge the optimal number of classes and that variables of mixed-scale type can be accommodated (there is also no need to standardize variables) (Magidson and Vermunt, 2002). Finally, a major advantage in the context of the present research is that a latent class model can easily be extended to a panel data context, resulting in a latent class transition model (Collins and Lanza, 2009).

The data used for the analyses are derived from the Dutch mobility panel, a 10-wave survey among Dutch households conducted over a 5-year period (from March 1984 to March 1989). The structure and aim of this panel are described in Golob et al. (1985) and Meurs and Van Wissen (1987). While the Dutch mobility panel has been used to answer an extensive range of research questions (for an overview see Van Wissen and Meurs (1989)), none of the reported studies attempted to reveal latent travel behavior clusters or transitions in these clusters over time. The data are nonetheless well-suited for this purpose.

## 2. Theoretical background and expectations

Various mechanisms may be identified why membership of initial travel patterns will differently influence membership of future travel patterns. As mentioned in the introduction, some modes may complement each other in specific ways. Hence, since the bicycle may function as an important access and egress mode, it may be expected that a car user who also (occasionally) uses the bicycle may be more likely to switch to a public transit profile than someone who only uses the car.

A second mechanism relates to the notion that travelers who use only a single mode develop different expectations and attitudes toward various modes than multi-modal travelers (Diana and Mokhtarian, 2009). For example, it has been shown that car users generally have biased views toward possible public transit alternatives, overestimating their travel times and costs (Pedersen et al., 2011). Car users, who also use public transport, will not be affected by such biases. Hence, given that multi-modal travelers generally have more realistic perceptions on the available options and their attributes than single-mode travelers, they may also be expected to adjust their behavioral patterns more readily.

A third possible mechanism relates to the notion that multi-modality in itself can be regarded as a reflection of a trait representing the degree to which an individual deliberately chooses a mode (dependent on the context) as opposed to an individual who habitually (i.e. without deliberation) chooses a single particular mode (irrespective of the context). Hence, a person who uses multiple modes can be regarded as a deliberate choice traveler, whereas a person who exclusively uses a single mode is more likely to be a habitual traveler. Previous research, in this respect, has indeed shown that travelers can into be identified along, what can be termed, a rational-habitual dimension (Van Exel et al., 2011).

If behavioral patterns, i.e. single versus multi-modal, indeed reflect such a dimension, it may be expected that multi-modal travelers are more likely to switch between behavioral patterns, as they more readily react to (information about) changed environmental conditions (because they consciously evaluate new information). Based on a stated-choice experiment, Diana (2010), in this respect, found that multi-modal travel habits indeed influenced (stated) mode switching. People who were more familiar with multiple transport modes were found to have a greater switching propensity.

Summering the above, different mechanisms may account for the expectation that that membership of past travel patterns will differently influence membership of future travel patterns. Two expectations may be formulated on beforehand: (1) cycling aids in the transition from a car to a public transport profile and (2) multi-modal travelers are less inert than single-mode travelers. Given that it is still unknown which behavioral clusters will be found, it is difficult to formulate additional or more specific expectations. Hence, similar to the study of Goulias (1999), the present study is also partly explorative in nature.

## 3. Model conceptualization

To reveal travel behavior clusters appropriate indicators should be selected. In the Dutch mobility panel respondents were asked to register their trips and related characteristics (purpose, mode(s), duration and distance) for the period of a week. Multiple indicators of travel behavior were therefore available. However, given the self-reported nature of the data, which negatively affects the reliability of the duration and distance variables, the present study only relied on the (weekly) trip frequency with various modes.

Three transport modes were considered: car, public transport (train, bus, tram or metro) and the bicycle. Walking as a mode was excluded as it was previously found that the reporting of walking trips was severely biased (Golob and Meurs, 1986). In addition, the trip purposes are not specified as indicators (as this would lead to identifying activity patterns), but are included as *inactive* covariates. These variables are not assumed to actively contribute to the model but are included to additionally profile the clusters.

Within a latent class model the associations between the indicators are assumed to be the result of an underlying latent categorical variable (McCutcheon, 1987). Thus, in the present analysis, the variables representing weekly trip rates with the three modes are assumed to be independent conditional on the effects of the existing travel behavior clusters (a latent categorical variable). The measurement model in the top of Fig. 1 graphically reflects these assumptions.

The indicators in the present study, i.e. the trip rate variables, constitute count variables (i.e. variables with only zero or positive integer values). It is therefore naturally to assume that a mixture of Poisson distributions underlies these outcomes (Magidson and Vermunt, 2004). This means that for each class in the model(s) a different mean Poisson rate will be estimated.

To assess whether cluster membership is predictive of future cluster membership, the model is extended by including the same latent class variable at a second point in time, resulting in a latent class transition model. Since the latent class variable represents a nominal variable, a multinomial logit model is used to estimate the relationship between the consecutive latent class variables. The parameters of this part of the model can be translated to a matrix of transition probabilities. These

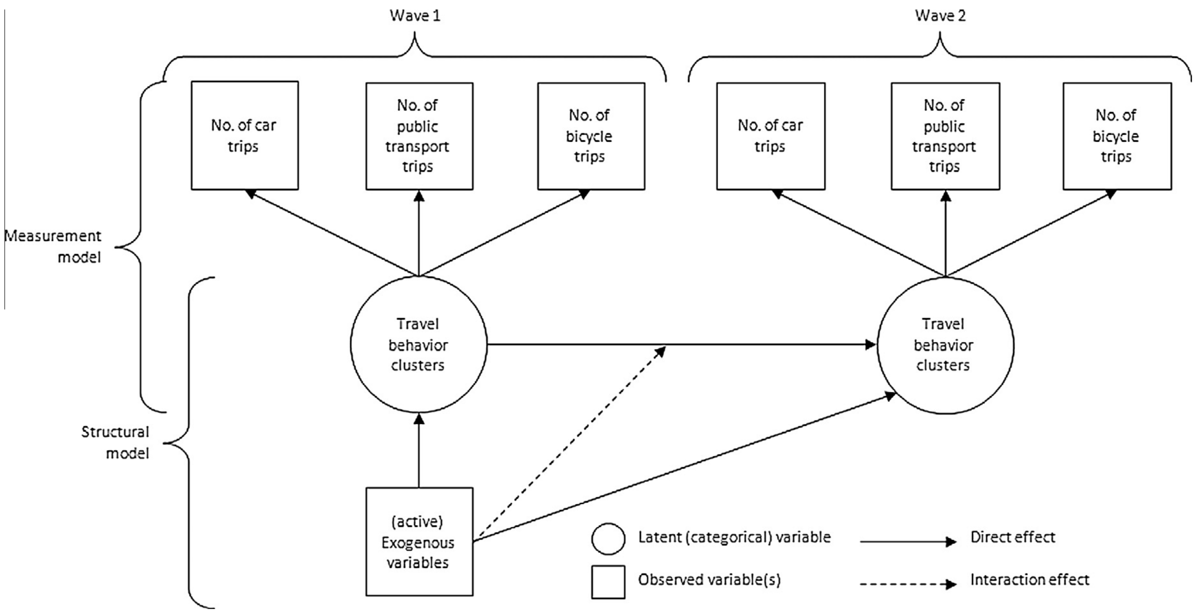


**Fig. 1.** Model conceptualization.

probabilities reflect latent class membership at the second point in time conditional on latent class membership at the first point in time.

The exogenous variables are assumed to influence both initial cluster membership as well as the transition probabilities between the latent classes over time. Again, multinomial logit models are used to estimate these relationships. In order to let the exogenous variables differently impact the transition probabilities between the first and second point in time, they are interacted with class membership at the first point in time. Hence, the effects of the exogenous variables are specific for each latent class. For example, some behavioral clusters may strongly be affected by a house move, while others are not affected by such an event. The interactions with initial cluster membership accommodate such differences. The structural model in the bottom of Fig. 1 graphically summarizes the above-stated hypothesizes.

## 4. Data and measures

The Dutch mobility panel covered a 5-year period (from 1984 to 1989) and consisted of 10 bi-annual waves (executed in March and September of each year). The first wave of this panel (March 1984) included 1764 households (3863 individuals) which were selected using a stratified design of different community types and life cycle/income groups. In consecutive waves the panel was continuously refreshed using information on the composition of the panel drop-outs. The survey is extensively described in Golob et al. (1985) and Meurs and Van Wissen (1987).

To exclude seasonal effects the sample used for the present study is formed based on the six March waves only. To form this sample a strategy of pooling wave-pairs is employed, similar to the approach described in Golob et al. (1986). Compared to using a pure stayer sample, a benefit of this strategy is that panel attrition bias is minimized as individuals that responded only (but at least) at two occasions are still included in the sample. Kitamura and Bovy (1987) and Golob and Meurs (1986) showed that panel drop-outs have lower mobility levels than the general population, which indicates that the panel is indeed at risk of suffering from such a bias. A related advantage of a pooled wave-pair sample, as indicated Golob (1990b), is that the observational frequency of rare events is increased. This advantage is particularly relevant in the context of the present study as the interest lies in uncovering the effects of moving house, which can be identified as a rare event. The strategy of pooling wave-pairs led to the selection of 15,517 wave-pairs and 5314 individuals.

A disadvantage of pooling available wave-pairs is that observations are no longer independent (since individuals with multiple wave-pairs are repeatedly included). There are several approaches to the analysis of complex (clustered) sample data. One is to compute standard errors and chi-square tests of model fit taking into account the effect of clustering. In this case, standard error are computed using a sandwich (Huber–White) estimator. This approach was adopted in the present study.

Table 1 presents the descriptive statistics on the variables used in the analyses at the two points in time. On average, people make seven trips by car, seven trips by bicycle and one trip by public transport per week. A problem of the Dutch mobility panel (which was also found in other panel studies) is respondents have a tendency to increasingly underreport their trips as the week progresses. Walking trips were found to be most affected by this bias (Golob and Meurs, 1986) and were (as explained in the previous section) therefore not considered in the analysis.

With respect to the other modes (bicycle, car and PT) no correction procedures were implemented, even though several have been proposed (Golob and Meurs, 1986). It was expected that any bias resulting from the underreporting of trips would primary affect the mean trip rates within the classes and only minimally affect the classification itself. For example, while the mean trip rate of somebody who only uses the bicycle would be underestimated, he or she would still be correctly identified as a (strict) bicycle user. Hence, this bias was not expected to interfere with the study's main objective of revealing and explaining transitions between behavioral patterns.

In total, seven (active) exogenous variables were considered in the analysis: sex, age, education level, occupational status, residential environmental and two dummy variables indicating respectively whether a person moved house or changed jobs in between the two waves.

With respect to residential environment three levels were identified: large city, mid-sized city and rural location. These are broadly representative for the existing environments in the Netherlands and strongly reflect the conduciveness of being able to travel with the three considered modes. Large cities (covering Rotterdam and Amsterdam) are most dense and have extensive public transport networks. As such, they are most supportive of traveling with public transport and generally unsupportive of car travel (as parking is difficult/expensive) and bicycle use (as most locations are within walking distance). Mid-sized city are less dense, but also have well-developed public transit networks. As such, all three modes are generally supported. Finally, rural locations, which are least dense and generally have fewer public transport options, are mainly supportive of car travel.

In principle, the model would be able to explore the effects of changes in the residential environment from the first wave to the second. However, in the wave-pairs in which a house move was observed ($N = 878$) a relatively small portion 16.5% ($N = 145$) moved to a different residential environment. Consequently, the observational frequencies of several changes were so small that it became impossible to consistently estimate their effects (e.g. there were only 14 wave-pairs in which people transitioned from a rural to one of the urban environments). Changes in the residential environment were therefore not explicitly modeled. To prevent that the effect of moving house would be conflated by (unmodeled) changes in the residential environment, wave-pairs with house-moves that involved a change in residential environment were excluded. In effect, the total sample was reduced to 15,372 wave-pairs and 5304 individuals.

**Table 1**
Descriptive statistics of the sample.

| Variable | | Wave 1 | Wave 2 |
|---|---|---|---|
| Trips by car | Mean (SD) | 7.3 (9.4) | 7.4 (9.3) |
| Trips by bicycle | Mean (SD) | 7.5 (8.6) | 7.2 (8.4) |
| Trips by public transport | Mean (SD) | 1.2 (3.1) | 1.2 (3.1) |
| *Active exogenous variables* | | | |
| Sex (%) | Male | 50 | 50 |
| | Female | 50 | 50 |
| Age | Mean (SD) | 38.1 (16.7) | 39.1 (16.7) |
| Education level (%) | High school/vocational education | 79 | 78 |
| | Higher education | 20 | 21 |
| Occupational status (%) | Works in government | 13 | 13 |
| | Works in company or self-employed | 30 | 31 |
| | Student | 20 | 18 |
| | Works in household | 23 | 23 |
| | Retiree | 7 | 8 |
| | Other | 7 | 7 |
| Residential environment (%) | Large city | 9 | 9 |
| | Mid-sized city (with train station) | 45 | 45 |
| | Rural location (no train station) | 46 | 46 |
| Moved house (%) | No | 93 | |
| | Yes | 6 | |
| Changed jobs (%) | No | 97 | |
| | Yes | 3 | |
| *Inactive covariates* | | | |
| Income (%) | 0–15,000 guilders | 52 | 49 |
| | 15,000–34,000 guilders | 37 | 36 |
| | >34,000 guilders | 6 | 8 |
| | Missing | 5 | 6 |
| Car license holder (%) | No | 38 | 36 |
| | Yes | 62 | 64 |
| Number of cars in household (%) | 0 | 19 | 19 |
| | 1 | 67 | 66 |
| | 2 or more | 14 | 15 |
| Train season-ticket holder (%) | No | 97 | 97 |
| | Yes | 3 | 3 |

Finally, four *inactive* covariates were also included in the analysis, namely income, having a car license, number of cars in the household and train season-ticket ownership. Since these factors cannot be assumed to be truly exogenous to travel behavior, they were not included as active predictors of latent class membership (as this would lead to problems with endogeneity). These variables were included, however, to additionally profile the travel behavior clusters.

## 5. Results

### 5.1. Cross-sectional analysis

To determine the optimal number of latent classes, models were first estimated for the two waves separately. Table 2 presents the model fit of consecutive models starting with a model with one class up to a model with ten classes. In these models the seven (active) exogenous variables were included as predictors of class membership. Because the effects of age were expected to be non-linear in parameters, it was itemized into 6 categories and included using five dummy variables. The software package Latent Gold was used to estimate the models. A desirable feature of this package in the context of the present research is that it can take into account inactive covariates (Vermunt and Magidson, 2005).

Various approaches exist to evaluate which number of latent classes is appropriate (Magidson and Vermunt, 2004). A common approach is the chi-square goodness-of-fit test (based on, for example, the likelihood-ratio chi-squared statistic $L^2$), in which the observed cell frequencies are compared with the model-implied cell frequencies for the various response patterns under the null-hypothesis that the difference is zero. However, if there are many possible response patterns, which is the case presently, many observed cell frequencies will be zero and the chi-squared statistic will no longer approximate a chi-square distribution. As can be observed from Table 2, based on the likelihood-ratio chi-squared statistic ($L^2$) all models would in fact be rejected.

**Table 2**
Model fit of the latent class models.

| $N$ = 5314 | Number of classes | LL | $L^2$ | $df$ | $p$-Value | % Reduction in $L^2$ ($H_0$) |
|---|---|---|---|---|---|---|
| Wave 1 | 1 | −250,242 | 367,702 | 15,514 | 0.00 | 1.00 |
| | 2 | −168,952 | 205,123 | 15,498 | 0.00 | 0.44 |
| | 3 | −142,135 | 151,488 | 15,482 | 0.00 | 0.59 |
| | 4 | −127,499 | 122,217 | 15,466 | 0.00 | 0.67 |
| | 5 | −118,661 | 104,541 | 15,450 | 0.00 | 0.72 |
| | 6 | −114,885 | 96,988 | 15,434 | 0.00 | 0.74 |
| | 7 | −111,327 | 89,873 | 15,418 | 0.00 | 0.76 |
| | 8 | −108,586 | 84,391 | 15,402 | 0.00 | 0.77 |
| | 9 | −106,337 | 79,893 | 15,386 | 0.00 | 0.78 |
| | 10 | −104,258 | 75,736 | 15,370 | 0.00 | 0.79 |
| Wave 2 | 1 | −246,110 | 360,301 | 15,514 | 0.00 | 1.00 |
| | 2 | −167,119 | 202,318 | 15,498 | 0.00 | 0.43 |
| | 3 | −140,621 | 149,323 | 15,482 | 0.00 | 0.57 |
| | 4 | −126,444 | 120,968 | 15,466 | 0.00 | 0.65 |
| | 5 | −117,560 | 103,201 | 15,450 | 0.00 | 0.70 |
| | 6 | −113,854 | 95,789 | 15,434 | 0.00 | 0.72 |
| | 7 | −110,405 | 88,890 | 15,418 | 0.00 | 0.74 |
| | 8 | −107,727 | 83,534 | 15,402 | 0.00 | 0.75 |
| | 9 | −105,556 | 79,192 | 15,386 | 0.00 | 0.76 |
| | 10 | −103,708 | 75,497 | 15,370 | 0.00 | 0.77 |

LL = log-likelihood.
$L^2$ = likelihood-ratio chi-squared statistic.
$df$ = degrees of freedom.

A less formal alternative approach relies on using the $L^2$ of the baseline model with 1 class ($H_0$) as a measure of the total association in the data (Magidson and Vermunt, 2004). By comparing the $L^2$ values of models with more than one class with this baseline value, the percent reduction in $L^2$ can be computed representing the percentage of the total association explained. Using this measure it can be observed that (in both waves) after 5 classes the reductions in $L^2$ become relatively small (<2%), suggesting that a 5-class solution adequately balances model fit and parsimony. Based on these results the 5-class solution is selected as optimal and will be interpreted in the following.

Table 3 presents the latent class profiles of the 5-class solution in the first wave. The Wald test statistics indicate that the three indicators are highly significant and thus strongly discriminate between the clusters. With the exception of the dummies variables for moving house and changing jobs, all of the exogenous variables (age, sex, education level, occupational status) also significantly affect initial cluster membership. The insignificant effects of moving house and changing jobs indicate that these events are independent of initial cluster membership. In other words, a person's initial travel behavior pattern is not predictive of whether (s)he will move house or change jobs. These events can therefore be considered as exogenous to travel behavior.

Overall, the five behavioral patterns are well interpretable. The first cluster (28% of the sample) represents a strict bicycle user. Subjects in this cluster make on average 17 trips by bicycle per week, make little use of the car (0.3 times per week) and occasionally use public transport (0.6 times per week). The cluster consists of relatively many young, low-income and (still) low educated people. Subjects in this cluster are mostly students (49%).

The second cluster is equal in size as the first (28%) and represents a strict car user. On average, subjects undertake over 18 trips per week by car and make little use of the bicycle (0.6 times per week) and public transport (0.2 times per week). Of all the clusters household car ownership is the highest in this one. Overall, the cluster consists of relatively many working males with high incomes.

Subjects in the third cluster (18% of the sample) are largely immobile traveling little with either of the three modes (termed from this point forward as the 'light traveler'). They reported, on average per week, one trip by car, (over) one trip by bicycle and half a trip by public transport. This cluster consists of relatively many females who work in the household. In addition, older and lower educated people with low incomes are strongly represented in this cluster. In part, the observed immobility in this cluster may be attributed to genuine causes, e.g. people who work in the household (or who are retired) do not have to travel to work. However, it is probably safe to conclude that this cluster is also most strongly affected by the underreporting of trips, which has been shown to increase with age and decrease with higher income and education levels (Van Wissen and Meurs, 1989).

The fourth cluster (17% of the sample) represents a joint car and bicycle user. Subjects in this cluster make, on average, 11 trips with each of these modes. Similar to the second cluster most people in this cluster have a job, yet, in contrast to the second cluster, slightly more people are employed by the government as opposed to being employed in a company. Finally, while people are better educated compared to the second cluster, they have, on average, lower incomes.

The final class (10% of the sample) represents a public transport user. Subjects in this cluster undertake on average over 9 trips by public transport (train, bus, tram or metro). Yet, they also travel with the two other modes making on average 5 trips

**Table 3**
Latent class profiles of the 5-class solution.

| | Class | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| Indicators | Class size (%) | 28 | 28 | 18 | 17 | 10 |
| Car trip rate (Wald = 4457, $p < 0.00$) | Mean | 0.3 | 18.4 | 0.8 | 10.9 | 1.1 |
| Bicycle trip rate (Wald = 4989, $p < 0.00$) | Mean | 17.0 | 0.6 | 1.4 | 11.2 | 5.1 |
| Public transport trip rate (Wald = 6776, $p < 0.00$) | Mean | 0.6 | 0.2 | 0.5 | 0.2 | 9.2 |
| *Active covariates* | | | | | | |
| Sex (%) | Male | 43 | 69 | 27 | 56 | 47 |
| (Wald = 242, $p < 0.00$) | Female | 57 | 31 | 73 | 44 | 53 |
| Age (%) | Mean | 28.8 | 41.1 | 47.5 | 40.1 | 35.4 |
| (Wald = 428, $p < 0.00$) | 12–17 | 36 | 0 | 5 | 0 | 17 |
| | 18–29 | 24 | 19 | 15 | 17 | 32 |
| | 30–39 | 18 | 33 | 17 | 38 | 16 |
| | 40–49 | 10 | 23 | 15 | 27 | 11 |
| | 50–64 | 9 | 17 | 25 | 13 | 12 |
| | >65 | 4 | 7 | 22 | 5 | 12 |
| Education level (%) | High school/vocational education | 84 | 75 | 91 | 70 | 77 |
| (Wald = 58, $p < 0.00$) | Higher education | 16 | 25 | 9 | 30 | 23 |
| Occupational status (%) | Works in government | 7 | 17 | 4 | 22 | 14 |
| (Wald = 714, $p < 0.00$) | Works in company or self-employed | 15 | 52 | 14 | 37 | 25 |
| | Student | 49 | 2 | 8 | 5 | 36 |
| | Works in household | 21 | 12 | 48 | 24 | 12 |
| | Retiree | 3 | 8 | 13 | 6 | 8 |
| | Other | 6 | 8 | 11 | 5 | 5 |
| Residential location (%) (Wald = 357, $p < 0.00$) | Large city | 4 | 8 | 13 | 4 | 26 |
| | Mid-sized city | 47 | 42 | 47 | 42 | 48 |
| | Rural location | 48 | 49 | 40 | 54 | 26 |
| Moved house (%) | No | 95 | 95 | 96 | 95 | 95 |
| (Wald = 4, $p = 0.61$) | Yes | 5 | 5 | 4 | 5 | 5 |
| Changed jobs (%) | No | 98 | 95 | 99 | 97 | 96 |
| (Wald = 6, $p = 0.23$) | Yes | 2 | 5 | 1 | 3 | 4 |
| *Inactive covariates* | | | | | | |
| Income (%) | 0–15,000 guilders | 75 | 24 | 66 | 41 | 57 |
| | 15,000–34,000 guilders | 17 | 59 | 24 | 48 | 33 |
| | >34,000 guilders | 1 | 12 | 2 | 8 | 5 |
| | Missing | 7 | 4 | 7 | 3 | 5 |
| Car license (%) | No | 74 | 2 | 58 | 3 | 67 |
| | Yes | 26 | 98 | 42 | 97 | 33 |
| Number of cars in household (%) | 0 | 31 | 1 | 27 | 3 | 47 |
| | 1 | 59 | 73 | 63 | 87 | 46 |
| | 2 or more | 10 | 26 | 10 | 10 | 7 |
| Train season ticket (%) | No | 98 | 99 | 98 | 99 | 80 |
| | Yes | 2 | 1 | 2 | 1 | 20 |
| *Car trip purposes* | | | | | | |
| Home | Mean | 0.1 | 7.4 | 0.4 | 4.4 | 0.4 |
| Work | Mean | 0.0 | 3.8 | 0.0 | 1.2 | 0.1 |
| School | Mean | 0.0 | 0.2 | 0.0 | 0.2 | 0.0 |
| Other | Mean | 0.1 | 7.1 | 0.4 | 5.2 | 0.5 |
| *Bicycle trip purposes* | | | | | | |
| Home | Mean | 7.4 | 0.2 | 0.6 | 4.9 | 2.3 |
| Work | Mean | 1.3 | 0.1 | 0.1 | 2.5 | 0.5 |
| School | Mean | 2.5 | 0.0 | 0.0 | 0.2 | 0.5 |
| Other | Mean | 5.8 | 0.3 | 0.7 | 3.6 | 1.8 |
| *Public transport trip purposes* | | | | | | |
| Home | Mean | 0.2 | 0.1 | 0.2 | 0.1 | 3.9 |
| Work | Mean | 0.0 | 0.1 | 0.0 | 0.0 | 1.7 |
| School | Mean | 0.1 | 0.0 | 0.0 | 0.0 | 1.5 |
| Other | Mean | 0.3 | 0.1 | 0.2 | 0.1 | 2.2 |

by bicycle and 1 trip by car per week. Thus, for public transport users the car and the bicycle are complimentary modes. As can be expected, the percentage of car license holders is smallest in this cluster and the percentage who have a train season ticket is the highest. While there are relatively many students in this cluster, other occupational statuses are also represented. Finally, in line with expectations, relatively many people in this cluster live in a large city.

The differences between the trip purpose variables between the 5 clusters are in line with the differences in occupational status: school trips are mostly undertaken in clusters 1 (strict bicycle user) and 5 (public transport user) and work-related trips in clusters 2 (strict car user) and 4 (joint car and bicycle user). It should be noted, however, that people with very different occupational statuses and activity patterns are also assigned to the same cluster. Hence, there is strong, but no one-on-one relationship, between activity and travel behavior patterns.

*5.2. Dynamic analysis*

Before presenting the results of the full model (Fig. 1) an additional step is to test whether the parameters related to the measurement model in each of the waves are equal, which would be indicative of so-called measurement invariance (Collins and Lanza, 2009). Establishing measurement invariance is needed to interpret the transitions between clusters (i.e. interpretation would be complicated if the clusters change over time). The normal procedure is to fit two models: one with parameters (related to the measurement model) estimated freely across the two waves and one with these parameters constrained to be equal. Since the latter model is nested in the first, a chi-square difference test (with degrees of freedom equal to the difference in degrees of freedom for these two models) can be used to test whether the parameters are equal or not. However, given the problems of the $L^2$ statistic with sparse data (see the discussion above), the present analysis relies on the Bayesian information criterion (BIC) to compare the two models. This measure weighs both model fit and parsimony and has been shown to perform well in the context of mixture modeling (Nylund et al., 2007). The model with lowest BIC value indicates the best fitting model. The results show that the fit of the constrained model is better (BIC = 482534) than the fit of the unconstrained model (BIC = 482585) which indeed supports invariance of the measurement models across the two waves.

Below the results of the full model (assuming measurement invariance) are presented. Since latent transition models cannot be estimated in Latent Gold, the software package Mplus is used for this purpose (Muthén and Muthén, 2010). The second parameterization described in Muthén and Asparouhov (2011) is used to specify the model. In the full model latent class membership in the second wave is assumed to be dependent on latent class membership in the first wave. In addition, the effects of seven exogenous variables on latent class membership in the second wave are assumed to be conditional on latent class membership in the first wave. To limit the number of parameters age is included as a (standardized) continuous variable here (as opposed to a nominal variable with 6 categories in the previous models), but to account for higher order effects a quadratic term of age is also included. In addition, occupational status is reduced from six categories to only two, namely employed and unemployed.

Table 4 presents the parameter estimates of the variables that predict latent class membership in the second wave. These estimates can be used to compute the matrix of transition probabilities for the sample as a whole (Table 5) as well as matrices for specific subgroups which result from combinations of different levels of the three included covariates (Table 6).

Table 4 shows that the intercepts for the wave-2 classes (in the first row) are all significantly negative, indicating that the reference class (the public transport cluster) has a positive effect on itself. Thus, if one is classified as a public transport user in one year, one has a large probability of staying a public transport user in the next. The slopes of the wave-1 classes on the wave-2 classes are all positive and comparatively large for the same respective wave-2 classes, indicating that, also for the four other clusters, people have the highest probability to stay in the same cluster.

The matrix of transition probabilities (Table 5) indeed shows that the greatest probabilities are on the diagonal. From this matrix it can be concluded that strict bicycle users and strict car users are particularly inert with respective probabilities of 0.75 and 0.81 of staying in the same class. For the light traveler, the joint car and bicycle user and public transport user these probabilities are 0.68, 0.66 and 0.67, respectively. These results fit with expectation that people who are familiar with multiple modes are more prone to switch modes. Still, also the multiple-mode users have large probabilities of staying in same respective clusters (>0.65).

The off-diagonal elements in the matrix of transition probabilities reflect the probabilities of transitioning from a particular class in wave 1 to a different class in wave 2. These probabilities are of substantive and practical interest. For example, only 1% of the strict car users transitions to a public transport profile (over the period of a year), while 9% transitions to the joint car and bicycle cluster. The promotion of the bicycle (as opposed to public means of transport) is therefore much more effective for this group. Joint car and bicycle users, on the other hand, run a high 'risk' of becoming strict car users (18%). Contrary to the expectation formulated in the introduction, they have an equally small chance (1%) of transitioning to the public transport profile. Thus, for the population as a whole, car users who also use the bicycle do not have a higher probability of transitioning to the public transport cluster than strict car users. Finally, public transport users have a much smaller risk of becoming a strict car user (8%). Instead, they have a relatively high probability of becoming a strict bicycle user (13%).

Turning to the effects of the covariates it can be observed that 79 estimates are significant at the 5% level, indicating that the transition probabilities vary significantly across different levels of the covariates. Judged by the t-values, age, residential environment, moving house and changing jobs have the largest effects on the transition probabilities. These are discussed below.

The linear effects of age show that, in all clusters, the probabilities of moving to the light traveler profile increase with age, which corresponds with the results of the cross-sectional analysis. Among joint car and bicycle users increasing age increases the probability of transitioning to one of the first four clusters and thereby lowers the probability of transitioning to the public transport profile. This means that younger people in the joint car and bicycle cluster (in line with the expectation formulated in Section 2) have a higher probability of moving to the public transport profile. With increasing age people in the public transport profile are less likely to switch to the strict bicycle cluster and more likely to switch to the strict car cluster.

**Table 4**
Parameter estimates of wave-2 latent class membership.

| | | Wave 2 cluster membership | | | | |
|---|---|---|---|---|---|---|
| | Parameter | SB | SC | LT | JCB | PT (ref.) |
| | Intercept | **−0.67 (−2.23)** | **−1.10 (−3.02)** | **−1.70 (−5.16)** | **−2.24 (−3.69)** | 0 |
| Strict bicycle user (wave 1) | Slope | **3.68 (9.39)** | **1.75 (3.47)** | **2.91 (7.28)** | **3.63 (5.45)** | 0 |
| | Female (ref. = male) | −0.23 (−1.75) | **−1.13 (−4.49)** | −0.11 (−0.63) | −0.30 (−1.61) | 0 |
| | Age (standardized) | 0.21 (2.82) | −0.38 (−1.10) | **0.75 (8.55)** | **0.35 (2.86)** | 0 |
| | Age$^2$ | −0.12 (−1.61) | **−1.42 (−4.87)** | **−0.36 (−3.84)** | **−0.91 (−7.26)** | 0 |
| | Higher education (ref. = lower) | −0.36 (−1.93) | −0.63 (−1.92) | **−0.57 (−2.36)** | −0.05 (−0.25) | 0 |
| | Employed (ref. = unemployed) | 0.22 (1.08) | **1.21 (3.44)** | 0.11 (0.45) | **0.89 (3.72)** | 0 |
| | Large city (ref. = rural) | **−1.48 (−7.18)** | **−1.54 (−3.32)** | **−1.44 (−4.16)** | **−1.93 (−5.42)** | 0 |
| | Mid-sized city (ref. = rural) | 0.00 (0.01) | **−0.55 (−2.16)** | −0.05 (−0.31) | **−0.42 (−2.29)** | 0 |
| | Moved house (ref. = no) | 0.01 (0.05) | **0.95 (2.35)** | 0.38 (1.05) | 0.48 (1.33) | 0 |
| | Changed jobs (ref. = no) | **−1.51 (−3.74)** | −0.79 (−1.42) | −0.90 (−1.62) | **−1.30 (−2.58)** | 0 |
| Strict car user (wave 1) | Slope | 0.92 (1.43) | **6.14 (10.29)** | **4.25 (8.00)** | **5.19 (7.11)** | 0 |
| | Female (ref. = male) | 0.86 (1.89) | −0.09 (−0.33) | **0.62 (2.02)** | 0.33 (1.12) | 0 |
| | Age (standardized) | −0.17 (−0.42) | 0.42 (1.83) | **0.50 (1.97)** | 0.28 (1.14) | 0 |
| | Age$^2$ | 0.13 (0.38) | −0.08 (−0.33) | 0.07 (0.27) | −0.11 (−0.46) | 0 |
| | Higher education (ref. = lower) | 0.42 (0.81) | 0.56 (1.64) | 0.15 (0.41) | 0.56 (1.55) | 0 |
| | Employed (ref. = unemployed) | 0.17 (0.33) | 0.41 (1.34) | 0.02 (0.06) | 0.13 (0.39) | 0 |
| | Large city (ref. = rural) | **−3.36 (−2.99)** | **−2.24 (−5.21)** | **−1.96 (−4.24)** | **−2.46 (−5.11)** | 0 |
| | Mid−sized city (ref. = rural) | **−1.28 (−2.60)** | **−1.45 (−3.95)** | **−1.36 (−3.56)** | **−1.37 (−3.64)** | 0 |
| | Moved house (ref. = no) | −0.25 (−0.43) | **−1.18 (−3.05)** | **−1.07 (−2.33)** | −0.83 (−1.94) | 0 |
| | Changed jobs (ref. = no) | −1.94 (−1.75) | **−1.27 (−3.08)** | **−1.33 (−2.58)** | **−1.36 (−2.99)** | 0 |
| Light traveler (wave 1) | Slope | **2.71 (5.79)** | **3.73 (7.13)** | **4.93 (9.45)** | **4.02 (5.51)** | 0 |
| | Female (ref. = male) | 0.00 (0.01) | **−0.80 (−2.87)** | 0.35 (1.39) | −0.49 (−1.52) | 0 |
| | Age (standardized) | −0.11 (−0.86) | **0.68 (5.01)** | **0.83 (6.73)** | **0.66 (3.89)** | 0 |
| | Age$^2$ | −0.12 (−1.39) | **−0.56 (−5.72)** | **−0.26 (−3.38)** | **−0.72 (−4.98)** | 0 |
| | Higher education (ref. = lower) | **−0.81 (−2.58)** | **−0.83 (−2.58)** | **−1.16 (−4.25)** | −0.10 (−0.28) | 0 |
| | Employed (ref. = unemployed) | −0.35 (−1.13) | **0.61 (1.98)** | −0.09 (−0.33) | 0.58 (1.64) | 0 |
| | Large city (ref. = rural) | **−1.62 (−4.50)** | **−1.23 (−3.47)** | **−1.04 (−3.41)** | **−3.03 (−4.54)** | 0 |
| | Mid−sized city (ref. = rural) | −0.46 (−1.62) | **−0.84 (−2.79)** | −0.40 (−1.49) | **−1.45 (−4.18)** | 0 |
| | Moved house (ref. = no) | 0.11 (0.19) | 0.50 (0.86) | −0.02 (−0.05) | −0.06 (−0.08) | 0 |
| | Changed jobs (ref. = no) | −0.64 (−0.76) | 0.14 (0.20) | −0.66 (−0.97) | −1.44 (−1.18) | 0 |
| Joint car and bicycle user (wave 1) | Slope | **3.55 (4.89)** | **5.05 (6.74)** | 3.85 (5.03) | **7.44 (7.66)** | 0 |
| | Female (ref. = male) | 0.79 (1.94) | −0.10 (−0.27) | **0.90 (2.02)** | 0.15 (0.40) | 0 |
| | Age (standardized) | 0.35 (1.23) | **0.61 (2.26)** | **0.96 (3.13)** | **0.89 (3.37)** | 0 |
| | Age$^2$ | −0.08 (−0.30) | −0.29 (−1.09) | −0.21 (−0.75) | −0.44 (−1.70) | 0 |
| | Higher education (ref. = lower) | −0.64 (−1.70) | **−0.80 (−2.21)** | −0.81 (−1.89) | −0.53 (−1.52) | 0 |
| | Employed (ref. = unemployed) | 0.00 (−0.00) | 0.08 (0.20) | −0.12 (−0.27) | 0.21 (0.53) | 0 |
| | Large city (ref. = rural) | **−2.16 (−3.15)** | **−1.82 (−2.89)** | **−2.38 (−3.02)** | **−2.39 (−3.89)** | 0 |
| | Mid-sized city (ref. = rural) | **−1.32 (−2.92)** | **−1.10 (−2.49)** | **−1.49 (−3.10)** | **−1.34 (−3.07)** | 0 |
| | Moved house (ref. = no) | −0.28 (−0.46) | −0.47 (−0.78) | 0.07 (0.10) | −0.63 (−1.07) | 0 |
| | Changed jobs (ref. = no) | **−1.78 (−2.51)** | −0.51 (−0.96) | −0.70 (−0.96) | **−1.53 (−2.82)** | 0 |
| Public transport user (wave 1) (ref.) | Slope | 0 | 0 | 0 | 0 | 0 |
| | Female (ref. = male) | −0.12 (−0.72) | −0.14 (−0.68) | **0.43 (2.15)** | −0.03 (−0.10) | 0 |
| | Age (standardized) | **−0.25 (−2.36)** | 0.01 (0.09) | **0.28 (2.75)** | −0.20 (−0.85) | 0 |
| | Age$^2$ | **−0.37 (−3.20)** | **−0.68 (−3.31)** | −0.17 (−1.76) | **−0.68 (−2.70)** | 0 |
| | Higher education (ref. = lower) | −0.12 (−0.54) | −0.02 (−0.07) | −0.27 (−1.04) | **0.68 (2.02)** | 0 |
| | Employed (ref. = unemployed) | **−1.24 (−4.81)** | 0.41 (1.46) | −0.28 (−1.01) | −0.58 (−1.46) | 0 |
| | Large city (ref. = rural) | **−0.77 (−2.92)** | **−0.97 (−3.35)** | 0.00 (0.02) | **−1.24 (−2.10)** | 0 |
| | Mid-sized city (ref. = rural) | −0.12 (−0.60) | **−0.82 (−3.26)** | −0.21 (−0.83) | −0.08 (−0.19) | 0 |
| | Moved house (ref. = no) | **0.95 (3.15)** | 0.69 (1.75) | 0.22 (0.51) | 0.51 (0.79) | 0 |
| | Changed jobs (ref. = no) | 0.60 (1.33) | 0.43 (1.15) | −0.37 (−0.60) | 0.07 (0.08) | 0 |

*T*-values are presented in the parentheses.
Estimates in bold are significant at $p < 0.05$.

Thus, when public transport users ‘retire’ from their profile at older age they are relatively more likely to resort to the strict car cluster.

The (significant) quadratic effects of age are all negative, indicating that for the respective cluster-pairs the transition probability is (relatively) larger for middle-aged people (around the mean age of 37 years) and smaller for people who are younger or older. For example, middle-aged bicycle users are more likely to transition to the strict car cluster or joint car and bicycle cluster than young or old age bicycle users. The same effects can be observed for public transport users. Off course, since the linear effects of age are also significant for these cluster-pairs, the total effects are combinations of the linear and quadratic effects2.

**Table 5**
Matrix of transition probabilities.

| N = 5341 | Wave 2 | | | | |
|---|---|---|---|---|---|
| Wave 1 | SB | SC | LT | JCB | PT |
| Strict bicycle user | 0.75 | 0.03 | 0.08 | 0.07 | 0.07 |
| Strict car user | 0.01 | 0.81 | 0.08 | 0.09 | 0.01 |
| Light traveler | 0.13 | 0.12 | 0.68 | 0.04 | 0.04 |
| Joint car and bicycle user | 0.10 | 0.18 | 0.04 | 0.66 | 0.01 |
| Public transport user | 0.13 | 0.08 | 0.10 | 0.03 | 0.67 |

**Table 6**
Matrices of transition probabilities for different subgroups.

| | | | Wave 2 | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Mean age = 21 (mean − SD) | | | | | | | | | | Mean age = 55 (mean + SD) | | | | | | | | | |
| | | | Rural location | | | | | Large city | | | | | Rural location | | | | | Large city | | | | |
| Wave 1 | | | SB | SC | LT | JCB | PT | SB | SC | LT | JCB | PT | SB | SC | LT | JCB | PT | SB | SC | LT | JCB | PT |
| Did not move house | Did not change jobs | SB | 0.77 | 0.03 | 0.06 | 0.08 | 0.06 | 0.66 | 0.03 | 0.05 | 0.05 | 0.22 | 0.70 | 0.01 | 0.15 | 0.10 | 0.03 | 0.64 | 0.01 | 0.15 | 0.06 | 0.14 |
| | | SC | 0.02 | 0.78 | 0.08 | 0.12 | 0.01 | 0.01 | 0.75 | 0.10 | 0.09 | 0.06 | 0.01 | 0.81 | 0.09 | 0.09 | 0.00 | 0.00 | 0.78 | 0.12 | 0.07 | 0.03 |
| | | LT | 0.30 | 0.16 | 0.41 | 0.08 | 0.05 | 0.19 | 0.15 | 0.47 | 0.01 | 0.18 | 0.07 | 0.18 | 0.64 | 0.09 | 0.02 | 0.04 | 0.17 | 0.72 | 0.01 | 0.05 |
| | | JCB | 0.17 | 0.20 | 0.04 | 0.58 | 0.01 | 0.16 | 0.27 | 0.03 | 0.44 | 0.10 | 0.07 | 0.14 | 0.06 | 0.72 | 0.00 | 0.08 | 0.22 | 0.05 | 0.63 | 0.02 |
| | | PT | 0.15 | 0.11 | 0.08 | 0.04 | 0.62 | 0.08 | 0.05 | 0.09 | 0.01 | 0.76 | 0.09 | 0.12 | 0.13 | 0.02 | 0.63 | 0.05 | 0.05 | 0.16 | 0.01 | 0.73 |
| | Did change jobs | SB | 0.59 | 0.05 | 0.08 | 0.08 | 0.20 | 0.35 | 0.03 | 0.05 | 0.03 | 0.54 | 0.55 | 0.01 | 0.22 | 0.10 | 0.12 | 0.39 | 0.01 | 0.16 | 0.04 | 0.39 |
| | | SC | 0.01 | 0.78 | 0.07 | 0.11 | 0.02 | 0.00 | 0.66 | 0.08 | 0.07 | 0.18 | 0.00 | 0.81 | 0.09 | 0.08 | 0.01 | 0.00 | 0.74 | 0.11 | 0.06 | 0.09 |
| | | LT | 0.25 | 0.29 | 0.34 | 0.03 | 0.09 | 0.15 | 0.25 | 0.35 | 0.00 | 0.25 | 0.06 | 0.35 | 0.53 | 0.03 | 0.03 | 0.04 | 0.31 | 0.57 | 0.00 | 0.08 |
| | | JCB | 0.10 | 0.40 | 0.06 | 0.41 | 0.04 | 0.07 | 0.41 | 0.04 | 0.24 | 0.24 | 0.04 | 0.30 | 0.10 | 0.55 | 0.01 | 0.04 | 0.40 | 0.07 | 0.41 | 0.07 |
| | | PT | 0.24 | 0.15 | 0.04 | 0.03 | 0.53 | 0.14 | 0.08 | 0.06 | 0.01 | 0.71 | 0.15 | 0.17 | 0.08 | 0.02 | 0.57 | 0.09 | 0.08 | 0.11 | 0.01 | 0.72 |
| Moved house | Did not change jobs | SB | 0.68 | 0.08 | 0.07 | 0.12 | 0.05 | 0.60 | 0.06 | 0.07 | 0.07 | 0.20 | 0.61 | 0.02 | 0.20 | 0.14 | 0.03 | 0.58 | 0.02 | 0.19 | 0.08 | 0.13 |
| | | SC | 0.05 | 0.70 | 0.08 | 0.15 | 0.02 | 0.01 | 0.63 | 0.09 | 0.11 | 0.16 | 0.02 | 0.76 | 0.10 | 0.12 | 0.01 | 0.00 | 0.71 | 0.12 | 0.09 | 0.08 |
| | | LT | 0.30 | 0.23 | 0.36 | 0.07 | 0.05 | 0.19 | 0.22 | 0.41 | 0.01 | 0.16 | 0.07 | 0.27 | 0.56 | 0.07 | 0.01 | 0.05 | 0.26 | 0.64 | 0.01 | 0.05 |
| | | JCB | 0.21 | 0.20 | 0.07 | 0.50 | 0.02 | 0.19 | 0.26 | 0.05 | 0.36 | 0.15 | 0.09 | 0.15 | 0.10 | 0.65 | 0.00 | 0.10 | 0.23 | 0.09 | 0.55 | 0.04 |
| | | PT | 0.28 | 0.16 | 0.07 | 0.04 | 0.45 | 0.18 | 0.09 | 0.09 | 0.02 | 0.62 | 0.18 | 0.18 | 0.13 | 0.03 | 0.48 | 0.11 | 0.09 | 0.17 | 0.01 | 0.62 |
| | Did change jobs | SB | 0.51 | 0.11 | 0.10 | 0.11 | 0.17 | 0.33 | 0.07 | 0.07 | 0.04 | 0.49 | 0.46 | 0.03 | 0.27 | 0.13 | 0.10 | 0.35 | 0.02 | 0.22 | 0.06 | 0.35 |
| | | SC | 0.02 | 0.70 | 0.07 | 0.14 | 0.07 | 0.01 | 0.45 | 0.06 | 0.07 | 0.41 | 0.01 | 0.76 | 0.09 | 0.11 | 0.03 | 0.00 | 0.60 | 0.10 | 0.07 | 0.23 |
| | | LT | 0.23 | 0.40 | 0.27 | 0.02 | 0.07 | 0.14 | 0.35 | 0.29 | 0.00 | 0.22 | 0.06 | 0.47 | 0.43 | 0.03 | 0.02 | 0.03 | 0.43 | 0.47 | 0.00 | 0.07 |
| | | JCB | 0.11 | 0.39 | 0.11 | 0.34 | 0.06 | 0.07 | 0.36 | 0.06 | 0.18 | 0.34 | 0.05 | 0.30 | 0.17 | 0.47 | 0.01 | 0.05 | 0.39 | 0.12 | 0.34 | 0.11 |
| | | PT | 0.39 | 0.20 | 0.04 | 0.04 | 0.34 | 0.28 | 0.12 | 0.06 | 0.02 | 0.53 | 0.27 | 0.23 | 0.07 | 0.03 | 0.39 | 0.18 | 0.13 | 0.11 | 0.01 | 0.57 |

The residential environment also has a strong influence on the transition probabilities. In all clusters, living in a large city strongly increases the probabilities of transitioning to (or remaining in) the public transport profile. The effects of living in a mid-sized city are similar albeit smaller in size and not always significant. For example, strict bicycle users in a mid-sized city are not additionally drawn to the public transport profile.

The effects of moving house are more differentiated across the various clusters. Light travelers and joint car and bicycle users are not significantly affected by a house move. Strict bicycle users, on the other hand, have an increased probability of moving to the strict car cluster. For strict car users the probability of transitioning to the public transport profile increases. Finally and closing the circle, public transport users have an increased probability of moving to the strict bicycle cluster. In sum, depending on initial cluster membership, moving house differently affects the transition probabilities. These results suggest that moving house indeed represents a window of opportunity to accommodate (latent) preferences.

Finally, changing jobs also significantly affects the transition probabilities. While light travelers and public transport users are not significantly affected, the other three clusters have an increased tendency of transitioning to the public transport profile. Hence, a job change will generally increase the share of public transport users, which is an interesting but not very intuitive result. A general conclusion is that (similar to a house move) a job change necessitates people to reevaluate their travel patterns.

The model parameters (Table 4) can be used to compute the transition probabilities for various subgroups. Table 6 presents the transitions probabilities which result from the combinations of two age levels (minus and plus one standard deviation (SD = 16.7) of the mean age of 38.1), living in a large city versus a rural location, moving house (no/yes) and changing jobs (no/yes) (thus $2^4 = 16$ combinations), while holding the other exogenous variables (sex, education level and employment status) at their mean values.

It can be observed that young people are generally less inert than older people. Young people are also more likely to switch from one of the car clusters to the bicycle or public transport cluster. Living in a large city (as opposed to a rural location) strongly increases the probabilities of transitioning to or remaining in the public transport profile. These effects are further strengthened by moving house and changing jobs. When moving house or changing jobs, public transport users, on the other hand, have an increased probability of moving to the bicycle cluster. In general, the events of moving house and changing jobs decrease the probability of staying in the same cluster and increase the probability of transitioning. This means that these events generally force people to reevaluate their travel behavior.

Finally, with respect to the expectation formulated in Section 2, it can be observed that only in particular subgroups do joint car and bicycle users have a higher probability than strict car users of transitioning to a public transport profile. For example, among young people who live in a large city. In sum, only for particular subgroups does the bicycle represent a relevant mode to aid in the transition from the car to public transport.

## 6. Conclusions and directions for future research

In this study a latent class transition model is estimated to explore the notion that qualitative differences in travel behavior patterns are substantively meaningful and therefore relevant from explanatory point of view. The results confirm the expectation that multiple-mode users compared to single-mode users are more likely to switch from one behavioral profile to another. In addition, the findings support the idea that the probabilities of remaining in the same behavioral patterns or transitioning to another over time are differently affected by initial cluster membership. However, the notion that joint car and bicycle users are more prone than strict car users to switch to a public transport profile could only be supported for particular subgroups.

Among the exogenous variables, age, the residential environment, moving house and changing jobs were found to have strong influences on the transition probabilities. In general, younger people, people who moved house and people who changed jobs were found to have lower probabilities of staying in the same cluster and higher probabilities of transitioning. Additionally, the effects of moving house and changing jobs were found to depend on initial cluster membership, suggesting that these events represent windows of opportunity to accommodate (latent) preferences.

Overall, it can be concluded that the latent class transition model provides an effective framework to explore changes in travel behavior over time. A general drawback of the latent transition model, however, is that it requires a large sample, especially if the effects of rare events are modeled. Since people's travel behavior is generally inert (thus with high probabilities on the diagonal) much observations are necessary to sufficiently fill the off-diagonal cells of the transition matrix. The strategy of pooling wave-pairs has proven (partly) effective to satisfy the sample size requirement. Still, many effects on the transition probabilities are insignificant, which may be due to the low number of observations in particular cells in the transition matrix.

A specific drawback of the present study relates to the used data which its relatively old (on average 25 years). Overall, the observed effects may be expected to exist for a population of today, but specific effects, such as those related to gender, will likely be different. This is due to the fact that over the past decades men and women have become more equal in terms of occupational status and activity patterns. Even though panel data are not often gathered to study travel behavior, new data would be necessary to draw firm conclusions with respect to the current (Dutch) population.

Regarding options for future research, the latent transition model could be applied to test more theory-driven models of behavioral change in the context of travel behavior. An example would be the transtheoretical model of Prochaska and DiClemente (1984), which has been applied in health psychology to study problem behaviors such as smoking and substance use (Prochaska et al., 1994). This theory assumes that behavioral change involves several stages which people have to pass before an undesirable behavior is terminated. The theory has previously been operationalized in a latent transition framework by Velicer et al. (1996) to study smoking cessation. Gatersleben and Appleton (2007) recently also applied the theory in a travel behavior context (to study bicycle use). This study relied on cross-sectional data, however, and therefore did not reveal the transition behavior between different stages of change. This would pose an interesting direction for future research.

Several other research directions are also suggested by this research. One would be to use other indicators to reveal the travel behavior clusters (e.g. travel distances or durations with various modes). Arguably the time spend with various modes determines the familiarity with that mode and therefore needs to be taken into consideration. Secondly, in addition to travel behavior clusters, activity clusters could be identified and their relationship with the travel behavior clusters explored. It could then be assessed how transitions in activity patterns influence transitions in travel behavior patterns. A third direction would be to study additional interactions. For example, it may be expected that the transition behavior of women who move house is different from the transition behavior of men who move house. To study such interactions, however, would require even larger samples. Finally, the model could be expanded to include additional waves (three or more). It would then also be possible to conceptualize a second-order latent class variable which can be assumed to explain the associations between the first-order latent class variables. A typical conceptualization in this context is the mover-stayer model (Langeheine and Van de Pol, 1994). All in all, the latent class transition framework provides many interesting avenues to further explore the cluster-based approach to panel data.

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