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Revealing transition patterns between mono- and multimodal travel patterns over time: A mover-stayer model

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Recent empirical evidence suggests that travellers are becoming increasingly multimodal. Coinciding with this trend, a growing interest can be observed in the transport literature to study the concept of multimodality. Most studies, in this regard, have focused on assessing the determinants of multimodal travel behaviour. While it is interesting to know which factors, at a certain moment in time, affect the membership of mono/multimodal travel patterns, one general omission in the current literature relates to the questions how and why travellers switch between the mono/multimodal travel patterns over time. This study aims to fill this knowledge gap. To this end, a mixture latent Markov model is specified and estimated using data from the German mobility panel. Our mixture latent Markov models consist of latent travel patterns as well as latent mobility styles. To acquire insights on changes in travel behaviour various model specifications are tested. The travel data is best explained by a model consisting of five latent travel patterns and three mobility styles. The five travel patterns are can be conceived as (1) strict car users, (2) public transport and occasional car users, (3) car passengers, (4) car and bicycle users and (5) bicycle and occasional public transport users, and the three underlying mobility styles are identified as (1) habitual travellers, who stay in their respective pattern for three consecutive years, (2) car (in)dependent choice travellers, who switch within car and non-car patterns, and (3) car users with an alternative mode preference, who switch between car and non-car patterns. Overall, it is concluded that mixture latent Markov models are effective to reveal (heterogeneity in) transition patterns.

Keywords: *multimodality, mobility panel data, mixture latent Markov model.*

1. Introduction

Recent empirical evidence suggests that travellers in several industrialized countries are becoming increasingly multimodal (Kuhnimhof et al., 2011; Kuhnimhof et al., 2012). Coinciding with this trend, a growing interest can observed in the transport literature to study the concept of multimodality (Buehler and Hamre, 2014; Diana and Mokhtarian, 2009). Most studies, in this regard, have focused on assessing the determinants of multimodal travel behaviour, such as age, education level, car availability, life stage, etc. (for an overview, see Buehler and Hamre, 2014). While it is relevant to know which structural factors, at a certain moment in time, affect the membership of mono/multimodal travel patterns, these studies do not provide insights on how and why travellers switch between the mono/multimodal travel patterns over time.

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Two papers by Ma and Goulias (1997) and Goulias (1999) are among the few that have explicitly addressed this knowledge gap. Using cluster analysis on data from the Puget Sound transportation panel, Ma and Goulias (1997) revealed four homogenous travel behaviour patterns that differ in their degree of mono-/multimodality.[3] By establishing the same behavioural clusters for the first two waves of the panel, they were able to explore travellers' (year-to-year) transitions between the travel patterns. A key finding of their study was that, while travel behaviour was generally found to be inert with many persons staying in their respective travel pattern, relatively many were also found to transition between (very) different patterns over time.

In a second follow-up paper, Goulias (1999) extended this analysis by considering four waves of the Puget Sound transportation panel (in a pairwise manner) and by accounting for two sources of heterogeneity; the first arising from the notion that there may be measurement errors in the behavioural clusters and the second from the notion that there may be unobserved groups of travellers who transition in different ways between the behavioural clusters. Such latent subgroups are typically referred to as Markov chains. To simultaneously account for these sources of heterogeneity as well as the year-to-year state dependency, Goulias (1999) estimated (a series of) mixed Markov latent class models. While evidence in favour of the first source of heterogeneity was found (the relationships between the observed behavioural clusters and latent states were found to be imperfect), Goulias (1999) found no evidence of unobserved heterogeneity in the transition probabilities, i.e. the data favoured a model with only one Markov chain.

More recently, Kroesen (2014) followed-up on the models developed by Goulias (1999) and estimated a latent class transition model based on data from the Dutch mobility panel. Conceptually, he enriched the approach by putting forth the idea that qualitative differences in the travel behaviour patterns are substantively meaningful and therefore relevant from explanatory point of view. In line with this idea, he found, for example, that persons belonging to multi-modal travel patterns more readily switch between behavioural patterns than those belonging to monomodal travel patterns. Methodologically, he extended the model of Goulias (1999) in two ways: (1) by incorporating multiple indicators of travel behaviour directly in the measurement (i.e. latent class) model and (2) by including covariates to predict initial cluster membership and the transition probabilities. With respect to the latter extension, he found, for example, that life events, such as moving house and changing jobs, generally lead to higher probabilities that a person transitions from one pattern to another (rather than staying in the same cluster), suggesting that these events necessitate travellers to reconsider their travel routines.

This paper aims to further advance the line of research set out by Ma and Goulias (1997) and Goulias (1999) and recently continued by Kroesen (2014), using data from a newer source, namely the German mobility panel (MOP). Similar to the model of Goulias (1999), the main objective of this study is to reveal heterogeneity in the probabilities associated with the travellers' transitions between the travel patterns over-time. Hence, an attempt is thus made to uncover (latent) groups with similar transition probabilities/Markov chains. In addition, similar to the approach of Kroesen (2014), the latent travel patterns will be measured by including multiple indicators of travel behaviour directly into the model. This means that subjects are probabilistically assigned to clusters instead of deterministically (as is the case in cluster analysis), which reduces misclassification biases. In summary, the model presented in this paper effectively combines desirable features of the models presented by Goulias (1999) and Kroesen (2014).

As a second, methodological oriented, contribution this paper explores a particular case of the mixture latent Markov model (Vermunt et al., 2008), namely the mover-stayer model. In the mover–stayer model, "the stayers" i.e. those who do no transition between the travel behaviour

[3] Note that the study was not aimed explicitly at identifying mono-/multimodal travel patterns

patterns over time are separated from "the movers" i.e. those that do transition between the travel behaviour patterns over time. This is done by defining one Markov chain for which the probabilities of staying in the same latent state (travel pattern) are fixed to 1 and the other (off-diagonal) transition probabilities to 0. The methodological advantage of separating the movers from the stayers is that the model is better able to reveal and capture the heterogeneity in the transition probabilities of the movers.

Finally, as a third and substantive contribution, this paper puts forth the idea that the Markov chains may be thought of as underlying and more generic mobility styles, which are defined in this paper as dispositions to either habitually or deliberately use the same / different modes over time. For example, the 'stayers' represent a mobility style which can be well-defined conceptually, namely as habitual travellers. We contend that the developed mixture latent Markov model can be thought of as a measurement model to simultaneously measure the concepts of multimodality and mobility styles.

2. Multi-modality and mobility styles

To clearly illustrate the contribution of the presented model we first discuss how previous studies have defined and operationalized the concepts of multimodality and mobility styles. These definitions/operationalisations are contrasted with the way our model operationalises these concepts.

2.1 Multimodality

While multi-modality is generally defined as the use of more than one mode during a specific time period (Buehler and Hamre, 2014; Kuhnimhof et al., 2006; Nobis, 2007), empirical studies have adopted various specific definitions/operationalisations of multi-modality. For example, Nobis (2007) used a straightforward definition of multimodality identifying any person who uses more than one mode of transportation (within one week) as multimodal, regardless of the frequency of use. Buehler and Hamre (2014), on the other hand, adopted a more complex operationalisation and distinguished three groups: monomodal car users who only used a car; (2) multimodal car users who used a car and at least one other mode of transportation and (3) users who only walk, cycle, or use public transportation. Instead of using some kind of a-priori classification scheme, other researchers have used post-hoc classification methods to reveal multimodality-based segments. For example, Diana and Mokhtarian (2009) applied cluster analysis to identify various travel segments that differ in their degree of multimodality. Finally, in addition to the above-mentioned discrete definitions/operationalisations of multimodality, continuous definitions have also been proposed. One relevant measure, in this regard, is the Herfindahl–Hirschman Index, which represents the balance in the distribution in which various modes are used. This measure has been proposed by Heinen and Chatterjee (2015) and used to assess the degree of modal variability among participants of the National Travel Survey in Great Britain.

Our operationalisation of multimodality mostly closely resembles the operationalisation of Diana and Mokhtarian (2009). Hence, instead of using an a-priori classification scheme, we rely on a post-hoc method (in our case a latent class model) to identify travel patterns that can be placed on a continuum from mono- to multimodal. The main benefit of an inductive approach over a-priori classification is that it can provide a more accurate (but still parsimonious) representation of travellers' behavioural patterns. With an a-priori classification scheme many different multi-modal patterns are actually subsumed in the multimodal category. This is not the case with a post-hoc classification method. Moreover, since a post-hoc method aims to identify those behavioural patterns that are most reflective of the actual behavioural patterns of the subjects in the sample, the revealed patterns are also informative from a substantive point of view. Hence, the inductive approach does not only represent a way of measuring the degree of multi-modality, it also provides valuable insights into what are the main shared travel behaviour patterns.

2.2 *Mobility styles*

The mobility style concept is generally defined as a latent construct comprising an individual's attitudes, values, and orientations towards travel and the mobility domain. The concept is derived from the lifestyle concept (representing more generic life orientations) and was first coined by Götz et al. (2003). Since then, numerous studies adopting the 'mobility style' approach have been conducted (Anable, 2005; Haustein, 2011; Hunecke et al., 2010; Krizek and El-Geneidy, 2007; Prillwitz and Barr, 2011; Pronello and Camusso, 2011; Shiftan et al., 2008; Vij, Carrel, and Walker, 2013). The study of Anable (2005) represents a particular compresensive study in this regard. Using a post-hoc classification method (factor analysis in combination with cluster analysis) she identified six groups of travellers which were homogenous with respect to a broad range of attitudes and values (mostly derived from social-psychological theories). The revealed mobility style segments were significantly correlated with travel behavior.

Since it is not predefined which attitudes should be included as relevant mobility style traits, studies have revealed a broad range of attitudinal profiles. Some typical 'meta' dimensions of these profiles relate to the degree of environmentalism (with typical profile labels such as 'aspiring environmentalists', 'paying ecologists' and 'consistent green travellers'), the sensitivity to time (with labels such as 'time addicts' and 'timeservers'), the preferences towards modes (with labels such as 'die hard drivers' and 'car-dependent travelers') and the degree of habituation (with labels such as 'choice riders', 'captive riders' and 'habitual drivers').

Our operationalisation of mobility style mainly taps into this latter dimension, i.e. the degree in which travellers habitually/deliberately use (a combination of) modes over time. However, instead of asking respondents directly to what extent they habitually/deliberately choose various modes (as is typically done in the mobility style approach), this dimension is inferred from behavioral data (in the respect, our approach is similar to Vij et al. 2013). For example, as mentioned in the introduction, those who stay in their respective travel pattern over time can be identified as habitual travellers. On the other hand, those that transition between travel patterns can be identified as choice travellers. These travellers can then be defined by the switching patterns they will reveal. This is the main substantive contribution of the present paper.

3. The mixture latent Markov model

Figure 1 presents the mixture latent Markov model conceptually. The key idea underlying the model is that travellers are assumed to belong to unchanging mobility styles, but at the same time, may change their behavioural pattern over time. For example, there may be travellers who always use the car to some extent (a possible mobility style), but they may use this mode in various combinations with other modes over time (hence switch between different travel patterns over time). To capture both the fixed as well as the transient aspect of travel behaviour our model consists of a two-layered measurement model. The first (highest) layer, which is assumed to be stable over time, aims to capture the mobility styles; the second layer aims to capture latent travel patterns which underlie the observed uses of various modes.

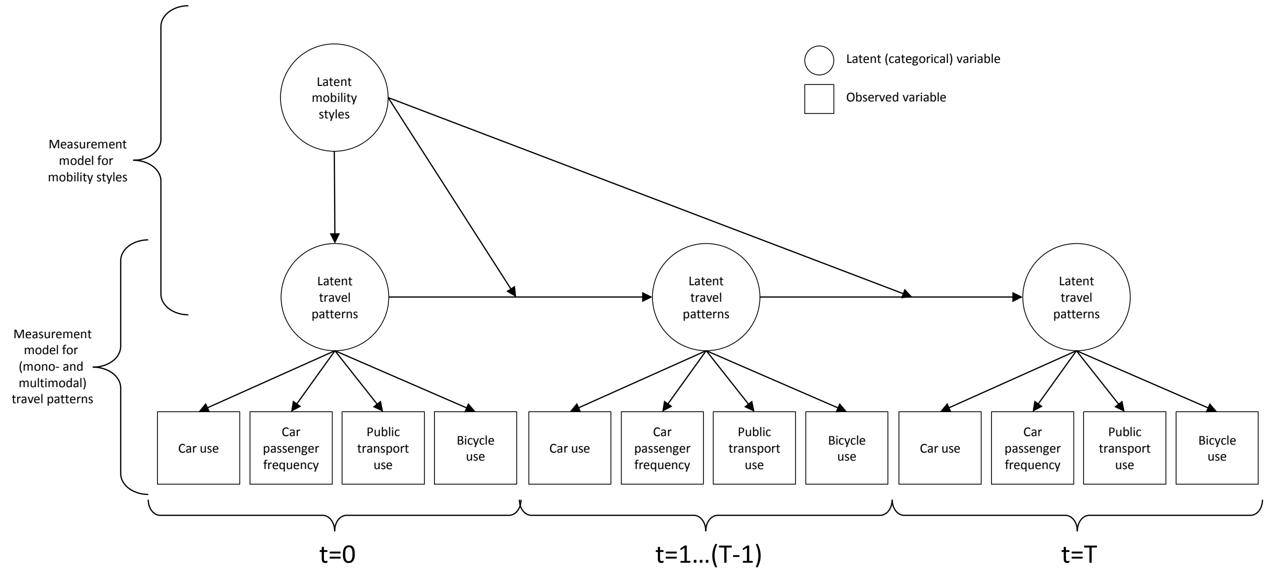

Figure 1. The mixture latent Markov model

Our model is based on five core assumptions. These assumptions result in model which is parsimonious and yet flexible enough to achieve the main objective: to reveal heterogeneity in the transition probabilities. Below we discuss briefly discuss these assumptions.

Firstly, it is assumed that the use of different modes can be captured by a (limited) number of underlying time-varying latent classes, which (at each point in time) parsimoniously capture and represent the (mono- and multimodal) travel patterns of the subjects in the sample. The four most important transportation modes in terms of daily use and distance covered are considered as indicators of these latent variables: car, car passenger, public transport (bus, tram, metro, S-Bahn and train) and bicycle (the indicator selection is further motivated in section 3). Furthermore, conditional on the latent travel patterns the observed indicators are assumed to be mutually independent (the so-called local independence assumption).

Secondly, it is assumed that the parameters describing the relationships between the latent travel patterns and the observed indicators are equal across waves. Hence, it is assumed that measurement invariance holds. Substantively, this means that the structure of the travel patterns is assumed to remain stable over time. This assumption is necessary to be able to interpret the transitions between the travel patterns over time. Evidently, this can only be meaningfully done if travellers transition between the same patterns over time. Note also that this assumption does not exclude the possibility that the distribution of latent travel pattern membership changes over time.

Thirdly, an additional time-constant latent class variable is assumed to explain initial travel pattern membership and the probabilities associated with the transitions between the latent travel patterns from one point in time to the next. In the context of the present analysis, this latent class variable can be thought of as a stable mobility style. For example, as mentioned in the introduction, an obvious mobility style would be the habitual traveller. The main objective of the present analysis is to confirm this idea and to reveal which other mobility styles exist in addition to this one (if any).

The fourth assumption is that, conditional on the mobility styles, latent travel pattern membership at a certain point in time is only associated with latent travel pattern membership at the previous and the next point in time. Hence, so-called second-order relationships between the latent travel patterns (e.g. from t=0 to t=2) are assumed to be non-existent. This is typically called the first-order Markov assumption.

Finally, it is assumed that the transition probabilities are time-homogenous. This means that the probabilities of transitioning from one travel pattern to another (or to the same) are restricted to be equal across pairs of consecutive points in time.

The model in figure 1 can also be represented mathematically. Let's first have a look at the measurement model, equation 1. This model predicts the probability of response y_{ntk} by traveller *n* – which is in our case the use of mode *k* at each time period *t* – conditional on the latent travel pattern class *s*. Since the response variables are count variables (i.e. the weekly frequencies of using the car, being car passenger, using public transport and using the bicycle, see next section) log-linear Poisson regressions models are used (Vermunt and Magidson, 2013). Finally, since the response is conditional on the latent travel pattern class, δ_s and δ_{sk} represent respectively class-specific, and class and mode specific constants.

$$P\left(y_{ntk}|s\right)=\frac{\left(\mu_{sk}\right)^{y_{ntk}}e^{-\mu_{sk}}}{y_{ntk}!}$$

$$where \quad \mu_{sk}=e^{\delta_s+\delta_{sk}} \tag{1}$$

Now we turn to the class membership model for the latent mobility styles. Membership to the travel mobility style, which we denote as *w,* is independent from the time period *t*. Equation **Error! Reference source not found.** gives the class membership model. To model the class membership probability a logit model is used, where $\alpha_1 ... \alpha_W$ denote the mobility style model coefficients. Note that allocation to travel mobility styles does not depend on (socio-demographic) characteristics of travellers. Therefore, in the present model specification mobility style membership is equal across all travellers. Future models may incorporate socio-demographic characteristics to assign travellers to travel mobility style classes.

$$\pi_n\left(w\right)=\frac{\exp\left(\alpha_w\right)}{\sum_{l=1}^{W}\exp\left(\alpha_l\right)} \tag{2}$$

In the core of our latent mixture Markov model is the travel pattern class membership model. This is where the Markov nature of the model manifests. The key feature of the mixture latent Markov model is that the travel pattern class membership probabilities in time period *t* is conditional on both the travel pattern class membership probabilities in the period before (i.e. time period *t-1*) as well as on the travel mobility style class membership. To model travel pattern class membership probability we again use a logit model. Equation 3 shows the probability of traveller *n* falling into class *s* in time period *t.* Ω_w denotes a square matrix (of size S x S) whose coefficients determine the transition matrix – which gives the probabilities that a traveller belonging to a certain class in time period *t-1* switches to another class in time period *t.* As alluded before, in the present model specification, Ω_w (and thus also the transition matrix) is assumed to be time-homogeneous. This implies that the probabilities of transitioning from one travel pattern class to another (or to the same) are restricted to be equal across pairs of consecutive points in time.

$$\pi_{nt}\left(s_t|s_{t-1},w\right)=\frac{\exp\left(\Omega_w\left[s_{t-1},s_t\right]\right)}{\sum_{q=1}^{W}\exp\left(\left[\Omega_q s_{t-1},s_t\right]\right)} \qquad where\ \Omega_q=\begin{bmatrix}\omega_{q11} & \omega_{q12} & \cdots & \omega_{1S}\\ \omega_{q21} & \omega_{q22} & & \vdots\\ \vdots & & \ddots & \vdots\\ \omega_{qS1} & \cdots & \cdots & \omega_{qSS}\end{bmatrix} \tag{3}$$

For the initial state (i.e. $t = 0$), the travel pattern class membership probabilities in time period *t-1* are inevitably missing. To deal with this, we define a separate class membership model for the initial stage, see equation 4. Note that class membership at the initial stage is conditional on the travel modality class membership only.

$$\pi_{n0}\left(s_0|w\right)=\frac{\exp\left(\gamma_{s_0w}\right)}{\sum_{q=1}^{W}\exp\left(\gamma_{s_0q}\right)} \tag{4}$$

Finally, by pulling together the sub models we can now write the probability of observing a particular sequence of trip frequencies for traveller *n* with regard to mode *k*, denoted $\Gamma_{nk}=\left[y_{nk1}...y_{nkT}\right]$, see Equation 5.

$$P_{nk}\left(\Gamma_{nk}\right)=\sum_{w=1}^{W}\sum_{s_{t=0}}^{S}\sum_{s_{t=1}}^{S}...\sum_{s_{t=T}}^{S}\pi_n\left(w\right)\pi_{n0}\left(s_0|w\right)\prod_{t=1}^{T}\pi_{nt}\left(s_t|s_{t-1},w\right)\prod_{t=0}^{T}P\left(y_{ntk}|s\right) \tag{5}$$

The mixture latent Markov model presented in Equation 5 is able to simultaneously take into account various aspects that are important for the analysis of panel data (Vermunt et al., 2008). More specifically, the mixture latent Markov model is able to account for (1) unobserved heterogeneity in the transition probabilities, (2) autocorrelation, and (3) measurement error. Unobserved heterogeneity in the transition probabilities is captured by the time-constant latent variable (w), autocorrelations are captured by the first-order Markov assumption in which the state at time point t depends on the state at time period t-1, and measurement error is captured through the specification of a latent class cluster model at each point in time. As such, the model allows for inter-individual variability in transition patterns, the tendency to remain in the same state over time and spurious change resulting from measurement error.

Lastly, it is worthwhile to spend some words on the possibility to include additional explanatory variables into the model. As alluded before, including additional observed variables as explanatory variables such as age, gender, income, etc. is an obvious extension to the model in Equation 5. Such variables are likely to influence the latent travel patterns, the transition probabilities and/or the latent mobility styles. Incorporating them in the model therefore may improve the model conceptually. However, for the present analysis, the decision was made to not include such variables in the model. The main rationale is that the model (as presented in Figure 1 / equation 5) is basically a measurement model. By including additional explanatory variables this model would be extended with a structural part. The estimation of this part may then interfere with the estimation of the measurement part of the model, i.e. the formation of the latent classes. This risk, which is well-acknowledged in the latent class modelling literature (Asparouhov and Muthen, 2014), is most easily avoidable by simply not including additional explanatory variables.

That being said, it is interesting to know how the distributions of travel pattern membership and mobility style membership relate to certain background characteristics. Within our conceptualization we assumed travel patterns membership is relatively transient, while mobility style membership is assumed to represent a stable individual trait. As such, we expect that travel pattern membership is comparatively strongly associated with relevant demographic and socio-economic characteristics. The following variables are considered: gender, age, employment status, the presence of children and the number of cars in the household. Since mobility style membership is assumed to reflect an individual's underlying disposition to use various modes, we expect less strong associations between these characteristics and this latent variable. To assess how these characteristics relate to travel patterns and mobility style membership (without interfering with the model estimation) they are included in the model as inactive covariates. This means that they are not part of the model, but that, using the model's posterior probabilities, their distribution is calculated for each category of the latent variables, thus for each travel pattern and mobility style.

4. Method

4.1 Data

To estimate the model in Figure 1 (equation 5) we use data from the German Mobility Panel. The German Mobility Panel is a rotating panel in which households participate maximally three times with intervals of one year before they rotate out. Instituted in 1994 it continues to the present day with yearly refreshments. The annual sample size consists of around 750 households. Each autumn, all household members aged 10 years or above are requested to complete a seven-day travel diary and a survey that covers relevant background information (MOP, 2013).

The MOP data used in this paper cover 10 years, from 1999 to 2009. Hence, there are 11 points in time ($0 \leq t \leq 10$). Only individuals who participated in all three years are included in the sample. This led to the selection of 3,750 individuals. Table 1 presents the numbers of respondents that participated in each year.

Table 1. Annual number of respondents and descriptive statistics of the travel indicators

t	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Year	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
1999	582	582	582								
2000		297	297	297							
2001			534	534	534						
2002				367	367	367					
2003					455	455	455				
2004						386	386	386			
2005							318	318	318		
2006								358	358	358	
2007									378	378	378
Total	582	879	1413	1198	1356	1208	1159	1062	1054	736	378
Car trips	12.1	11.6	11.4	10.7	10.5	10.4	10.7	11.1	11.0	10.9	10.6
Public transport trips	1.5	1.9	2.0	2.1	2.2	2.1	2.2	2.3	2.2	2.3	2.6
Bicycle trips	2.0	2.0	2.5	2.6	2.9	2.6	3.1	2.7	2.8	2.7	2.9
Car passenger trips	3.4	3.2	3.3	3.2	3.5	3.3	3.1	2.9	3.0	3.3	3.4

To reveal the travel patterns appropriate behavioural indicators should be selected. In the German 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 behaviour 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 used the (weekly) trip frequency with various modes.

For each point in time, the descriptive statistics of the four travel behaviour indicators, the weekly trip frequencies by car, car passenger, public transport and bicycle, are presented in the last four rows of Table 1. It can be observed that the mean (weekly) car trip rates decline in the observed period. The mean number of public transport and bicycle trips, on the other hand, show an increasing trend. These results are in line with the study of Kuhminhoff (2011), who report an increase in multimodal travel behaviour in the period 1997-2007. It should be noted that the present results should not be taken as new empirical evidence in favour of this trend, since they are (largely) based on the same data.

Table 2 presents the descriptive statistics of the included background characteristics for the year in which respondents were first recruited. As mentioned in the previous section, latent travel pattern and mobility style membership will be contrasted with these variables.

Table 2. Descriptive statistics of the background characteristics (N=3,750)

Variable	Labels	
Gender (%)	Female	53.3
	Male	46.7
Age	Mean (S.D.)	47.4 (17.9)
Presence of young children in the household	No	83.7
(<10 years) (%)	Yes	16.3
Employment status (%)	Unemployed	38.2
	Employed	61.8
Number of cars in the household (%)	0	12.4
	1	50.3
	2	30.5
	3 or more	6.0

4.2 Model estimation

As explained in the introduction, to be better able to reveal and capture the heterogeneity in the transition probabilities of the movers we separate the “stayers” i.e. those who do no transition between the travel behaviour patterns from the “movers” i.e. those that do transition between the travel behaviour patterns. This is done by pre-specifying a mobility style class in which the transition probabilities towards other than the initial travel pattern are zero .

To estimate our model we used the software package Latent Gold 5.0. This software package has been developed specifically to estimate latent class models and latent Markov models (Vermunt and Magidson, 2013). In this package, Maximum Likelihood (ML) estimates are found using of Expectation Maximization. A desirable property of this approach is that it can easily deal with missing data (Vermunt et al., 2008). This property is especially relevant in the present application, since each subject is surveyed only 3 instead of 11 times (see Table 1). For the missing values at the remaining points in time, the time-specific conditional densities of the indicator variables are set to 1, which means that the responses for these indicator variables at these time points are skipped in the ML estimation.

To determine the optimal number of travel patterns S, and mobility styles W, a two-step approach is adopted. First, the optimal number of travel patterns (S) is determined. To do so, it is assumed that observations are independent across occasions. Specifically, a single latent variable is assumed to explain the responses on the four indicator variables (independent from the various points in time). Through this approach the measurement invariance assumption can be assured and the optimal number of travel patterns can be determined without inference resulting from the state-dependency and the time-constant latent variable w. Subsequently, models having an increasing numbers of latent classes are estimated and compared to establish the optimal number of travel patterns.

After the optimal number of travel patterns is determined, a series of (mixture) latent Markov models is estimated to determine the optimal number of mobility styles W. Similar to the travel patterns, models with successive numbers of mobility styles are estimated and compared in terms of their model fit. Starting from the model with two mobility styles, variants with a stayer-class are also estimated.

To evaluate and compare models various fit indices are used. 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.

A typical approach to assess model fit in the case of sparse tables is the use of an information criterion, which weighs both model fit and parsimony (i.e. the number of estimated parameters). In the context of latent class models, the Bayesian information criterion has been shown to perform well (Nylund et al., 2007). The best fitting model is one with the lowest BIC value. Another approach suited in the case of sparse tables is to estimate the p-value associated with the chi-squared statistic by means of a parametric bootstrap (Langeheine et al., 1996; Magidson and Vermunt, 2004). In the end, substantive reasons may also enter into the consideration to select an optimal number of classes. The present analysis relies on a mix of these approaches.

5. Results

5.1 Model selection

Table 3 presents the model fits of successive models starting with a model with one class up to a model with ten classes. As can be seen, the BIC value consistently decreases indicating that the optimal model (based on this criterion) is one with at least 10 classes. Given that this number of latent classes is too high to be dealt with in the mixture Markov model, this criterion is not practical in our context to assess the optimal number of classes.

Table 3. Model fit of latent class models

Number of classes (travel patterns)	LL	BIC(LL)	Npar	L^2	*df*	p-value	Bootstrap p-value
1	-207995	416027	4	251613	11021	0.000	0.000
2	-153128	306340	9	141880	11016	0.000	0.000
3	-133309	266749	14	102242	11011	0.000	0.000
4	-124915	250007	19	85454	11006	0.000	1.000
5	-118847	237917	24	73317	11001	0.000	1.000
6	-114283	228835	29	64188	10996	0.000	1.000
7	-111075	222467	34	57774	10991	0.000	1.000
8	-108206	216776	39	52036	10986	0.000	1.000
9	-106280	212970	44	48183	10981	0.000	1.000
10	-104600	209656	49	44823	10976	0.000	1.000

LL = log-likelihood
BIC(LL) = Bayesian information criterion (based on log-likelihood)
Npar = number of model parameters
L^2 = likelihood-ratio chi-squared statistic
df = degrees of freedom

The bootstrap p-values indicate that from 4 classes onwards the models can accurately reproduce the observed response patterns. Statistically, the 4-class solution would therefore be the preferred model. Comparing this model with the 5-class model it was found, however, that the additional class, which could be identified as one of strict bicycle users, was meaningful and relevant from a substantive point of view. Therefore, the decision was made to opt for the model with 5 travel behaviour patterns in the complete mixture latent Markov model.

Table 4 presents the model fit of 7 latent mixture Markov models in which the number of Markov chains is varied from 1 to 4, and in which (from 2 classes onwards) variants with a stayer-class are estimated. Here, the BIC statistic is able to reveal the best fitting model and indicates that the solution with 3 mobility styles (1 stayer and 2 movers classes) is the optimal model (i.e. with the lowest value). Unfortunately, for these models, it was too computationally intensive to estimate the bootstrap p-value. Therefore, solely based on the BIC statistic, the model with 3 mobility styles (with 1 stayer and 2 movers classes) is identified as the optimal model and will be discussed in the next section.

Table 4. Model fit of mixture latent Markov models

Number of classes (mobility styles)	LL	BIC(LL)	Npar	L^2	*df*	p-value
1 mover class	-114337	229036	44	184343	3631	0.000
2 mover classes	-114155	228877	69	183979	3606	0.000
1 stayer class 1 mover class	-114211	228824	49	184090	3626	0.000
3 mover classes	-114070	228912	94	183809	3581	0.000
1 stayer class 2 mover classes	-114096	228799	74	183861	3601	0.000
4 mover classes	-114040	229057	119	183749	3556	0.000
1 stayer class 3 mover classes	-114053	228919	99	183775	3576	0.000

LL = log-likelihood
BIC(LL) = Bayesian information criterion (based on log-likelihood)
Npar = number of model parameters
L^2 = likelihood-ratio chi-squared statistic
df = degrees of freedom

5.2 Results and discussion

The parameter estimates of the final mixture Markov model (with 1 stayer and 2 mover classes) are presented in Table 9 in the Appendix. Using the Equations (1-4) these estimates can be used to compute the relevant model results, namely the profiles of the 5 latent travel patterns (Table 5), the class sizes of the travel patterns and the latent mobility styles (Table 6) and the matrices of transition probabilities (Table 7). These results are discussed below.

First, we turn to the profiles of the 5 latent travel patterns. Table 5 shows the average mode frequencies (profile) for each latent travel pattern. The travel patterns can be identified as (1) strict car users, (2) public transport and occasional car users, (3) car passengers, (4) car and bicycle users and (5) bicycle and occasional public transport users. It can be observed that the various travel patterns differ in their degree of mono-/multimodality. Strict car users (pattern 1) are most monomodal; travellers with this pattern use the car (on average) 19 times per week and make very little use of the bicycle (0.2 times per week) and public transport (0.4 times per week). On the other hand of the spectrum are car and bicycle users (pattern 4). With on average 13 trips by car and 8.5 trips by bicycle, these travellers are most multimodal. In between these extremes are the public transport and occasional car users (pattern 2), who mainly use public transport (9.5 times per week), the bicycle and occasional public transport users (pattern 5), who mainly use the bicycle (13 times per week), and the car passengers (pattern 3), who have the highest car passenger frequency (8.5 times per week).

Table 5. Profiles of the latent travel patterns

	1. Strict car users	2. PT and occasional car users	3. Car passengers	4. Car and bicycle users	5. Bicycle and occasional PT users
Car trips	19.1	1.2	2.1	13.4	0.4
Public transport trips	0.4	9.5	0.6	0.5	1.9
Bicycle trips	0.2	0.7	0.3	8.5	13.4
Car passenger trips	1.9	2.8	8.5	1.9	3.6

Table 6 presents the cross-table of travel pattern and mobility style membership. The distribution of travel pattern membership (in the last row) indicates that strict car users are most strongly represented in the sample (49%) (at t = 0). This pattern is followed by the PT and occasional car user and the car passenger pattern, which are more or less equal in size (16%). The car and bicycle user and the bicycle and occasional PT user represent the smallest patterns (both around 9%).

The distribution of mobility style membership (in the final column of Table 6) shows that over half of the sample (53%) is assigned to the first mobility style, representing the stayer class. This is in line with previous research in travel behaviour dynamics, showing that travel behaviour is strongly inert (Goulias, 1999). The two mover classes are more or less equal in size (23 and 24%).

The cross-tabulation of travel pattern and mobility style membership indicates that the distribution of travel pattern membership for the first modality class (the stayers) mirrors the overall distribution of travel pattern membership quite well. Hence, the ‘stayers’ or habitual travellers, are proportionally equally represented across the five travel patterns. This means, for example, that more mono-modal travellers (e.g. the strict car users) are not more prone to belong to the habitual mobility style (the stayer class) than multi-modal travellers (e.g. car and bicycle users). This is an interesting finding that we will return to momentarily. Regarding the second and third mobility style, it can be observed that the strict car users are more strongly represented in the third mobility style, while the four other travel patterns are more strongly represented in the second mobility style.

Table 6. Cross-table of travel pattern and mobility style membership

	Travel pattern at t = 0					
Mobility style	**1. Strict car users**	**2. PT and occasional car users**	**3. Car passengers**	**4. Car and bicycle users**	**5. Bicycle and occasional PT users**	**Total class size**
1 (stayers)	0.504	0.174	0.135	0.099	0.088	0.528
2	0.320	0.207	0.215	0.103	0.156	0.238
3	0.632	0.093	0.182	0.057	0.037	0.234
Total class size	0.490	0.163	0.165	0.090	0.092	

Table 7 presents the transition matrices of each of the three mobility styles as well as the (cumulative) transition matrix of the overall sample. The latter again shows that travellers are strongly inert overall; across the five travel patterns the probability of remaining in the same pattern over time is greater than 67%. It can be observed that strict car users are most strongly inert (85% probability of remaining in the same pattern), while car and bicycle users are most volatile (68% probability of remaining in the same pattern). In line with the findings of Kroesen (2014), mono-modal travellers are found to be less prone to switch between travel patterns than multi-modal travellers. The off-diagonal transition probabilities indicate car passengers and car and bicycle users have a strong inclination towards the strict car pattern, while bicycle and occasional PT users have a substantial probability of switching to the PT and occasional car user profile.

Table 7. Transition matrices of the overall sample and the three mobility styles

Overall sample		Travel pattern in period *t*				
	Travel pattern in period (*t*-1)	1	2	3	4	5
	1. Strict car users	**0.850**	0.026	0.050	0.070	0.004
	2. PT and occasional car users	0.080	**0.777**	0.075	0.011	0.057
	3. Car passengers	**0.159**	0.080	**0.688**	0.023	0.051
	4. Car and bicycle users	**0.200**	0.020	0.039	**0.676**	0.065
	5. Bicycle and occasional PT users	0.012	**0.108**	0.075	0.082	**0.723**
Mobility style	Travel pattern (*t*-1)					
1	1. Strict car users	**1**	0	0	0	0
1	2. PT and occasional car users	0	**1**	0	0	0
1	3. Car passengers	0	0	**1**	0	0
1	4. Car and bicycle users	0	0	0	**1**	0
1	5. Bicycle and occasional PT users	0	0	0	0	**1**
2	1. Strict car users	**0.560**	0.000	0.018	**0.422**	0.000
2	2. PT and occasional car users	0.026	**0.527**	**0.241**	0.026	**0.180**
2	3. Car passengers	0.026	**0.289**	**0.481**	0.018	**0.187**
2	4. Car and bicycle users	**0.560**	0.023	0.021	**0.395**	0.002
2	5. Bicycle and occasional PT users	0.001	**0.274**	**0.179**	0.009	**0.538**
3	1. Strict car users	**0.679**	0.095	**0.171**	0.039	0.015
3	2. PT and occasional car users	**0.479**	**0.462**	0.017	0.022	0.020
3	3. Car passengers	**0.563**	0.007	**0.364**	0.066	0.000
3	4. Car and bicycle users	0.001	0.052	**0.142**	**0.522**	**0.283**
3	5. Bicycle and occasional PT users	0.084	0.021	0.050	**0.566**	**0.279**

Note: substantial transition probabilities (greater than 0.1) are highlighted in bold.

In the mixture Markov model the overall transition matrix is decomposed into the three mobility styles (Markov chains). These mobility styles can be well-interpreted from a substantive point of view. As mentioned before, the first is a fixed pattern and represents the 'habitual traveller'. These are travellers who stay in their respective pattern. It may be speculated that these travellers do not deliberate their travel behaviour, but (unconsciously) adopt the same travel pattern each year. The first mover class can be identified as 'car (in)dependent choice travellers'. These travellers only switch either within car (travel patterns 1 and 4) or non-car travel patterns (travel patterns 2, 3 and 5). Hence, travellers with this mobility style either have or do not have the car in their consideration set. It may be speculated that, taken this constraint into account, travellers with this mobility style do deliberate about the travel pattern alternatives. The second mover class can be identified as 'car users with an alternative mode preference'. This style represents travellers who switch between car and non-car patterns. More specifically, strict car users are prone to transition to the PT and occasional car pattern and car passenger profile (and vice versa), while car and bicycle users are prone to transition to the bicycle and occasional PT pattern and car passenger profile (and vice versa). Hence, travellers belonging to the mobility style use the car, but also include PT and being a car passenger into their consideration set. Again, based from this type of switching behaviour, it may be speculated that travellers with this mobility style represent deliberate choice travellers.

Since the distribution of the five travel pattern within the habitual traveller style is equal to the distribution of the travel patterns in the sample as a whole (Table 6), it is interesting to note that the high stability of the strict car user pattern (85%) cannot be explained by the fact that they more often belong to the habitual traveller style (as one might expect), but this is due to the fact that, within the mover mobility styles, their stability is higher compared to the other travel patterns. Hence, strict car users are not more prone to be habitual travellers, but within the 'deliberate-choice mobility styles' (patterns 2 and 3) they more often 'choose' the strict car user pattern. Hence, these results suggest that the high stability of the strict car pattern is the result of repeated (conscious) 'rational' choice, resulting in the same outcome.

Finally, Table 8 presents the cross-tabulation of travel pattern and mobility style membership with the selected demographic and socio-economic characteristics. As expected, it can be observed that travel pattern membership is more strongly associated with these variables than mobility style membership. The probability that travellers belong to one of the car profiles (1 or 4) is higher if travellers are male (compared to female), have children (compared to no children) and have more cars in the household. The distribution of the variables (gender, presence of children and the number of cars in household) is more or less similar across the three mobility styles. Albeit less pronounced, this pattern of association (a stronger association with travel pattern membership compared to mobility style membership) can also be observed for age and employment status. This finding supports our conceptualisation that the mobility style membership represents a more stable individual trait while travel pattern membership is more volatile.

Table 8. Cross-tables of latent travel pattern and mobility style membership with demographic and socio-economic characteristics

	Travel pattern					**Mobility style**		
	1	**2**	**3**	**4**	**5**	**1**	**2**	**3**
Gender								
Female	0.44	0.61	0.73	0.45	0.62	0.54	0.54	0.52
Male	0.56	0.39	0.27	0.55	0.38	0.46	0.46	0.48
Age								
29 or below	0.30	0.43	0.27	0.27	0.41	0.29	0.38	0.34
30 to 49	0.44	0.27	0.30	0.38	0.26	0.37	0.31	0.40
50 or above	0.26	0.31	0.43	0.35	0.34	0.34	0.31	0.26
Presence of children in HH								
No	0.81	0.87	0.90	0.80	0.86	0.84	0.83	0.83
Yes	0.19	0.13	0.10	0.20	0.14	0.16	0.17	0.17
Employment status								
Not employed	0.27	0.50	0.52	0.37	0.50	0.38	0.44	0.33
Employed	0.73	0.50	0.48	0.63	0.50	0.62	0.56	0.67
# cars in household								
0	0.01	0.40	0.13	0.03	0.29	0.15	0.16	0.04
1	0.50	0.36	0.59	0.61	0.47	0.49	0.50	0.54
2	0.39	0.20	0.23	0.31	0.19	0.30	0.28	0.33
3 or more	0.10	0.03	0.05	0.06	0.04	0.06	0.06	0.09

6. Conclusion

This study has investigated travellers' latent transition patterns between mono- and multimodal travels patterns. A mixture latent Markov model has been estimated to this end. The substantive contributions of this paper are threefold. Firstly, three mobility styles are identified: 'the habitual travellers', 'the car (in)dependent choice travellers', and 'car users with an alternative mode preference'. Unlike typical studies adopting a mobility style approach, these mobility styles were inferred from behavioural data only.

Secondly, we find evidence for that the high stability of the strict car user pattern cannot be explained by the fact that car users more often belong to the habitual traveller style (as one might expect), but rather is due to the fact that, within the mover mobility styles, their stability is higher compared to the other travel patterns. Hence, strict car users are not more prone to be habitual travellers, but within the 'deliberate-choice mobility styles' they more often 'choose' the strict car user pattern. As such, it may be speculated that the high stability of the strict car pattern is the result of repeated 'rational' choice that simply result often in the same outcome (namely the car). This finding contrasts with previous research in the mobility style domain, where the car-dependent traveller is usually identified as the one with the strongest habit.

Thirdly, in line with expectations, the results indicate that, while the travel patterns are strongly associated with socio-demographic background characteristics, the modality styles are not. This fits the conceptualization of modality styles as unchanging dispositions to either habitually or deliberately use the same / different modes over time.

The main substantive contribution of this paper relates to the idea that the Markov chains may be thought of as underlying and more generic mobility styles, in this particular case, habitual and deliberate-choice travellers. Hence, by conceptualizing a two-layered measurement model, we were able to infer a psychological construct (habit) solely from behavioural data. An obvious limitation of this conceptualization is the assumption that travellers do not change their mobility style over time, which is unlikely as various studies have shown that people do change their attitudes over time (for a recent study in a transport context see Wang and Chen, 2012). It should be noted, though, that, since subjects in the sample are only observed for a period of three years, changes in attitudes/mobility styles are arguably small/few.

While the model presented in this paper is already quite extensive many variations can still be explored. As mentioned in the paper, one interesting direction is to include additional covariates in the model to predict the latent travel patterns, the transition probabilities and/or the latent mobility styles. It would be particularly interesting, in this respect, to contrast latent mobility style membership with self-reported measures of habit (e.g. Verplanken and Orbell, 2003) and the extent in which people report to deliberately choose from a set of modes for each trip. This would provide a cross-validation of both types of operationalizations.

Secondly, in line with the mobility biographies approach (Lanzendorf, 2010.; Müggenburg et al., 2015; Scheiner, 2007), key life events (moving house, changing jobs, childbirth, etc.) may be included in the model. These life events may be assumed to trigger behavioural change and therefore represent relevant variables in explaining the transition probabilities.

Thirdly, various model assumptions may be relaxed, for example, the assumption of measurement invariance or the assumption of equal transition probabilities between consecutive time points. This first would allow us to answer the question whether the structure of the travel patterns also changes over time, which is especially relevant for particular groups, namely young or old people. Because of recent societal trends, in particular, the declining car use among the young (Davis et al., 2012) and the increasing car use among the old (Haustein and Siren, 2015), it would be interesting to assess whether new mobility styles are emerging among these groups. The framework presented in this paper could be used to this end.

Fourthly, the model could be expanded by considering different or additional indicators for the latent travel patterns, for example, relating to trip distances, trip durations or trip purposes. This could potentially yield even richer behavioural profiles.

Overall, there is ample opportunity to extend the framework presented in this paper to answer relevant research questions in the domain of travel behaviour dynamics.

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Appendix A

Table 9. Parameter estimates of the mixture latent Markov model

Model for observed indicators (Equation 1)								
	Car use		**PT use**		**Bicycle use**		**Passenger freq.**	
Travel pattern	**Est.**	**t-value**	**Est.**	**t-value**	**Est.**	**t-value**	**Est.**	**t-value**
1	1.84	116.13	-0.99	-35.28	-1.93	-50.17	-0.52	-43.18
2	-0.94	-28.45	2.10	134.92	-0.66	-17.15	-0.11	-6.98
3	-0.35	-12.60	-0.66	-18.44	-1.43	-29.01	0.98	88.87
4	1.48	94.40	-0.93	-22.75	1.78	98.49	-0.49	-25.52
5	-2.02	-37.43	0.48	15.15	2.24	128.54	0.14	8.41
Constant	1.12	69.96	0.16	10.39	0.35	19.60	1.15	165.00
Model for mobility style membership (Equation 2)								
Mobility style	**Est.**	**t-value**						
1	0.54	9.53						
2	-0.26	-3.71						
3	-0.28	-3.29						
Model for travel pattern membership at t (Equation 3 and 6)								
	Mobility style 1		**Mobility style 2**		**Mobility style 3**			
Transitions	**Est.**	**t-value**	**Est.**	**t-value**	**Est.**	**t-value**		
1→1	0.00	.	0.00	.	0.00	.		
1→2	-15.00	.	-8.01	-1.08	-1.96	-8.72		
1→3	-15.00	.	-3.44	-4.47	-1.38	-6.52		
1→4	-15.00	.	-0.28	-1.23	-2.85	-7.92		
1→5	-15.00	.	-8.85	-1.19	-3.80	-10.73		
2→1	-15.00	.	-3.01	-4.10	0.04	0.12		
2→2	0.00	.	0.00	.	0.00	.		
2→3	-15.00	.	-0.78	-3.04	-3.29	-1.54		
2→4	-15.00	.	-2.99	-5.72	-3.05	-2.84		
2→5	-15.00	.	-1.08	-4.01	-3.12	-2.43		
3→1	-15.00	.	-2.93	-2.19	0.44	2.18		
3→2	-15.00	.	-0.51	-1.86	-3.98	-1.76		
3→3	0.00	.	0.00	.	0.00	.		
3→4	-15.00	.	-3.31	-4.09	-1.71	-5.00		
3→5	-15.00	.	-0.95	-3.45	-7.28	-0.98		
4→1	-15.00	.	0.35	1.63	-6.25	-0.85		
4→2	-15.00	.	-2.86	-4.00	-2.30	-4.09		
4→3	-15.00	.	-2.96	-3.72	-1.30	-3.38		
4→4	0.00	.	0.00	.	0.00	.		
4→5	-15.00	.	-5.30	-0.78	-0.61	-1.74		
5→1	-15.00	.	-6.60	-0.98	-1.20	-2.27		
5→2	-15.00	.	-0.67	-2.49	-2.60	-1.80		
5→3	-15.00	.	-1.10	-3.87	-1.71	-2.30		
5→4	-15.00	.	-4.05	-1.47	0.71	1.86		
5→5	0.00	.	0.00	.	0.00	.		
Model for travel pattern membership at t=0 (Equation 4)								
	Mobility style 1		**Mobility style 2**		**Mobility style 3**			
Travel pattern	**Est.**	**t-value**	**Est.**	**t-value**	**Est.**	**t-value**		
1	1.15	16.36	0.54	2.63	1.68	8.40		
2	0.09	1.10	0.10	0.41	-0.24	-0.81		
3	-0.16	-1.98	0.14	0.51	0.44	1.80		
4	-0.48	-4.97	-0.60	-2.17	-0.73	-2.08		
5	-0.60	-5.78	-0.18	-0.72	-1.16	-2.61		