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# Behavioural micro-dynamics of car ownership and travel in the Seattle metropolitan region from 1989 to 2002

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In this paper data from 230 households observed in ten different occasions (waves) from 1989 to 2002 in the Puget Sound region are used to explore relationships among number of cars owned, number of trips driving alone, and number of trips sharing cars with household members. Using a mixture latent class Markov model we identify four distinct groups that are a *High Mobility* group with more cars and car trips, an *Average Mobility* group with lower car ownership and trips driving alone, a third group with relatively high car ownership but few car sharing trips, and a fourth group of *Low Mobility* characterized by the low car ownership and trips. Households change behaviour adapting to internal and external changes to their environment but they also anticipate changes and go through a "preparation" stage (e.g., adding another car in their fleet in expectation of adding another employed person). Land use plays a somewhat secondary role. The analysis also reveals three classes (hidden Markov chains) of households underlying behavioural dynamics with increases in the low car ownership categories (zero and one car per household), decreases in the high car ownership (three cars and four or more cars per household) and stable behaviour in the two cars per household group. Household membership in these classes is significantly influenced by householder ratings to parking availability, schedule flexibility, bus transfers, and day-to-day costs of driving. The findings here show attitudes and land use enhance understanding of longitudinal heterogeneity.

*Keywords*: panel data, behavioural dynamics, adaptation, anticipation, car ownership, mobility

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## 1. Introduction

Car ownership and use is a fundamental research area in travel behaviour analysis because it is used to assess the success of policies aiming at curbing car use and increasing the use of other modes. Car ownership models are also used in more recent activity-based travel demand forecasting models. Understanding the dynamic interplay between car ownership and car use and the interplay with changing demographics and land use evolution are key in developing these "new generation" models. In this paper, we examine changes in car ownership and travel from 1989 to 2002 to identify the triggers of these changes and if households adjust to demographic and land use changes but also if they anticipate them. We also explore heterogeneity of car ownership and use, employing a method that uncovers hidden chains of transitions exploiting the relationship between sequences of car ownership and use. Membership to these chains are also regressed on attitudes by the participating households.

The model used here is the longitudinal mixed Markov latent class model developed to describe stochastic processes in discrete time and space by Langeheine and van de Pol, 1990, and van de Pol and Langeheine, 1990. It is also a generalization of one of its variants used by Goulias (1999) to analyse patterns of activity and travel in the first four waves of the Puget Sound Travel Panel (PSTP). We view the modelling exercise in this paper as a pattern recognition technique in a database that includes households participating in all waves of the PSTP (230 households) matched with land use data surrounding their residence. In essence, we create clusters of behaviours called "states" and groups of households called "classes" as well as transition probabilities from one state to another over time. In this paper the states are derived from observed data at each of the ten waves (time points) spanning more than a decade (1989 to 2002). The model is based on a few fundamental elements. First, our sample is classified in categories of a set of observed variables that are measured at ten occasions (panel waves). These observed variables are car ownership, number of trips by car alone, and number of trips car-sharing. These variables are an imperfect measurement of another set of unobserved (latent) variables and their categories are called states that represent a set of behaviours from low mobility and ownership to high mobility and car ownership. Transitions from one category of one latent variable at one time point to another category of another latent variable of the next time point in the sequence are modelled as functions of within a household events (e.g., increase in the number of adults) and they are assumed to be first-order Markovian (i.e., they depend on the immediately previous point), they are driven by past and future within household events and by past and future outside the household events. To account for possible heterogeneity in the transitions from one state to another we also assume the existence on another latent categorical variable that classifies the sample based on sequences of states and the categories of this latent variable are called classes. This latent variable and its categories represent a finite number of preferred behavioural styles (classes) of mobility and ownership around which households oscillate as they experience changes. Membership to these classes is in turn a function of attitudes measured at the beginning of the panel survey.

Transitions among different behavioural states are functions of average age of the household, household demographic changes, and changes in land uses surrounding the household residence. Classes are groups of households with commonalities in patterns of behavioural change from one state to another over time. Changes within the household and changes in land use around the household's residence are treated as leads and lags of a latent class clustering model system to explain transitions among different states. The lag represents a household's "reaction," or adaptation to a change, and the lead represents an anticipation of a forthcoming change. In this way, we can statistically test the significance and impact on behavioural change of past events and future internal to the household and external to the household evolving events. We examine changes due to new-born children, growth of children in ages 6 to 17, changes in number of adults, number of workers, number of cars, and density and diversity of

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land use surrounding the panel participants' residences. In the paper we illustrate the method and a selection of important findings.

Key research questions in this paper include: Can we identify a few groups of similar car ownership and use behaviour? As time progresses and households jump from one group of behaviour to another are they influenced by their internal sociodemographic changes over time (internal changes), and are they also a function of land use change? What are some significant relationships worthy of studying further? Are there different sequences of change in behaviour over time and are they influenced by attitudes?

## 2. Brief Literature Review

Many car ownership and use studies have either (a) focused on the vehicle type characteristics of the most recently purchased or the most driven household vehicle (Kitamura *et al.*, 2000, Train and Winston, 2007, Spissu *et al.*, 2009), (b) confined attention to vehicle type characteristics of the most frequently used vehicle (Choo and Mokhtarian, 2004), (c) examined ownership and vehicle type choices for only households with two vehicles or less to reduce the number of possible vehicle type combinations (Mannering and Winston, 1985, West, 2004, and Feng *et al.*, 2005), or (d) used aggregate classifications of vehicle types such as car versus non-car or sports utility vehicles (SUV) versus non-SUV (Feng *et al.*, 2005, Brownstone and Fang, 2009). A few of these studies have also considered the amount of use (annual mileage) of each household vehicle (Mannering and Winston, 1985, Golob and van Wissen, 1989, de Jong, 1990, Feng *et al.*, 2005, Fang, 2008). There are also many articles that develop methods to enhance modelling of car ownership and type choices (see Bhat and Sen, 2006, Bhat, 2008, and Bhat *et al.*, 2009). In a more recent application, SimAGENT for the Southern California Association of Governments (Goulias et al., 2012), a car ownership simulator recreates the decisions within a household (Vyas et al., 2012, Paleti et al., 2013) mimicking intra-household decision making, car assignment to household members, and accounts for land use characteristics surrounding a household's residence.

Many of these analyses and models use cross-sectional data and are based on strong assumptions about the underlying behavioural process. Kitamura (1990) points out that fundamental implied assumptions of this practice includes: 1) instantaneous reaction to changes; 2) symmetric and reversible changes; and 3) behavioural reactions that are stationary over time. When households delay their reaction to internal or external changes (e.g., birth of a child or diversity of land use surrounding their homes) and when households anticipate changes in their composition and change their travel behaviour accordingly (e.g., a household member learning how to drive and purchasing an additional car), these implied assumptions are violated. Longitudinal data and models that depict these evolutionary changes can help us test many hypotheses about behavioural changes with the caveat of potentially added complexity (Kitamura, 1990). Despite their advantages, longitudinal data models are not especially common (Dargay and Hanly, 2004). There are many areas that still need to be examined because of this. Some examples of longitudinal car ownership data analysis include studies by Golob and van Wissen, 1989, Pendyala, *et al.*, 1995, Bhat and Koppelman, 1993, Dargay and Hanly, 2004, Golob, 1990, Kitamura and Bunch, 1990, and Sunkanapalli *et al.*, 2000. Although these papers all focus on car ownership, very few look at land use, demographics, and attitudes jointly. Golob (1990) does examine land use by using residence locations as explanatory variables in the model. The residence locations examined include metropolitan areas, regional centers, suburbs with commuter rail service, and rural areas. The scope of this analysis, however, did not include car ownership dynamics. We come back to this study in the conclusions. Also related to the type of data used here is a study by Sunkanapalli *et al.* (2000) who analysed the attitudes from the same panel data that this paper examines (the PSTP) and the mode switching behaviour and its correlation with attitudes analysed in Wang and Chen (2012). In these analyses the authors explored the dynamics of

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attitudes but not car ownership and use. In addition, none of the studies we reviewed examine car ownership and use in long periods of observation (e.g., a decade) to identify longitudinal behavioural heterogeneity. In terms of latent Markov models, Kroesen (2014) examines patterns of multiple-mode users compared to single-mode users and finds differences in switching from one behaviour style to another over time employing latent transition analysis. In addition, researchers used hidden Markov chains to explain latent preferences of mode choice (Vij et al., 2013), searching and switching in mode choice (Xiong and Zhang, 2015), longer-term dynamics of discrete mode choices using a subset of the Puget Sound Transportation Panel data (Xiong et al., 2015), to uncover the dynamics underlying drivers behaviour as they enter a freeway (Chaudhury et al., 2010), and to capture a measure of emotions of driver behaviour in a simulator experiment using students as subjects (Danaf et al., 2015).

## 3. Data Used

We use two sources of data that are a longitudinal database (PSTP) of household demographics with a 2-day diary of travel behaviour and a longitudinal database of businesses establishments.

### 3.1 The Puget Sound Panel Data

The Puget Sound Transportation Panel (PSTP) is a "general purpose" urban household panel survey that was created as a tracking device (Murakami and Watterson, 1990, Murakami and Ulberg, 1997). PSTP represents approximately 3.3 million residents (based on data from the US Census of 2000) in Seattle and its surroundings. The survey started in 1989 and ended in 2002 in the four counties (King, Kitsap, Pierce, and Snohomish) of the Puget Sound region in the Northwest corner of the continental US surrounding Seattle. In each wave a household questionnaire and a two-day travel diary are administered on households. PSTP takes similar measurements of travel behaviour repeatedly on the same observations over time. Each wave of the PSTP includes a travel survey that collects information on household demographics, person social and economic circumstances, and reported travel behaviour on two consecutive days for each person 15 years or older. Available data are from ten travel surveys in the years 1989, 1990, 1992, 1993, 1994, 1996, 1997, 1999, 2000, and 2002. More details about this panel can be found with an annotated bibliography in http://www.psrc.org/data/surveys/pstp-survey/).

In this paper, we use the ten-wave database that contains 230 households that participated in all ten waves (we used this sample in a parallel analysis comparing the behaviour of these participants with the behaviour of participants in five waves, Goulias et al., 2014). We also used this same sample to study the longitudinal change in activity and travel behaviour (Lee et al., 2015). We focus the analysis on *number of cars owned* by the household, *number of trips driving alone*, and *number of trips car sharing with household members*. Table 1 shows the descriptive statistics of travel behaviour indicators and household characteristics over time. We observe a gradual decrease in most travel behaviour indicators and the number of household members over time based on mean and median values. This is an expected trend because average age within households is increasing and the children grow up and leave the household. As we illustrate later this is the result of multiple trajectories by different types of households.

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**Table 1.  Descriptive Statistics**

| Year of wave | Statistics | 1989 | 1990 | 1992 | 1993 | 1994 | 1996 | 1997 | 1999 | 2000 | 2002 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Daily Number of Trips Driving Alone | Mean | 5.0 | 5.5 | 5.4 | 5.2 | 4.9 | 5.1 | 4.9 | 4.9 | 4.8 | 4.6 |
| | Std. Dev. | 3.1 | 3.4 | 3.6 | 3.5 | 3.5 | 3.6 | 3.5 | 3.6 | 3.5 | 3.1 |
| | Minimum | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| | Median | 4.8 | 5.0 | 5.0 | 4.3 | 4.5 | 4.5 | 4.5 | 4.0 | 4.5 | 4.5 |
| | Maximum | 15.0 | 19.5 | 24.5 | 20.5 | 19.5 | 19.0 | 24.0 | 18.0 | 21.5 | 13.0 |
| Daily Number of Trips with Relatives | Mean | 3.1 | 3.1 | 2.7 | 2.7 | 3.0 | 3.0 | 2.6 | 3.1 | 2.4 | 2.4 |
| | Std. Dev. | 3.4 | 3.5 | 3.2 | 3.3 | 3.4 | 3.6 | 3.4 | 3.3 | 3.2 | 3.4 |
| | Minimum | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| | Median | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 | 1.0 | 0.3 |
| | Maximum | 18.5 | 14.5 | 15.0 | 16.0 | 12.0 | 13.5 | 19.0 | 13.5 | 17.0 | 17.5 |
| Number of household vehicles | Mean | 2.28 | 2.29 | 2.33 | 2.20 | 2.13 | 2.15 | 2.10 | 2.17 | 2.18 | 2.15 |
| | Std. Dev. | 1.14 | 1.04 | 1.09 | 1.03 | 1.00 | 0.99 | 0.97 | 1.10 | 1.14 | 1.15 |
| | Minimum | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | Maximum | 8 | 5 | 6 | 6 | 8 | 5 | 6 | 8 | 8 | 7 |
| Household size | Mean | 2.57 | 2.58 | 2.53 | 2.50 | 2.44 | 2.42 | 2.40 | 2.39 | 2.32 | 2.19 |
| | Std. Dev. | 1.16 | 1.17 | 1.14 | 1.15 | 1.13 | 1.14 | 1.12 | 1.11 | 1.14 | 1.00 |
| | Minimum | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | Maximum | 6 | 7 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 |
| Number of adults (18+) | Mean | 1.99 | 2.00 | 2.01 | 1.97 | 1.94 | 1.96 | 1.96 | 1.98 | 1.95 | 1.90 |
| | Std. Dev. | 0.60 | 0.63 | 0.65 | 0.65 | 0.62 | 0.66 | 0.65 | 0.64 | 0.68 | 0.65 |
| | Minimum | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | Maximum | 4 | 5 | 5 | 4 | 5 | 5 | 5 | 4 | 5 | 5 |
| Number of children (6-17) | Mean | 0.40 | 0.40 | 0.39 | 0.40 | 0.39 | 0.37 | 0.36 | 0.35 | 0.29 | 0.25 |
| | Std. Dev. | 0.78 | 0.79 | 0.77 | 0.82 | 0.80 | 0.77 | 0.76 | 0.75 | 0.67 | 0.60 |
| | Minimum | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | Maximum | 4.00 | 4.00 | 3.00 | 4.00 | 4.00 | 4.00 | 4.00 | 3.00 | 3.00 | 3.00 |
| Number of children (<6) | Mean | 0.19 | 0.18 | 0.14 | 0.13 | 0.10 | 0.08 | 0.08 | 0.06 | 0.07 | 0.03 |
| | Std. Dev. | 0.47 | 0.45 | 0.44 | 0.44 | 0.40 | 0.33 | 0.33 | 0.29 | 0.32 | 0.18 |
| | Minimum | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | Maximum | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 1 |
| Number of employed in household | Mean | 1.39 | 1.29 | 1.38 | 1.26 | 1.15 | 1.11 | 1.11 | 1.19 | 1.22 | 1.06 |
| | Std. Dev. | 0.86 | 0.82 | 0.81 | 0.88 | 0.90 | 0.92 | 0.95 | 1.03 | 1.12 | 0.99 |
| | Minimum | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | Maximum | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 | 5.00 | 4.00 | 4.00 | 4.00 | 4.00 |
| Average Age in Household | Mean | 46.82 | 47.72 | 49.55 | 50.04 | 51.60 | 53.43 | 54.45 | 55.77 | 56.50 | 59.13 |
| | Std. Dev. | 13.30 | 13.26 | 13.39 | 13.29 | 13.40 | 13.73 | 13.89 | 14.24 | 14.66 | 14.73 |
| | Minimum | 24.00 | 25.00 | 26.00 | 28.00 | 27.00 | 25.67 | 26.67 | 29.00 | 27.00 | 23.80 |
| | Median | 44.75 | 45.75 | 48.00 | 48.17 | 51.00 | 54.00 | 55.17 | 55.75 | 57.00 | 60.50 |
| | Maximum | 74.00 | 75.00 | 77.00 | 78.00 | 79.00 | 81.00 | 82.00 | 84.00 | 85.00 | 86.50 |

Table 2 shows a list of attitudinal variables tested as significant predictors of car ownership and use sequencing.  These are the answers of the household members that functioned as the spokesperson of the household (called householder herein). As we will discuss later only a few of these variables were found as significant predictors of class membership.

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**Table 2. Dummy Variables based on Attitudes of 230 Householders (spokesperson in household)**

| Question | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|
| *Importance Ratings (Important and Extremely Important)* | | | | |
| Parking Availability | 0 | 1 | 0.53 | 0.500 |
| Short Waiting Time | 0 | 1 | 0.47 | 0.500 |
| Day-to-day Costs | 0 | 1 | 0.37 | 0.485 |
| Flexibility to Change Plans | 0 | 1 | 0.57 | 0.496 |
| Ability to Arrive on Time | 0 | 1 | 0.68 | 0.468 |
| *SOV Performance Ratings (Well and Extremely Well)* | | | | |
| Parking Availability Performance | 0 | 1 | 0.48 | 0.501 |
| Minimizing Pollution | 0 | 1 | 0.14 | 0.347 |
| Ability Travel When Desired | 0 | 1 | 0.75 | 0.433 |
| Flexibility to Change Plans | 0 | 1 | 0.75 | 0.435 |
| Day-to-Day Costs | 0 | 1 | 0.27 | 0.447 |
| Ability to Arrive on Time | 0 | 1 | 0.69 | 0.463 |
| *Agreement Ratings (Strongly and Very Strongly Agree)* | | | | |
| Not Fair Having HOV Lanes | 0 | 1 | 0.08 | 0.269 |
| SOV Should Pay More | 0 | 1 | 0.20 | 0.398 |
| Would Carpool with Strangers | 0 | 1 | 0.14 | 0.351 |
| I Hate Transferring Buses | 0 | 1 | 0.38 | 0.487 |
| I Like Freedom of Driving Cars | 0 | 1 | 0.51 | 0.501 |
| No Answers to these questions | 0 | 1 | 0.19 | 0.394 |

*3.2 National Establishment Time-Series (NETS) Database*

The National Establishment Time-Series (NETS) Database (1990-2010) is a byproduct of the Dunn&Bradstreet inventory of business establishments. In this paper, we use it in an aggregate form to enumerate land use characteristics surrounding the residence of each household.  To do this, we build concentric circles surrounding each household residence as buffers. We then count the number of business establishments within each circle.  In total, five distance values are used as circle radii for this enumeration: 0.5, 1.0, 1.5, 2.0, 2.5 miles. The spatial area used for the closest distance (0.5 mile) is shaped as a circle, but all the others are shaped as annuli (donut shape), because we removed the duplicated business establishments to avoid strong correlation between spatial variables. Therefore, we used 0.5mile radius buffer, and 0.5-1 mile, 1-1.5 mile, 1.5-2 mile, 2-2.5 mile annuli in enumeration of land use characteristics. The density is the total number of employees in business establishments within each buffer; whereas, the Shannon Index is used to assess diversity of business establishment surrounding each residence. Both density and diversity increased between 1990 and 2002 due to the economic development in this area. The further away from each household buffers have higher values in both spatial indices, simply because the further away zones have a larger area of enumeration. The land use density grew with some fluctuations in 1992 and 1994, but the diversity had gradually increased over time relatively.   A more detailed analysis of the data is provided in Lee *et al.*, 2015.

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## 4. Longitudinal Mixed Markov Latent Class Models

The technique selected to identify groups of patterns of car ownership and use in the approximately 13-year long record of PSTP is a *longitudinal latent class cluster analysis*.

This technique:

   a) includes a multi-category latent variable (w) representing household heterogeneity and its categories are called classes;

   b) uses many "dependent" or response variables forming another set of categorical latent variables at 10 time points and its categories are called states;

   c) transitions from one state at one time to other states at other time points are estimated and they are functions of triggers;

   d) uses and tests the effect of covariates of many different specifications of the models; and

   e) is a model-based clustering approach providing probabilistic membership of observations in clusters of classes and clusters of states.

In this paper we use notation and model formulation based on Vermunt et al., 2008. We have three observed indicators of behaviour. PSTP includes a two-day diary and we compute for each household the two-day average number of trips driving alone, two-day average number of trips car sharing with household members, and the numbers of household cars in each year of the panel. These are three response variables (y) observed at 10 time points.

We assume there are L classes of households of fundamentally different behaviour and we use a latent categorical variable w to indicate them. This variable does not change over time but the average behaviour within the categories of this variable can change. We also assume a second latent variable exists, x, that is also categorical (with K categories) and it is time-varying ($x_t$, t=0,....,T). As mentioned above, we name the categories of this variable the "states" and they represent summaries of groups of behaviours (car ownership and use) at each wave of the panel.

The probability density associated with the Y (upper case letter indicates multiple variables) responses of household i with independent variables Z is defined by Equation 1.

$$P(Y_i \mid Z_i) = \sum_{w=1}^{L} \sum_{x_0=1}^{K} \sum_{x_1=1}^{K} \ldots \sum_{x_T=1}^{K} P(w, x_0, x_1, \ldots, x_T \mid Z_i)\, P(Y_i \mid w, x_0, x_1, \ldots, x_T, Z_i) \qquad (1)$$

The class membership probabilities (also called mixture proportions) are defined in Equation 2.

$$P(w, x_0, x_1, \ldots, x_T \mid Z_i) = P(w \mid Z_i)\, P(x_0 \mid w, Z_{i0}) \prod_{t=1}^{T} P(x_t \mid x_{t-1}, w, Z_{it}) \qquad (2)$$

Equation 3 shows the class-specific densities. They are the product over occasions (T+1) of the probability of a specific observed value of a response variable j at time point t ($y_{ijt}$) conditional on the latent state at time point t ($x_t$), class membership (w), and the values of the independent variables $Z_{it}$.

$$P(Y_i \mid w, x_0, x_1, \ldots, x_T, Z_i) = \prod_{t=0}^{T} P(Y_{it} \mid x_t, w, Z_{it}) = \prod_{t=0}^{T} \prod_{j=1}^{J} P(y_{itj} \mid x_t, w, Z_{it}) \qquad (3)$$

Each probability in Equations 1, 2, and 3 is a regression equation and parameterized accordingly. Then, estimation using maximum likelihood proceeds in similar ways as in other mixture regression models. The number of components of the joint distribution of this model is $L * K^{T+1}$. All probabilities (P) is equations 1,2, and 3 are logit models specified with linear combinations of coefficients and Zs.

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We create four types of independent variables (Zs). The time points (waves) in PSTP are unequally spaced and the data are collected at different seasons in a few of these waves. To control for this and to represent the time trend when the data were collected, we used a time variable in months (called elapsed time herein) from the first wave of PSTP (1989) and its square to represent nonlinearity of the time trend. We also use the average age of each household at each measurement occasion to capture "personal" time in the life course of each household. The second type of variables represents changes in household characteristics between survey years. For transitions among states we compute the difference between $Z_{it-1}$ and $Z_{it}$, and between $Z_{it}$ and $Z_{it+1}$ to create lagged changes ($Z_{it} – Z_{it-1}$) and anticipated changes ($Z_{it+1} – Z_{it}$). The time trends and changes in sociodemographics within the household and the surrounding area of its residence are used in estimating transition probabilities from one wave to the next. These are the *triggers* of behavioural change. The Zs used for transitions among states are variables describing changes within the household and changes in land use around the residence of a household. In this paper we also test past and future changes at one time point in the past (lagged covariate) and one time point in the future (lead covariate). Average age of the household is also used as an explanatory variable of transition to account for aging of household members and for children reaching driving age (in the US a person can drive a car at age 16 and older).

The variables in the third type are used as instruments for the initial (T =0) states and they are the values of sociodemographic characteristics of the households in the first wave of this panel in 1989. We use number of adults in the households, number of children ages 1 to 5 and number of children 6 to 17 to account for different household compositions. We also use number of employed persons to account for different needs to commute and availability to drive children to schools.

The variables in the fourth type are the attitudinal and judgment variables of Table 2 and they are used to explain class membership (w). Model specification is as follows. The Zs used as covariates for the classes (w) are the initial attitudinal variables of Table 2. In this way we can test if a thirteen-year sequencing of transitions from one state to another is an oscillation around a preferred behavioural pattern that is a function of attitudes about ownership of cars and car use.

Estimation is performed with a particular type of maximum likelihood estimation developed by Vermunt and Magidson (2002) and Vermunt et al., (2008) discuss a method they call a generalized Baum-Welch algorithm and it is implemented in the Latent Gold software (Vermunt and Magidson, 2013). An iteration of different specifications testing with multiple models using different initial trial values for the parameters (see also Goulias, 1999, Lee et al., 2015) was employed in a search for the best model. Goodness of fit and model performance is judged using BIC, AIC or CAIC values (McCutcheon, 2002, Nylund et al., 2007). Model estimation to reach the final form of the model in this paper started with a one-class and 2-state model and in two parallel streams (one increasing the number of classes and another increasing the number of states) we reached the same conclusion that the best model before the algorithm reaching impossible to estimate parameters is a 4-state and 3-class model. Then, a local search by imposing different restrictions in the transition probabilities and inclusion of different covariates (Z) in different components of the model, helped us reach the final model presented here. In addition, tests of a possible mover-stayer version (in essence allowing some households not to transition among states and called the stayers) showed that the hypothesis of a stayer group is not supported by the model performance criteria.
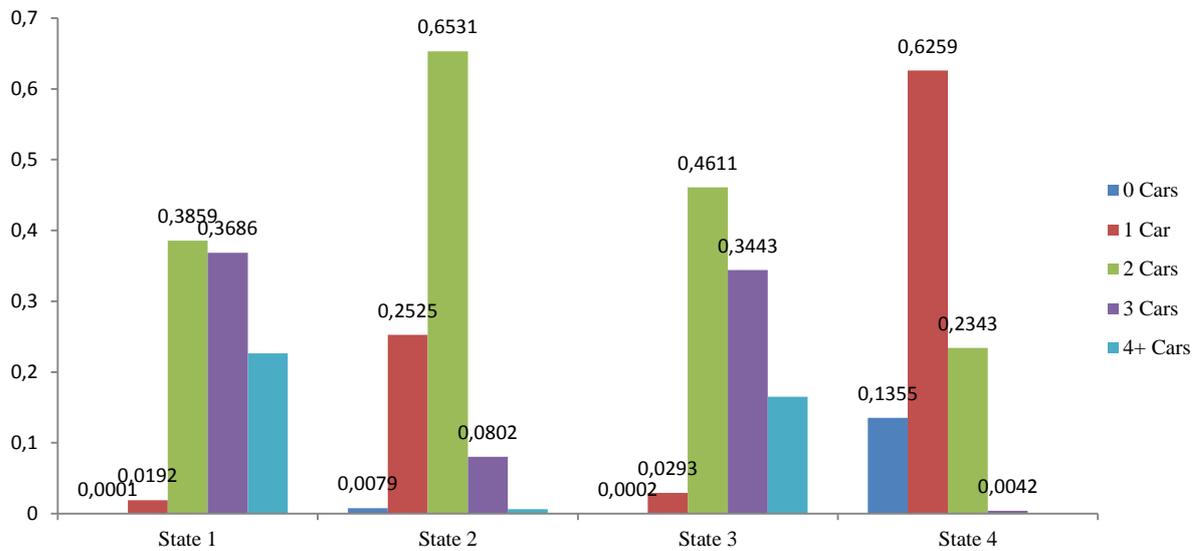
## 5. LCMC Model and Findings

Figure 1 provides a summary of the 4 states identified with this model. State 1 (31.4%) has the highest car ownership and the highest number of trips (driving alone and car sharing) and we call this state the *High Mobility*. State 2 (30.9%) shows much lower car ownership (one car less on

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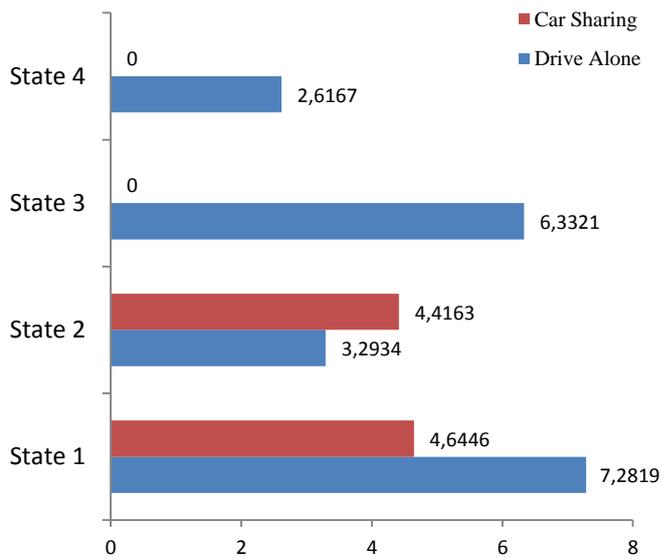
average) that State 1 and less than half the trips of driving alone (3.29 per day) than State 1 and we call this group *Average Mobility*. State 3 (19.4%) and State 4 (18.3%) are characterized by no car sharing trips, with State 3 having a high car ownership. We call State 3 *High Cars No Share*. State 4 also has the lowest number of trips and we call this group *Low Mobility*. The reported numbers are average numbers over all ten waves of the panel. Households switch between one state and another as they progress through the panel. This portion of analysis answers the first research question posed in the introduction of identifying significantly different behaviours (the four states). We turn now to the second question of identifying triggers and studying the role played by sociodemographic changes and land use changes.

Table 3 summarizes the way that households transition between states. This table shows the average probability of transitioning from one state to another across all waves and across all classes. Recall that State 1 is the *High Mobility* group. As Table 3 shows, households in State 1 have a 73.3% chance of staying in this category from one year to the next, and a 21.3% chance to move to State 3, *High Cars No Sharing*. With a combined 94.6% remaining in high car ownership categories from year to year, these car-oriented households are very unlikely to let go of their vehicles. State 2 is the *Average Mobility* group. Households in State 2 also have high inertia: they have a 76.6% chance of staying in their current state. If these households do transition to a new state, they are most likely to move to the *Low Mobility* State 4 (a 14.2% probability). State 2 households are presumably not as attached to their cars. Households in State 3 are in the *High Cars No Sharing* category. With just a 51.6% probability of staying in their state, they are the least stable of the four states. State 3 households are most likely to transition to the *High Mobility* State 1 (25.7% probability). They also have an 18.6% probability to transition to State 2. Recall that State 4 is the *Low Mobility* category. When they do move, it is most often to State 2 (19.8%), the "average mobility" group. Similar to States 1 and 2, these households have a 74.7% probability of staying in State 4, meaning it is unlikely that this group will transition to a higher state of mobility each year.

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**Figure 1a Number of Cars and States**



**Figure 1b Trips Alone vs. With Relatives by State**
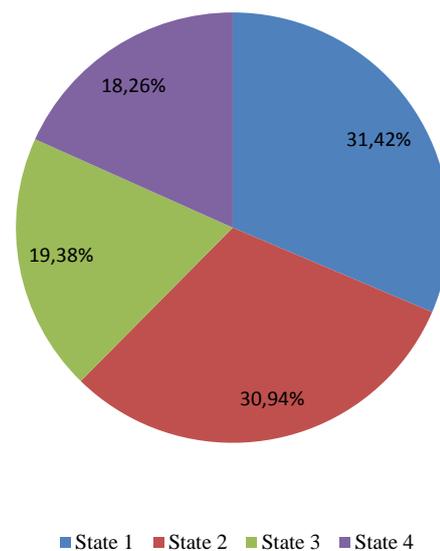


**Figure 1c State Frequencies**



*Figure 1. The Four Behavioural States*

**Table 3. State Transition Probabilities**

|                        | Time T                    |                              |                              |                           |
| ---------------------- | ------------------------- | ---------------------------- | ---------------------------- | ------------------------- |
| Time T-1               | State 1<br>High Mobility  | State 2<br>Average Mobility  | State 3<br>HighCarsNoShare   | State 4<br>Low Mobility   |
| State 1 High Mobility  | 0.733                     | 0.048                        | 0.213                        | 0.007                     |
| State 2 Average Mobility | 0.045                   | 0.766                        | 0.048                        | 0.142                     |
| State 3 HighCarsNo Share | 0.257                   | 0.186                        | 0.516                        | 0.041                     |
| State 4 Low Mobility   | 0.020                     | 0.198                        | 0.036                        | 0.747                     |

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Examining the significance and magnitude of the regression coefficients of variables representing future changes we identify significant triggers of changes in behaviour. We observe asymmetry in transitions. For example, we have different and extremely small probabilities of transition from State 1 to State 4 (0.7%) and a small probability from State 4 to State 1 (2%). We also observe symmetry between State 1 and 2 with 4.8% for the State 1 to State 2 transition and 4.5% for the State 2 to State 1 transition (4.5%). The transitions also show that we have a substantial number of households gaining mobility from State 4 to State 2 (19.8%), due to an increase in adults, but also loss of mobility with transition from State 2 to State 4 (14.2%). Transition from State 1 to State 3 is not influenced by anticipation, but the transition from State 1 to State 2 is heavily positively influenced by the anticipated increase in children 6 to 17 years old, meaning anticipating children getting older (coefficient: 4.50; p-value: $6.4 \times 10^{-4}$ ). This is an interesting asymmetry to the negative impact of increases in children's ages in the past (coefficient: -2.44; p-value: 0.036). The transition from State 3 to State 2 is an extreme behaviour change: households reduce their trips driving alone, increase their shared trips, and reducing the number of cars. Reducing the number of workers (coefficient: -1.00; p-value: 0.036) and the number of adults (coefficient: -1.79; p-value: 0.0062) increases the probability of households transitioning to State 2. Changes in business diversity have an even stronger impact on State 3 households' travel behaviour towards State 2 than the previously mentioned variables. Growth of business diversity within a 0.5-mile radius of a household raises the transition probability (coefficient: 6.61; p-value: 0.0029). Remarkably, the results show an even more powerful reverse effect within 1 to 1.5 miles from the household (coefficient: -8.26, p-value: 0.0022). In this distance range, a drop in business diversity increases the likelihood of transitioning to State 2.

Households moving from State 2 to State 4 are moving from an average number of cars and trips to a low number of cars and trips. When determining the transition probability from State 2 to State 4, the household mean age, number of adults, and surrounding business diversity are the significant variables. The probability of a household changing behaviour enough to transition to State 4 goes up when the mean household age increases (coefficient: 0.033; p-value: 0.0054). If adults leave the household, transition probability also increases (coefficient: -1.94; p-value: $5.2 \times 10^{-4}$). If business diversity within a 0.5-mile radius decreases, households will be less likely to maintain their mobility and the probability of transition to State 4 will increase (coefficient: -2.34, p-value: 0.027). Oddly enough, the results show that households anticipating increases in business diversity within 0.5 to 1 miles of their residence contradict this, and have a larger effect on transition probability (coefficient: 3.76; p-value: 0.0088). They are more likely to reduce mobility and move to State 4 before business diversity increases.

The following variables were found to be significant for determining whether households transition from high car ownership and high number of trips (alone and sharing) in State 1 to high car ownership and low car sharing in State 3. If mean household age goes up, then the odds for a household to transition from State 1 to State 3 increases (coefficient: 0.048; p-value $1.2 \times 10^{-5}$). If a household gains an adult, then the transition probability decreases (coefficient: -0.54; p-value: 0.014). Corresponding to this, if the number of children between 6 and 17 decreases (likely meaning they turned 18 or left the household), then the likelihood of a household transitioning to lower car sharing increases (coefficient: -0.95; p-value: 0.0046).

When households change from State 3 to State 1 behaviour, they are slightly reducing their car ownership and increasing their number of trips alone and sharing cars. This transition probability is affected by mean age, number of workers, number of adults, and anticipated increase in children ages 6 to 17. When a household's mean age lowers – meaning young children become teenagers or adults leave – the probability that they will share cars more and move to State 1 rises (coefficient: -0.033; p-value: 0.045). The transition probability also increases when the number of workers in a State 3 household grows (coefficient: 0.54; p-value: 0.057). Correspondingly, the number of adults increasing raises transition probability (coefficient: 0.78; p-value: 0.026). An anticipated decrease in the number of children between ages 6 and 17 will

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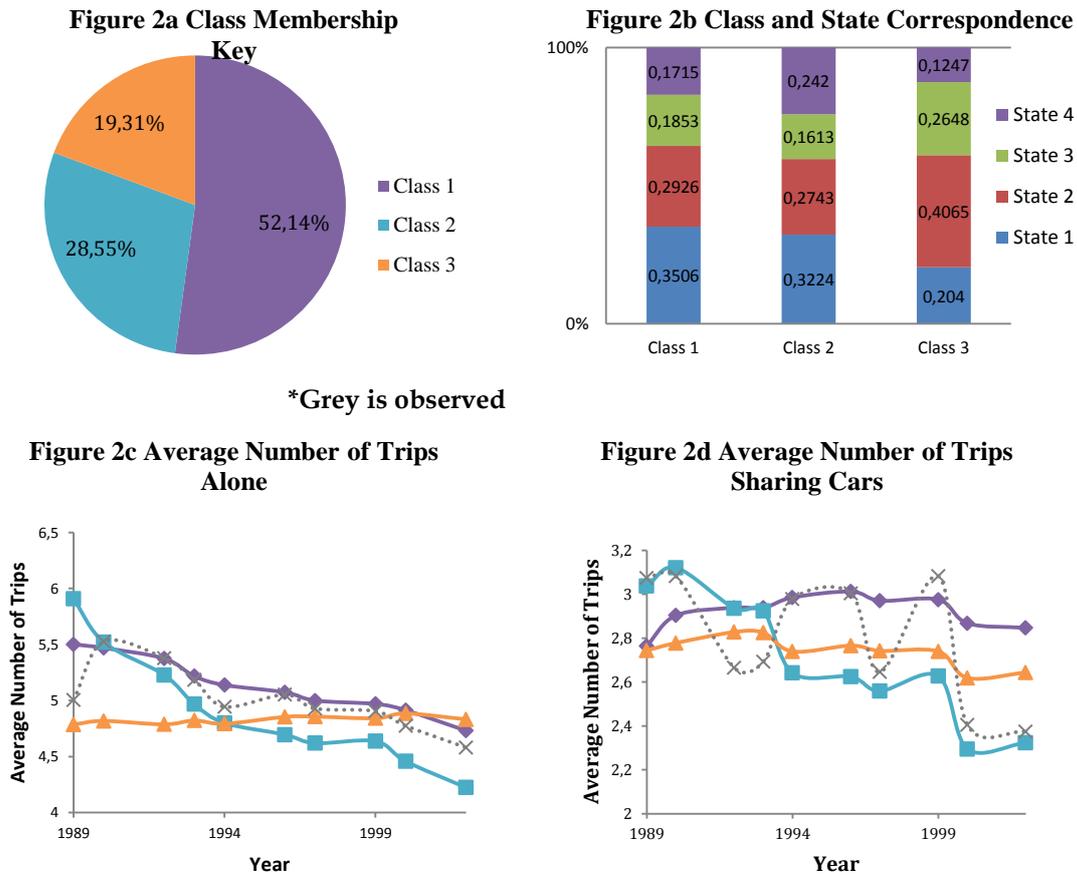
increases the probability of transition to State 1 (coefficient: -4.80; p-value: 0.037), presumably because children turn 18 and then fall into the categories of adult –and possibly worker – mentioned previously.

Based on the significant variables uncovered in analysis, those in State 1 are presumably families with car-positive attitudes who do not get rid of their vehicles when their children grow up and move out. State 2 households are likely not as attached to their cars. When they perceive less of a need for vehicles, they are more willing to get rid of them. State 2 households are likely to have older children who are eventually moving out, at which time these households get rid of cars and their number of trips drops.

State 3 households are very reliant on their vehicles to get from place to place. They do not share cars, so they most likely do not have children at school ages. Based on the low number of trips, low car ownership, and influence of number of adults, State 4 households are likely one or two person households, low-income households, or households with roommates – not relatives. This group most likely relies on public transportation for most of its trips.

Although it seems like state changes happen abruptly, longitudinal studies only capture a window of time in the lives of respondents. In reality, behaviour changes are gradual, taking months or even years to occur. The manner through which households move among different behavioural states is one way long-term shifts can be observed. For example, low-mobility households tend to stay in low-mobility states. Years in the future they could end up with high mobility, but they would most likely go through in-between states along the way.

We turn now to the analysis of classes. Classes are derived from sequences of states. Households belong to each class and they do not move from class to class. They instead move from state to state. In addition, class membership is explained using attitudinal data as explained later. To account for possible class-specific transitions from state to state (across years of observation) we also use class membership as an explanatory variable of transitions. The LCMC model identified 3 classes as a satisfactory description of sequencing of switching among states in this model. Figure 2a shows the proportion of household belonging to each class. Figure 2b shows the composition averaged over time of each class in terms of different behavioural states. Figure 2c shows the within class average number of trips alone for each class (red, green, and blue) together with the observed trips (purple) in the ten waves. Figure 2d shows the within class average number of trips car sharing for each class (red, green, and blue) together with the observed trips (purple) in the ten waves.

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**Figure 2a Class Membership Key**



**Figure 2b Class and State Correspondence**



*Grey is observed*

**Figure 2c Average Number of Trips Alone**



**Figure 2d Average Number of Trips Sharing Cars**



*Figure 2. Classes and their Characteristics*

Class 1 is primarily made up of households in the high-mobility State 1 (35%) and the average-mobility State 2 (29%). The percentage of households in States 3 and 4 is about equal (18.5% and 17.1% respectively). For households in Class 1, the number of trips alone drops slowly over time and the number of trips with relatives stays somewhat steady.

Class 2 has a very similar distribution to Class 1, except it has noticeably more households in low-mobility State 4 than in the unstable State 3 (24.2% in State 4 versus 16.1% in State 3). Class 2 households experience the most acute drop in trips both alone and with relatives over time. The drop in trips with relatives appear to occur in "steps." The number of trips remains steady for some time and then suddenly drops to a new number, maintains that for sometime, then drops again.

Class 3 has the most unique distribution of States. Unlike the other two Classes where State 1 and 2 have similar distributions, Class 3 is 40.6% composed of State 2, and the second highest is State 3 with 26.5% of households. State 1 makes up just 20.4% of Class 3, with State 4 at 12.5%. For both trip types – alone and with relatives – the number of trips stays steady.

Figure 3 offers another important aspect of this type of model. Number of cars in a household can be analysed as categories to reflect important differences between having no cars representing severe restrictions to mobility and having one or more cars. The sample used here shows a distribution of number of cars per household centered around 2 cars. Figure 3 shows a substantial number of households in each of the three classes have 2 cars and these households are a stable situation. In contrast, household that belong to Class 2 show a relatively (when

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compared to the other 2 classes) increase in the zero cars and 1 car categories with concomitant decreases in the more than 2 cars categories.   It should be noted, however, that the percent of households with no cars is much smaller than any other percent in Figure 3.  We turn now to another important aspect of our analysis on the role of attitudes.



**Figure 3a No Cars**



**Figure 3b One Car**



**Figure 3c Two Cars**



**Figure 3d Three Cars**



**Figure 3e Four or more Cars**



**Figure 3f Class Membership Key**
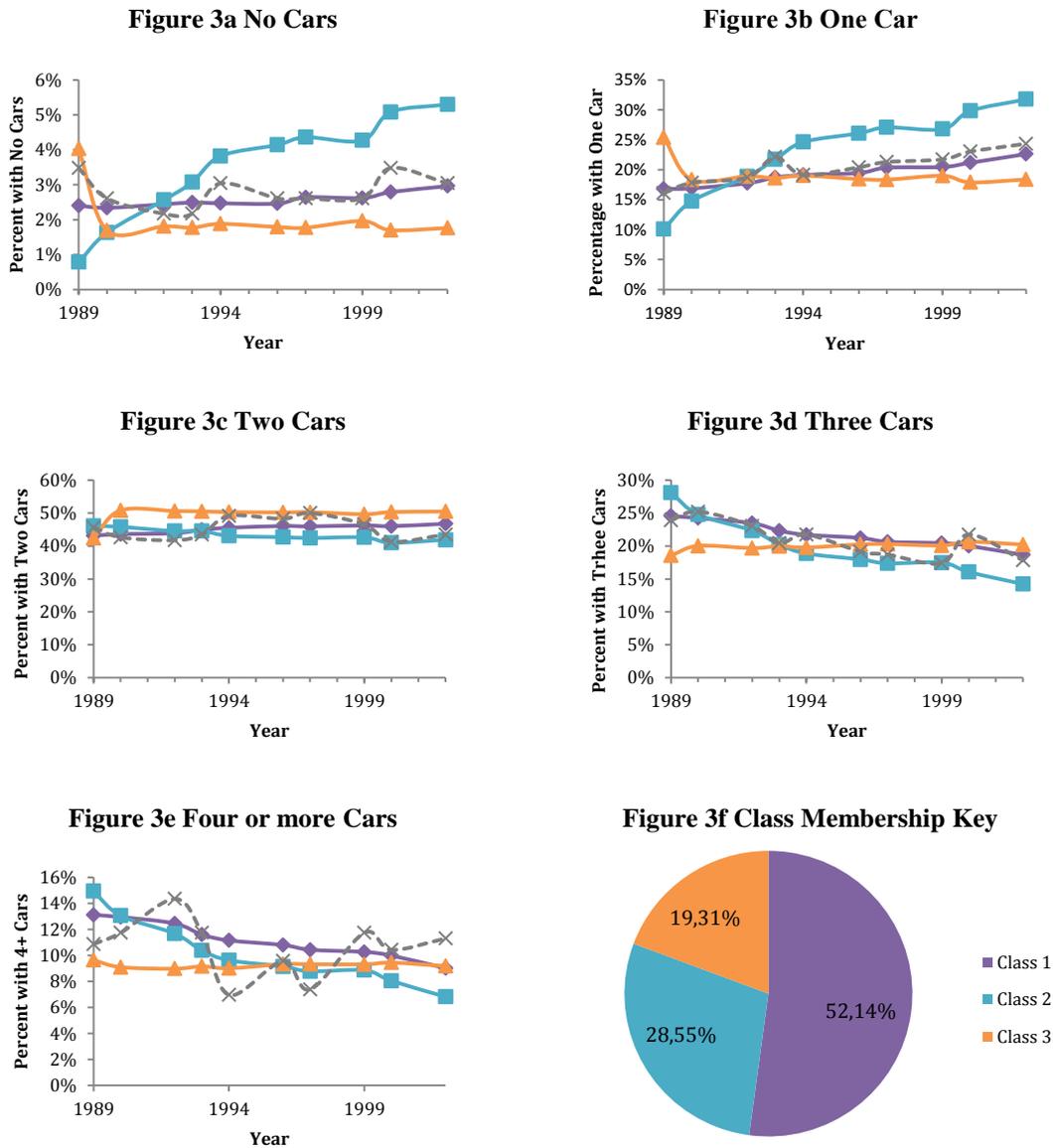
**\*Grey is Observed**

*Figure 3. Car Ownership and Categories over Time*

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In terms of the correlation between attitudes and class membership, we found only five variables as significant predictors of class membership (flexibility to change plans, performance of parking availability and day-to-day costs, and agreement that HOV lanes are unfair and dislike bus transfers). Households that answered it is "important" and "very important" to have flexibility to change plans are less likely to be in Class 2 or Class 1, and more likely to be in Class 3. Recall that Class 3 is the class of households with high car ownership and no car sharing. On the other hand, households that judge availability of parking performance to be good or extremely good are more likely to be in Class 1. Moreover, households judging the day-to-day car costs as well and extremely well are more likely to be in Class 3. Similarly, households that think it is unfair having HOV lanes are also more likely to be in Class 3. Finally, households that hate bus transfers (agree and strongly agree) are more likely to be in Class 2. All this taken together shows that we can identify additional "traits" for these classes using attitudinal data from the beginning of the panel. However, the findings here are only a first exploration of the relationship between attitudes and class membership. For this reason, we used data from the first person in the PSTP files (used as the household spokesperson).

In summary, Class 3 is stable in its behaviour and has attitudes that support a car based "culture" because they like flexibility to change plans, find car costs agreeable, and they dislike HOV lanes. Class 2 is also a car friendly group but at a lower level than Class 3 with a particular dislike for bus transfers. They experience rapid mobility decreases, with changes happening at a faster pace at the extremes of the car ownership groups i.e., higher than average car ownership decreases and lower than average car ownership increases (see the proportion of one car households increases from approximately 10% to approximately 30%). Class 1 is the largest and most moderate among the 3 groups. They judge parking availability as good to extremely good with a moderate decrease in mobility. None of the other variables of Table 2 had a significant influence on the transitions among states. The evidence here suggests that attitudinal questions at the beginning of a panel survey may be a strong predictor of evolutionary patterns over a long period of time.

The state of each household at the initial time point (0 in equations 1, 2, and 3) is also a function of class membership and number of adults in the household, number of workers, children of ages 1 and 5 and children of ages 6 to 17. All these variables are significantly different than zero and define the "initial conditions" of this panel analysis.

## 6. Summary and Conclusion

In this paper we explore the longitudinal relationships among number of cars owned by households, number of trips driving alone, and number of trips car sharing with household members. We use data from 230 households observed in ten different occasions (waves) from 1989 to 2002. Using a mixture latent class Markov model we identify four distinct groups of car ownership and use that are a *High Mobility* group with more cars and car trips, an *Average Mobility* with lower car ownership and trips alone than the first group, a third group with relatively high car ownership but few car sharing trips, and a fourth group of *Low Mobility* characterized by the fewest cars and trips. As time progresses households jump from one group of behaviour to another and they are influenced by their internal sociodemographic and land use changes around their residence. Intra-household demographic changes (number of workers and coming of age of other children) and land use diversity around the household residence cause both adaptation and anticipation by households as they change behaviours. This implies that households not only adapt to internal and external changes to their environment but they also anticipating changes go through a "preparation" stage (e.g., adding another car in their fleet in expectation of adding another employed person). Land use, although significant for some transitions, plays a somewhat secondary role.

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The analysis also reveals three classes (hidden Markov chains) of households underlying behavioural dynamics with increases in the low car ownership categories (zero and one car per household), decreases in the high car ownership (three cars and four or more cars per household) and stable behaviour in the two cars per household. Through analysis we identify three different classes of households that exhibit heterogeneous sequences of behavioural change (longitudinal heterogeneity). This allowed the decomposition of observed changes in three different patterns. All three classes display decrease in the number of trips driving alone and one of the classes shows a clear increase in the number of trips with household members. The three classes are also different in the way car ownership changes for them except for the households that own 2 cars and they seem to stay in the same car ownership level for a substantial amount of time. The classes extracted here are also found to be significantly influenced by householder ratings to parking availability, schedule flexibility, bus transfers, HOV related attitudes, and day-to-day costs of driving. This also implies we need a more complex dynamic specification for models of car ownership and use than currently used in micro-simulators of travel demand. We also need repeated observations in the form of panel data surveys of the same households over time that are coupled with data about changes in the built environment surrounding the persons we track to analyse their behaviour.

The analysis presented in this paper provided many new insights about behavioural dynamics that paves a new direction in travel behaviour research. There are, however, many limitations worth mentioning. First, the 230 households analysed here are the "stayers" of a larger panel survey and they are significantly different than the entire panel survey and the Puget Sound region (see the analysis by Ma and Goulias, 1997) that show initial self-selection is even more detrimental that systematic panel attrition (Pendyala et al., 1993, Chung and Goulias, 1995). For these reasons they do not represent the area in which they reside. In a future application we will need to examine methods to make the findings representative of the Puget Sound region. Second, we selected number of cars and trips for joint analysis as a pilot test of our method. Car type(s), their age, and kilometres travelled could be also included in this analysis for completeness and comparison with other studies. Third, land use surrounding residences is not the only built environment description that impacts behaviour. In fact land uses around workplaces and schools as well as an account of the level of service offered by the transportation infrastructure are good next steps in this analysis. Last, policies are only captured by the density and diversity of business establishments that we believe capture land use growth policies in the Puget Sound region. However, other policies such as pricing of services could potentially be included in applications.

## Acknowledgement

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