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


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Number of Words = 5608
Number of Tables and Figures = 5*250 = 1250
References = 34 = 500
Total equivalent = 7358


Paper accepted for 95th Annual Transportation Research Board Meeting, Washington, D.C., January 10-14, 2016

**GEOTRANS REPORT 2015-07-02**

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## ABSTRACT

In this paper we explore the longitudinal relationships among number of cars owned by households, number of trips driving alone, and number of trips sharing cars with household members. We use data from 230 households observed in ten different occasions (waves) from 1989 to 2002. The analysis reveals three classes (hidden Markov chains) of households underlying behavioral 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 behavior in the two cars per household group. Also, 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. These classes are significantly influenced by householder ratings to parking availability, schedule flexibility, bus transfers, and day-to-day costs of driving. 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 behaviors. This implies that households not only adapt 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, although significant for some transitions, plays a somewhat secondary role. 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 analyze their behavior.

Paper submitted for 95th Annual Transportation Research Board Meeting, Washington, D.C., January 10-14, 2016

## 1. INTRODUCTION

Car ownership and use is a fundamental research area in travel behavior 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 main analytical tool used here is longitudinal mixed Markov latent class analysis to explore patterns of car ownership and use change in the ten waves of the Puget Sound Transportation Panel (PSTP). We employ this pattern recognition technique in databases that include households participating in all waves (230 households) matched with land use data surrounding their residence. In essence, we create clusters of behaviors 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 based on car ownership, number of trips driving alone and number of trips car sharing with household members at each of the ten waves (time points) spanning more than a decade (1989 to 2002). Transitions among different behavioral 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 behavioral 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 behavioral change of past events and future internal to the household and external to the household evolving events. We examine changes due to newborn 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 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: Are there different sequences of change in behavior over time and are they influenced by attitudes? Can we identify a few groups of similar car ownership and use behavior? As time progresses and households jump from one group of behavior 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?

## 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 modeling 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 are based on strong assumptions about the underlying behavioral 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) behavioral 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 behavior 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 behavioral 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. It should also be noted that Sunkanapalli *et al.* (2000) analyzes the attitudes from the same panel data that this paper examines (the PSTP). The analysis is done using the analysis of variance (ANOVA) method, to explore the dynamics of attitudes but not car ownership and use. None of the studies we reviewed examine car ownership and use in long periods of observation (e.g., a decade) to identify longitudinal behavioral heterogeneity.

## 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 behavior 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 behavior 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 behavior 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 behavior of these participants with the behavior of participants in five waves, Goulias et al., 2014). We also used this same sample to study the longitudinal change in activity and travel behavior (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 behavior indicators and household characteristics over time. We observe a gradual decrease in most travel behavior 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.

**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 |

**TABLE 1 Descriptive Statistics (continued)**

| Year of wave | Statistics | 1989 | 1990 | 1992 | 1993 | 1994 | 1996 | 1997 | 1999 | 2000 | 2002 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 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. We show the indicator variables tested for significance in the model building. 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.

**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, 1.5, 2, 2.5 mile. 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.

## 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 indicators of behavior (two-day average a number of trips driving alone, two-day average number of trips car sharing with household members, and numbers of 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 behavior and we use a latent categorical variable w to indicate them. This variable does not change over time but the average behavior 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 behaviors (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 2.

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

The class membership probabilities (also called mixture proportions) are defined in Equation 3.

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

Equation 4 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 $Z_{it}$.

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

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 $L * K^{T+1}$.

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 capture 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 behavioral change. 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. The variables in the fourth type are the attitudinal and judgment variables of Table 2 and they are used to explain class membership.

Estimation is performed with a particular type of maximum likelihood estimation developed by Vermunt and Magidson (2002) and Vermunt et al., (2008), and follows an iteration of different specifications testing multiple models using different initial trial values for the parameters (see also Goulias, 1999, Lee et al., 2015). Goodness of fit is judged using BIC, AIC or CAIC values (McCutcheon, 2002, Nylund et al., 2007).

## 5. LCMC MODEL AND FINDINGS

We start with a series of models by increasing sequentially the number of states until a reasonable representation of the data is found. Then, we increase the number of latent classes (hidden Markov chains) until a model that reaches the minimum BIC and AIC is found. Different combinations of initial Zs and triggers are tested in this way. The model selected for illustration here contains *4 states* and *3 classes*.

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 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.

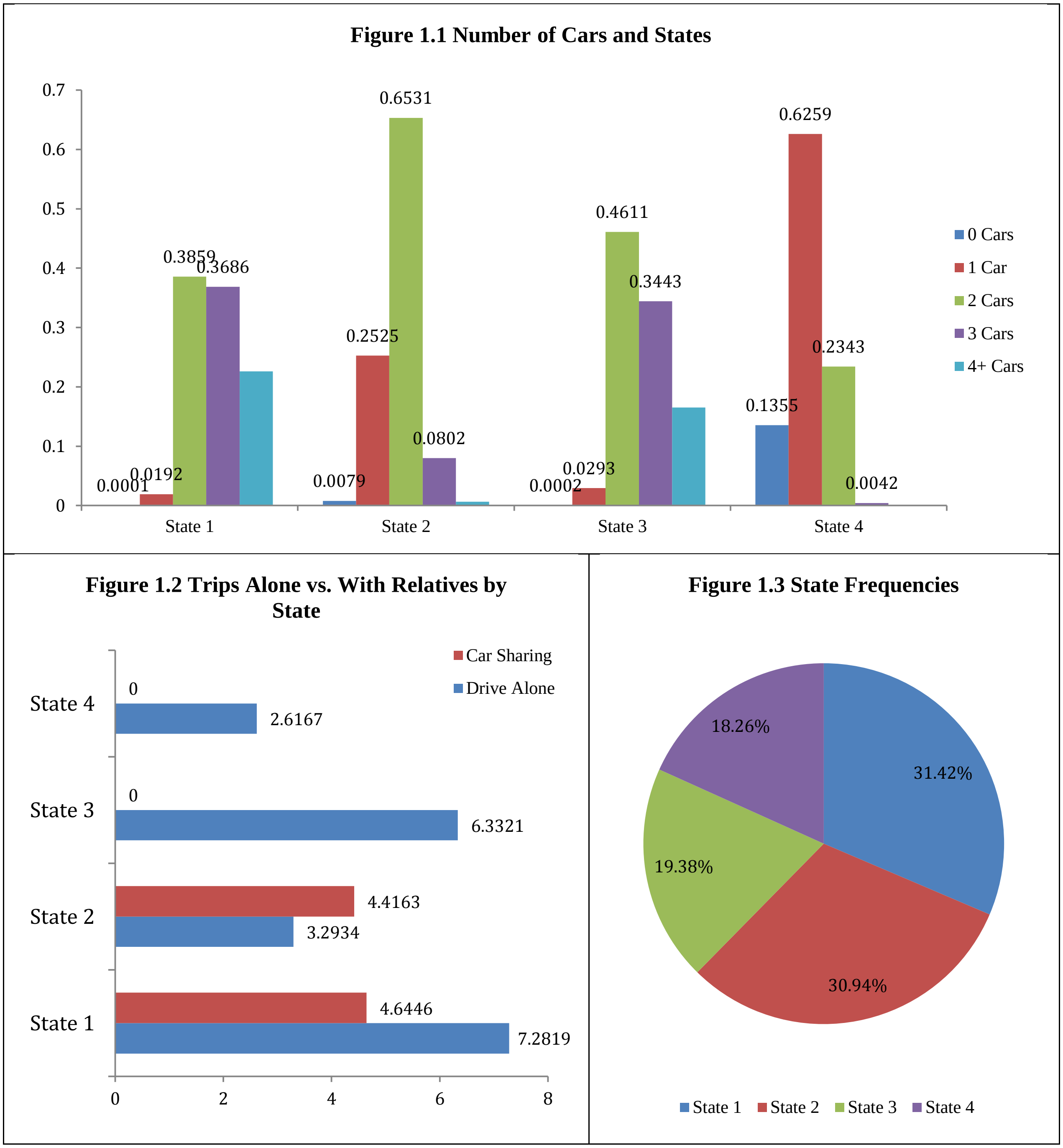



**FIGURE 1 The Four States**

Table 3 summarizes the way that households transition between states. 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.

Examining the significance and magnitude of the regression coefficients of variables representing future changes we identify significant triggers of changes in behavior. 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 expected increase in children 6 to 17 years old (presumably children getting older). This is an interesting asymmetry when compared to the impact of increases in children in the past (which has a negative impact on this probability of transition). The transition from State 3 to State 2 is an extreme behavior change: households reduce their trips driving alone, increase their shared trips, and reducing the number of cars. Reducing the number of workers and the number of adults increases the probability of households transitioning to State 2. Changes in business diversity have an even stronger impact on State 3 households' travel behavior 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 (positive significant coefficient). Remarkably, the results show an even more powerful reverse effect within 1 to 1.5 miles from the household (coefficient). 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 behavior in this direction goes up if the mean household age increases (coefficient). If adults leave the household, transition probability also increases (coefficient). 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). 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). 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). If a household gains an adult, then the transition probability decreases (coefficient). 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).

When households change from State 3 to State 1 behavior, 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. The transition probability also increases when the number of workers in a State 3 household grows. Correspondingly, the number of adults increasing raises transition probability. An anticipated decrease in the number of children between ages 6 and 17 will increases the probability of transition to State 1, 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, behavior changes are gradual, taking months or even years to occur. The manner through which households move among different behavioral 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. The LCMC model identified 3 classes as a satisfactory description of sequencing of switching among states in this database. Figure 2a and Figure 2b provide a summary of these classes.

**Figure 2.1 Class Membership**

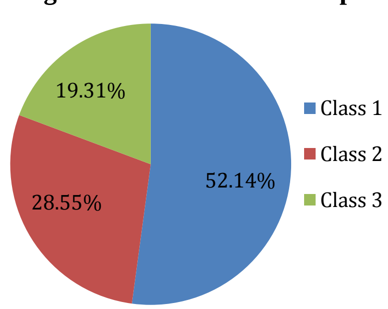
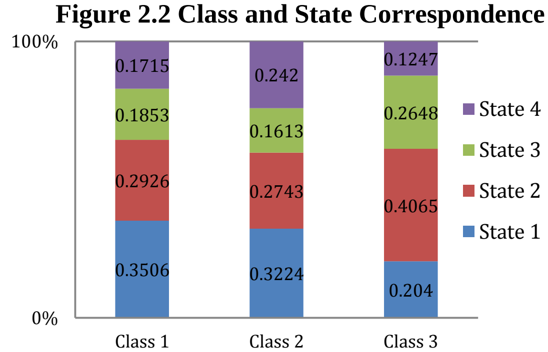



**Figure 2.2 Class and State Correspondence**



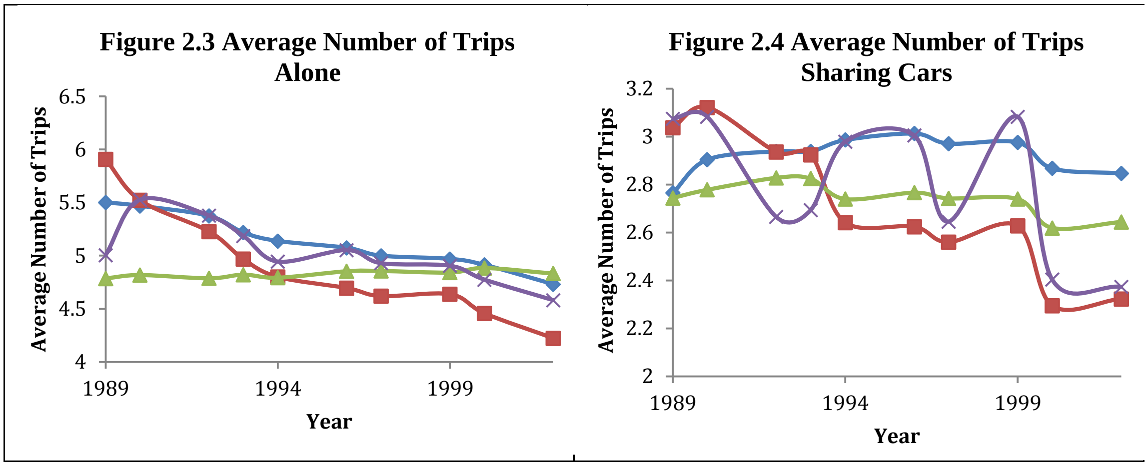



**FIGURE 2 Classes and their Characteristics**

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.

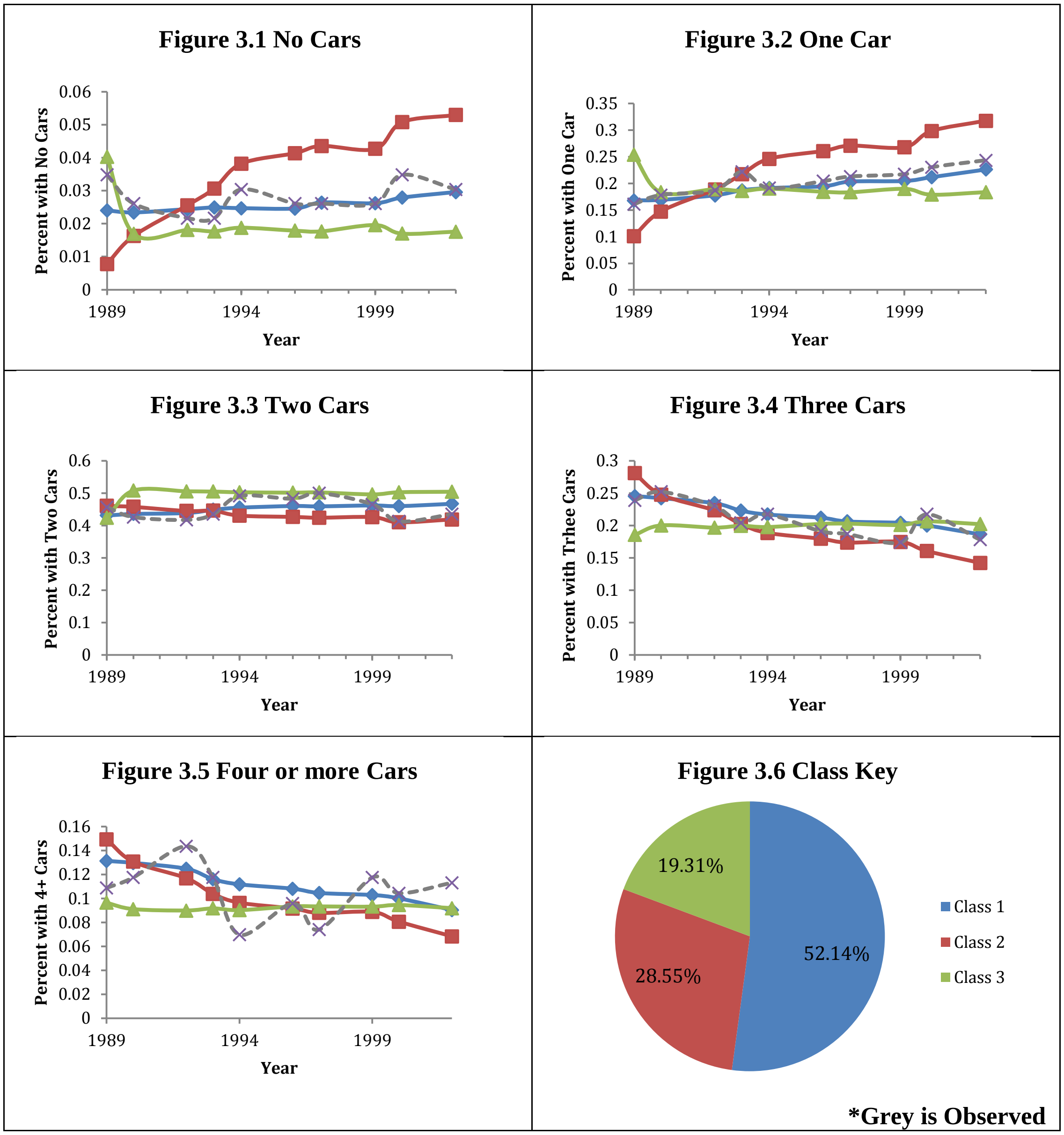



**FIGURE 3 Car Ownership and Categories over Time**

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 behavior 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 and experiencing rapid mobility decreases with changes happening at a faster pace at the extremes of the car ownership groups (higher than average car ownership decreases and lower than average car ownership increases (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 that judges 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 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.

## 5. 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. The analysis reveals three classes (hidden Markov chains) of households underlying behavioral 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 behavior in the two cars per household. Through analysis we identify three different classes of households that exhibit heterogeneous sequences of behavioral 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. These classes 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. 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 behaviors. This implies that households not only adapt 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 although significant for some transitions play a somewhat secondary role. 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 analyze their behavior.

The analysis presented in this paper provided many new insights about behavioral dynamics that paves a new direction in travel behavior research. There are, however, many limitations worth mentioning. First, the 230 households analyzed here are the "stayers" of a larger panel survey and they significantly different than the entire panel survey and the Puget Sound region. For this reason 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) and kilometers traveled could be also included in this analysis for completeness and comparison with other studies. Third, land use is not the only built environment description that impacts behavior and accounting for transportation infrastructure is the next step 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

Funding for this research was provided by the Multicampus Research Program Initiative on Sustainable Transportation, the University of California Transportation Center (UCTC), the University of California Center on Economic Competitiveness in Transportation (UCCONNECT), and grants of the University of California Santa Barbara Office of Research and the College of Letters and Science.

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