

# Capturing Modality Styles Using Behavioral Mixture Models and Longitudinal Data

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## **Abstract**

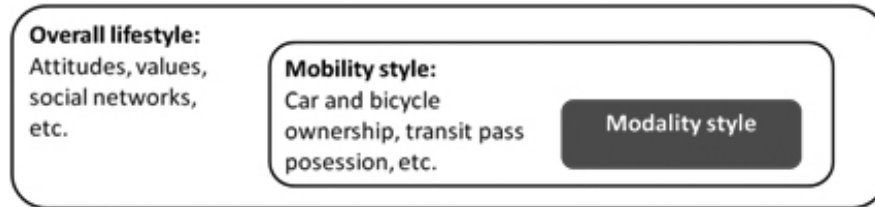
Modality styles are defined as behavioral predispositions characterized by a certain mode or set of modes that an individual habitually uses. They are reflective of higher-level orientations, or lifestyles, that are hypothesized to influence all dimensions of an individual's travel and activity behavior. The objectives of this paper are to understand and quantify different modality styles, and to show how the modality styles construct can be operationalized within the context of traditional travel demand models. We employ the six-week MOBIDRIVE travel diary and estimate behavioral mixture models in which the modality style provides a behavioral rationale to the way in which unobserved heterogeneity is specified in the travel model. Our analysis consists of two stages: First, we explore the presence and types of modality styles suggested by the data through the means of a descriptive analysis. Next, we develop a model that captures the influence of modality styles on two dimensions of an individual's travel behavior: mode choice for work tours and mode choice for non-work tours. The modality styles are specified as latent classes; heterogeneity across modality styles include both the modes considered (choice set) and the values of taste parameters. The modality style of an individual then influences all of his/her mode choice decisions for work-tours and non-work tours. In addition, error components capture unobserved correlation between alternatives and across mode choice decisions made by the same individual. Our results from both stages indicate the presence of "quasi-unimodal auto" individuals who display a strong bias for using the automobile and "multimodal" individuals who exhibit variation in their modal preferences. Multimodal behavior is further distinguished by those whose auto use is minimal at best (termed "multimodal green") and those who display significant auto use ("multimodal all"). These three modality styles comprise roughly equal segments within the sample population. The behavioral mixtures model provides a better fit to the data than other modeling approaches, such as random parameters. Moreover, by providing a behavioral underpinning to unobserved heterogeneity, it provides a richer and more robust framework for interpretation and policy analysis.

## 1. Introduction

The automobile's continued preeminence in much of the developed world, and its more recent proliferation in many developing countries, is a source of grave concern to the health of our cities and the global environment at large. Alternative modes of travel, such as public transit and bicycling, have the potential to offer a more sustainable solution to our mobility requirements. However, policies meaning to affect a modal shift often come unstuck against long ingrained lifestyles and deeply entrenched habits built around the use of the automobile. Travel demand models form an important component of the planning and policy-making process, being widely used to make forecasts, which in turn are driven by the assumptions that these models make about how individuals arrive at decisions. Traditional travel demand models assume that an individual is aware of the full range of alternatives, and that a conscious choice is made based on a tradeoff between perceived costs and benefits associated with level-of-service attributes, and individual and household characteristics. Heterogeneity in the choice process is typically represented as systematic taste variation or random taste variation to incorporate both observable and unobservable differences in sensitivity to attributes. Often though, these models overlook the effects of inertia, incomplete information and indifference that are reflective of more profound individual variations in preferences and attitudes. Furthermore, the shared influence of these variations across different choice dimensions is either only indirectly captured or captured in a manner that lacks behavioral underpinning.

Empirical evidence increasingly indicates the existence of higher-level orientations, or lifestyles, that influence all dimensions of an individual's travel and activity behavior. These include both short-term decisions, such as where to go and what modes to use (Krizek and Waddell, 2002; Srinivasan and Ferreira, 2002; Johansson et al., 2006), and more long-term choices, such as whether to buy a car (Choo and Mokhtarian, 2004). Past research examining the role of lifestyles on travel behavior has used the term "mobility style" to refer to the mobility-related component of an individual's lifestyle (Lanzendorf, 2002). An intricate part of mobility behavior, and therefore lifestyle, is mode choice. Given that lifestyle is a longer-term and partially subconscious choice, we argue that the assumption that people choose their mode of travel independently for every trip or tour likely does not hold true. Instead, we emphasize the existence of "modality styles", or behavioral predispositions, characterized by a certain mode or set of modes that an individual habitually uses (Kuhnimhof, 2006). For instance, consider a unimodal auto user who views the world from behind the steering wheel, imagining distances in terms of driving times and locations in terms of parking availability. A unimodal auto user might not be aware of the alternatives at his disposal, or chooses not to consider them, irrespective of the nature of the trip. He knows merely to drive. At the other end of the spectrum, we have a multimodal user who thinks of the available destinations in conjunction with their accessibility by different modes, and optimizes her choice of mode prior to every trip. Irrespective of where an individual lies within the spectrum, we hypothesize that the individual's modality style is inextricably linked with other short and long-term travel decisions. Figure 1 outlines the relationship between lifestyle, mobility style, and modality style. In this paper we focus on the innermost component, namely modality styles and their effects on two different choice situations: mode use for work tours and mode use for non-work tours.

The objectives of this paper are two-fold: to identify different modality styles, recognizing the repetitive nature of mode choice to demonstrate the influence exerted upon it by higher level orientations, and to show how the modality style construct can be integrated into the framework of traditional travel demand models. We hypothesize that modality styles are difficult to infer from standard one or two day activity diaries, leading us to employ longitudinal travel-diary data over a six-week observation period. The discrete choice modeling approach that we adopt is the behavioral mixtures model, where a behavioral rationale is used to inform the mixing distribution that captures unobserved heterogeneity. Our analysis consists of two stages: First, we identify different modality styles within the sample population through a *descriptive analysis*, investigating possible correlations between mode choices for work and non-work tours. This is followed by the *econometric analysis*, where we develop travel demand models using both



*Figure 1: Relationship between lifestyle, mobility style, and modality style*

latent class and continuous logit mixture techniques to deduce unobserved modality styles and their effects on travel behavior. The stages are linked as findings from the first stage inform the process of model development.

Our work builds upon existing bodies of literature on lifestyle and travel demand, simultaneous choice models, and choice set generation. Contributions are both conceptual, in terms of the modality style construct and its pervasiveness in mode choice behavior over different types of tours over a period of time, and empirical, in terms of inferring the modality style construct from a longitudinal travel diary survey without the use of additional survey questions, such as attitudinal statements regarding modes. While our focus here is on mode choice, the model framework developed can be extended along multiple choice dimensions, lending a more behaviorally realistic representation of individual travel behavior.

The paper is organized as follows: Section 2 reviews pertinent literature. Section 3 describes the dataset used in the empirical work. Section 4 consists of a descriptive analysis that seeks to identify different unimodal and multimodal groups in our sample population based on their observed choices, or lack thereof. Section 5 presents results from the econometric analysis, comparing our model framework with other approaches to incorporating heterogeneity in choice models. Section 6 concludes the paper with a discussion of our findings and implications.

## 2. Literature Review

In this section, we first review literature examining the notions of lifestyles, mobility styles and modality styles. We then discuss approaches used in the literature to incorporate the effects of mobility and modality styles in choice models.

### 2.1 Lifestyles, mobility styles and modality styles

To this point, there is no general consensus among social scientists on the exact definition of “lifestyle”. Jensen (2007) examines lifestyle from the social sciences perspective, and argues that it needs to be understood on four different levels, from a global to an individual lifestyle. He positions mobility-related decisions on the third (sub-cultural) and fourth (individual) levels, where decisions involve the choice of activity locations, travel frequency and mode choice. These visible actions are a manifestation of a person’s self-identity (Wilska, 2002), and they are strongly connected with behavioral patterns and habits (Chen, 2004). Cao (2005) indicates that travel liking and desired mobility also form part of a person’s self-identity.

Some of the earliest papers by transportation scientists on the link between lifestyle and travel behavior were published by Salomon and Ben-Akiva (1982, 1983), who defined lifestyle groups by the time individuals spent in distinct activities. Later, Pas (1988) used the weekly travel-activity pattern as a description of the travel-related lifestyle, and Kitamura (1988) examined the link between lifestyle and travel expenditure. More recently, among publications that have related certain aspects of a person’s mobility decisions (e.g., residential location choice, automobile type and activity participation) to lifestyle

variables are Kitamura et al. (1997), Krizek and Waddell (2002), Lanzendorf (2002), Choo and Mokhtarian (2004), Johansson et al. (2006), and Ory and Mokhtarian (2009), who found correlations between lifestyle-related explanatory variables and transportation choices. The argument has been made that long-term decisions, such as residential location or motor vehicle ownership, are not exogenous determinants of a person's short-term mobility decisions, but rather a proxy for underlying "true" explanatory variables related to lifestyle (see, for example, Boarnet and Crane, 2001; Cervero and Duncan, 2002; Srinivasan and Ferreira, 2002; Schwanen and Mokhtarian, 2005; or Walker and Li, 2006).

Our work focuses on capturing modality styles and their influence on mode choice decisions. By the assumptions of traditional travel demand models, mode choice decisions are made at the planning stage of every trip or tour. However, empirical evidence suggests that not all behavior is preceded by a deliberate decision-making process. When an action has been repeated frequently in stable contexts in the past, only minimal, sporadic thought is required to initiate, implement, and terminate it (Wood et al., 2002). As a consequence, people might continue to repeat past behavior even when new information has changed the contextual environment. Aarts et al. (1997), in a study of students from the University of Nijmegen, Netherlands, report that habitual bicyclists use significantly less information about the circumstances of the trip being made, when deciding whether to bicycle, than occasional bicyclists. Thøgersen (2005), in a study on transit use in Denmark, finds that past behavior explains consistency in travel choices that cannot be accounted for by the temporal stability of level-of-service attributes, indicating that the choices people make are often based on information that has long ceased to be pertinent.

Recent research further points to a gap between perceptions about the availability of transit and the actual level of service. From a survey administered in Salt Lake City, Utah, Outwater et al. (2010) observe that 77% of travelers are aware of the full set of transit services within half-a-mile of their home, but only 24% of travelers are aware of the full set of transit services within 3 miles of their home. Their findings are supported by a Federal Transit Administration report that examines local familiarity with transit systems in a wide variety of cities across the United States (Wirthlin Worldwide and FJCanon, 2000). The report finds that 44% of all Americans are not familiar, and nearly one-in-four Americans know nothing about public transportation in their neighborhood.

Work by Kuhnimhof et al. (2006) indicates the existence of "unimodal" and "multimodal" travelers, i.e. segments of the population that are primarily oriented towards one mode and other segments that are more flexible in their mode choice and exhibit variation over time. Kuhnimhof et al. (2006) introduced these notions, and later defined a measure for determining a person's degree of multimodality (Kuhnimhof, 2009). In several recent publications, researchers have used cluster and factor analysis to construct lifestyle types from survey data. Krizek and Waddell (2002), Lanzendorf (2002) and Ohnmacht et al. (2009) focused on mobility and modality styles, using attitudinal and value data. They identified several distinct population segments which differed, among other factors, by activity participation and attitudes towards modes, travel frequencies and distances, as well as the habitual choice of travel mode(s).

These findings substantiate the claim that modality styles form part of a person's mobility style, and thus lifestyle, and that everyday mode choice decisions are strongly correlated with higher level orientations. The next subsection reviews previous work that has sought to represent the role of mobility and modality styles in discrete choice models, and how it informs the methods used in this paper to integrate the modality style construct with traditional travel demand models.

## **2.2 Integrating mobility and modality styles with travel demand models**

Discrete choice models often represent heterogeneity in the choice process through the use of observable socio-economic variables, such as gender and income, either as alternative-specific variables or by interacting them with level-of-service attributes (see, for example, Bowman, 1998). Since mobility styles can evolve with changing socioeconomic conditions, these variables serve as useful proxies for attitudes

and motivations underlying observed behavior. More recent examples that have relied on the idea of systematic taste heterogeneity include Vovsha (2009), who proposes a modeling framework that captures the effect of socio-economic variables on two long-term mobility decisions: household car ownership and individual transit pass holding.

However, capturing heterogeneity systematically may be insufficient when tastes vary with unobservable variables or purely randomly, and can result in inconsistent parameter estimates (Chamberlain, 1980). This inadequacy has resulted in the growth in popularity of mixed logit models. Mixed logit is a highly flexible model form that can approximate any random utility model (McFadden and Train, 2000). It allows for random taste heterogeneity, in addition to unrestricted substitution patterns and a rich error correlation structure. Early applications of the random parameters approach to incorporate unobservable taste heterogeneity in discrete choice models involved only one or two dimensions of integration (see, for example, Ben-Akiva et al., 1993). Advances in computational power, and corresponding leaps in simulation methods, have since helped set off a veritable explosion in the development and application of these models (see Train, 2009). Numerous distributions have been employed, the most popular being the normal and the lognormal, and attempts have also been made to describe these distributions as functions of covariates to improve fit and ease interpretation. For example, Bhat (2000) specifies the means of the random parameters as functions of observed individual characteristics. Hensher and Greene (2006) extend this framework to include heterogeneity in the variance, or heteroscedasticity, of the random parameter distribution.

More recently, interest in simultaneous choice models has prompted the use of mixture distributions to correlate choices across multiple dimensions. Bhat and Guo (2007) analyze the effects of the built environment on car ownership through the means of a mixed multinomial logit-ordered response structure. In a similar study by Pinjari et al. (2007), a simultaneous mixed logit model of residential location and mode choice for work tours is used to examine the effects of residential self-selection on the latter. Eluru et al. (2010a) develop a joint multiple discrete continuous extreme value (MDCEV) framework that models an individual's choices across the following five choice dimensions: activity type, time of day, mode, destination, and time use allocation. Eluru et al. (2010b) employ a copula-based framework to capture unobservable correlation between residential location and car ownership on the one hand, and vehicle miles traveled on the other.

While the use of mixture distributions often provides an excellent fit to the data, it has been argued that the correlation structure is a black box in that the cause of the distribution is not readily apparent (Walker and Ben-Akiva, 2011). Significant increases in the number of estimated parameters can make the model hard to interpret, and can result in a tendency to overfit the data. The use of these models for forecasting further requires the researcher to assume that the mixture distributions are temporally stable, which need not necessarily be true. Other criticism of the random parameters approach has drawn attention to its requirement of the analyst to make an a priori assumption about the mixture distribution for each randomly distributed coefficient (Hess and Rose, 2006). Fosgerau (2005) and Hess et al. (2005) discuss some of the deleterious effects of a wrongly specified distribution on parameter estimates and the attendant model interpretation. Since distributional assumptions exert influences of their own on the results (Hess, 2005), it has also been argued that simply knowing that a parameter is distributed randomly across respondents might be of limited utility to policy makers (Hess et al., 2009).

Efforts to overcome some of the limitation of mixture models described above, and to provide insights into individual preferences, have led to interest in the behavioral mixtures approach (Walker and Ben-Akiva, 2011). Behavioral mixtures models employ latent constructs to represent the influence of higher-level attitudes and orientations on the choice process, such as modality styles in our case, and provide a behavioral rationale to the mixture distribution. The mixture distributions can be discrete, as in the case of latent class models, or continuous. The use of continuous behavioral mixtures in the context of mode choice models has previously been demonstrated by Kitamura et al. (1997), who developed travel demand

models that incorporated individuals' attitudes toward various aspects of urban life as explanatory variables. They found that these attitudes are closely linked with the use of different modes. Johansson et al. (2006), working with data from a survey of commuters in Sweden, observed that latent attitudes towards modal attributes such as flexibility and comfort, and personality traits such as concern for the environment, significantly influenced mode choice. Their observations are echoed by Outwater et al. (2010), who found that individual perceptions, beliefs and feelings about transit services often override actual level-of-service attributes, underlining the need to distinguish between the two.

Our focus is to characterize such orientations as a discrete latent construct, namely modality styles, to capture distinct segments in the population that differ in their awareness of and proclivity towards different modes. These differences are indicative of an overarching modality style for an individual that influences her modal choices over multiple transport-related decisions over time. Further, these differences likely manifest themselves through the alternatives that enter the individual's decision protocol. Therefore, central to the idea of modality styles is the notion of heterogeneous choice sets. Travel demand models typically assume that individual-specific choice sets can be deterministically estimated by the analyst, thereby ignoring unobservable heterogeneity that might be ascribed to lack of information or habitual behavior. Swait and Ben-Akiva (1986) demonstrate how an incorrectly specified choice set can lead to biased estimates of individuals' sensitivity to level-of-service attributes; Cantillo and Ortuzar (2005) find that the use of standard mixed logit models with pre-specified choice sets can lead to potentially severe estimation and forecasting errors.

Latent class choice models are apposite in choice modeling situations such as ours where heterogeneity can be characterized as a discrete construct (Gopinath, 1995). Some of the earliest examples of latent class models that addressed the issue of heterogeneous choice sets assumed the existence of random constraints or thresholds that preclude the availability of certain alternatives, similar to the elimination by aspects heuristic first proposed by Tversky (1972). These models most often followed Manski's two-stage theoretical framework (1977), where the first stage consists of estimating the probabilities of all possible subsets of the universal choice set. Since even a small number of alternatives can generate an intractable number of choice sets, early applications of Manski's formulation employed a latent captivity representation, where the simplifying assumption was made that an individual is either captive to an alternative or is free to choose from the full choice set (see, for example, Gaudry and Dagenais, 1979). Swait and Ben-Akiva (1987) proposed the use of random constraints conditioned on both individual characteristics, such as car ownership, and level-of-service attributes, such as distance to the bus stop, to generate the probability that an alternative is part of an individual's choice set or not. Using combinatorics, they then estimated choice set generation probabilities for every possible subset of the universal choice set. Ben-Akiva and Boccara (1995) expanded this framework to include the influence of attitudes and perceptions. Choice set generation has received considerable attention in the realm of route choice, where the number of possible alternatives can virtually stretch to infinity. Notable among these studies is the implicit availability and perception (IAP) model developed by Cascetta and Papola (2000), an alternative formulation to Manski's two-stage framework which penalizes the utility of an alternative based on its perceived availability. Swait (2009) proposed an ideologically similar model form where the utility of an alternative is specified as a continuous probability density function with one or two mass points, the mass points allowing for an alternative to be either extremely unattractive or entirely dominant.

This paper builds upon these past studies on heterogeneity in travel preferences, simultaneous choice models, and choice set generation. Although the existence of modality styles has previously been suggested (Kuhnimhof, 2006; Kuhnimhof et al., 2009), we demonstrate how the modality styles construct can be operationalized within the context of travel demand models. The model framework developed in this paper captures the influence of modality styles on two dimensions of individual travel behavior - mode choice for work tours and mode choice for non-work tours, and the framework can be extended

along other dimensions. Unlike other attitudinal studies, the proposed framework does not require the use of attitudinal indicators (although could be extended to incorporate such information). The data set at hand - a six-week travel diary survey, offers a unique opportunity to observe modality styles in a longer term setting, which is more consistent with the time scale of the modality styles construct. Further, when compared with other approaches to simultaneous choice models that rely on complex specification of the covariance structure, the behavioral mixture approach of specifying latent classes potentially offers a richer and more robust behavioral framework for interpretation and policy analysis. The next section describes the dataset in fuller detail, followed by a section each on the results from the two stages of our empirical analysis, and our conclusions.

### **3. Data Set**

Travel demand models traditionally employ cross-sectional travel diary data recorded over one or two days, observation periods that are likely too short to discern the effects of individual habits, routines and predispositions that are reflective of more long term orientations. Therefore, the decision protocol generally assumed by these models for all individuals is that of multimodal users. Given our research objectives, a longer observation period is useful, and so the data set that we use consists of six-week travel diary surveys administered as part of the *MOBIDRIVE* research project (Axhausen, 2002). The survey was conducted in the two German cities of Karlsruhe and Halle in the fall of 1999. A total of 317 persons over 6 years of age in 139 households participated in the study. The survey consisted of a face-to-face interview in which socio-demographic characteristics and household information were collected. This was followed by a self-administered travel diary survey in which participants recorded for each trip during the six-week study period the day the trip was made, trip purpose, modes used, departure and arrival times, accompanying individuals, etc. During post-processing, the level-of-service for all modes (walk, bike, auto, and transit) was generated from transportation network data for the city of Karlsruhe. More details on the survey and the resulting data set can be found in Axhausen (2002).

We aggregate unlinked trips into home-based work and non-work tours, following an approach similar to Cirillo et al. (2006). For each trip, the data contain the modal chain (including access and egress modes for transit). A “main mode” for a tour is defined to be the mode used to cover the greatest motorized distance, tacitly assuming that mode choice is dictated by the longest leg of the tour. Four main modes are defined: auto, transit, bike, and walk. Trips taken as car passengers are counted under auto, as are trips made by motorcycle (less than 2 percent). We perform two types of analysis on these data: descriptive and econometric, each of which is described in detail below. Note that the descriptive analysis uses data from both Karlsruhe and Halle, whereas the econometric analysis uses only data from Karlsruhe. This is because level-of-service attributes were not available for the city of Halle and so mode choice modeling was not possible.

### **4. Stage I: Descriptive Analysis of Modality Styles**

The six-week survey provides a unique window into how individuals use the transportation system over an extended period of time. In this descriptive stage of the analysis, our objective is to explore the presence and types of modality styles that are suggested by the data. First we discuss modality styles as reflected by unimodal and multimodal orientations, and we classify individuals’ modality styles based on their mode use for work and non-work tours over the six week period. We then explore the size of the modality style segments in the population, how they vary across gender and across work and non-work tours, and the relationships between an individual’s work and non-work modality styles.

#### **4.1 Defining unimodality and multimodality**

Unlike the continuous measure of multimodality proposed by Kuhnimhof (2006), we sought a discrete classification of modality styles. This is consistent with the notion of lifestyle categories that have been created by previous researchers (e.g., Ohnmacht, 2009), and are consistent with our notion of mobility style as having distinct and discrete latent classes. We base our classification on the reported use of the three aggregated main tour modes – transit, auto, and biking/walking. Note that in the econometric model that follows, biking and walking are separate alternatives; however, they were combined into a single category for the descriptive analysis because their shares were not large enough to produce meaningful results individually.

The most intuitive definition of a unimodal person would be somebody who uses the same mode for 100% of all tours. However, we find that this criterion is too strict in view of the length of the observation period, as even unimodally oriented people use other modes on an occasional basis, but this behavior is not consistent enough to be a significant part of their travel lifestyle. For example, a strongly auto oriented individual is likely to walk on occasion, particularly for short distance trips. Furthermore, one needs to consider that the three main modes do not serve the same mobility purposes. An automobile can fulfill practically all mobility needs, regardless of distance and trip purpose. Walking, biking and transit are specialized modes, each of which has a specific range of trip distances and mobility needs for which it is best suited. These considerations lead us to adjust the threshold, and consequentially our nomenclature, as follows: A person with an auto mode share of 90% or above is considered a quasi-unimodal auto user, whereas the threshold for quasi-unimodal bike/walk and transit users is set at 80%. We choose these thresholds because they can be understood and communicated in a simple fashion: Using the example of a person who makes one tour every workday (e.g., commute to work), a quasi-unimodal auto user would use another mode at most once every two weeks, and a quasi-unimodal transit user or walker/biker would use another mode at most once every week.

We define multimodality as the mixing of modes across tours (rather than within tours, for which we observed very few cases of mixing modes other than access and egress modes for transit). In view of our a-priori beliefs on modality styles and possible policy applications to promote sustainability, we create two multimodal categories, one including auto use and one excluding it. Any individual who is not classified as quasi-unimodal is considered multimodal. Following the same reasoning as for the definition of unimodality, a tolerance is introduced: A multimodal person who made less than 10% of all tours by auto is classified as multimodal green. If that person made more than 10% (but less than 90%) of all tours by auto, the person is considered multimodal all.

The setting of thresholds is a balancing act; increasing the unimodality threshold would cause more people to be classified as multimodal, whereas decreasing the threshold would increase the share of quasi-unimodal people. While our definitions are admittedly simple, the goals are to explore the existence of modality styles in long-term observations and to inform the process of model development.

#### **4.2 Unimodality and multimodality in the study population**

To ensure a meaningful definition of modality styles in terms of mode shares, only adults who have recorded five or more tours (work or non-work, depending on the category) are included in the analysis. In total, 121 working adults with five or more reported work tours and 206 adults with 5 or more non-work tours are included in our modality analysis. Furthermore, 226 individuals are categorized based on their pooled work and non-work tours. The modality styles observed in the sample are presented in Figure 2.



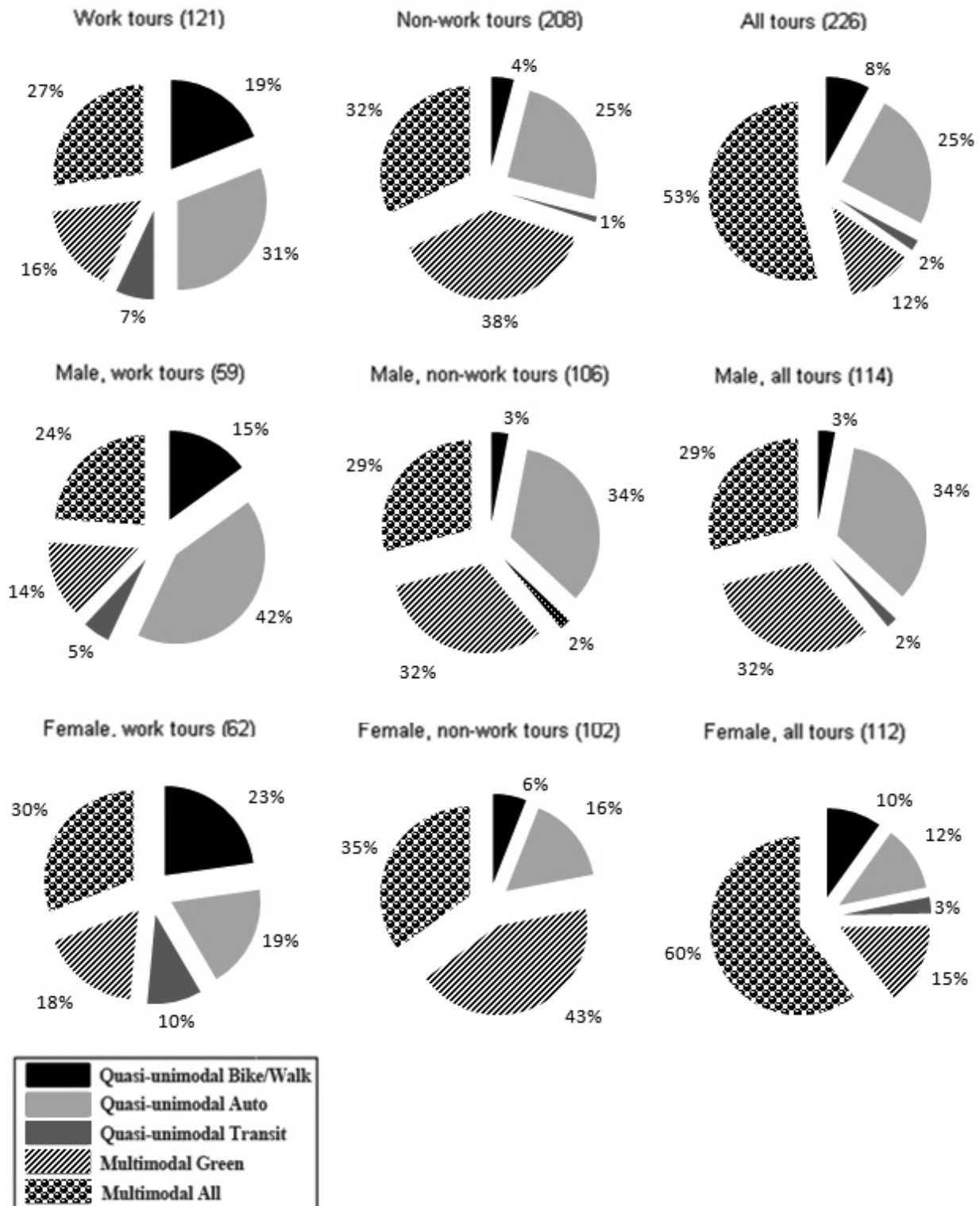


Figure 2: Modality styles among urban adults in the MOBIDRIVE dataset, the numbers in parentheses denote sample sizes

One interesting result is the sizes of the modality styles, particularly comparing those who use auto and those that do not. As can be seen in the top row of Figure 2, only 58% of the working group and 57% of the non-work group use the automobile in any substantial way, and in both cases, roughly half of those people exhibit multimodal behavior. It is surprising to see that even for commute tours, which one may think of as a highly habit-driven mode choice, almost half of all regular or occasional auto users adjust their mode according to other factors. There is also a sizable number of quasi-unimodal bikers, walkers and transit users in work tours, but for non-work tours, it appears that many of them are absorbed into the multimodal green group. The size of the quasi-unimodal walking/biking group may in part be due to the relatively dense settlement patterns and central job and activity locations in both cities. Furthermore, transit, walking and biking are specialized modes, and people who use one of these modes for commuting may “optimize” their choice once and then use that mode on a permanent basis, but for non-work tours, as destinations and trip purposes vary, they are more likely to choose between these modes.

Since the automobile is not a specialized mode, we did not expect this reasoning to hold true for auto users. 37 out of the 121 individuals making work tours are quasi-unimodal auto users, compared to 52 out of the 208 individuals making non-work tours. The two groups do not fully overlap. Of the 121 working individuals, only 101 made enough non-work tours to be included in that group as well. Relatively speaking, the share of quasi-unimodal auto users is smaller for non-work tours than for work tours; nonetheless, a quarter of the population does not vary their mode choice and almost exclusively uses the automobile. Expectedly, the quasi-unimodal groups for transit and bike/walk for non-work tours are much smaller. Averaged across all tours, we find that only 53% of the sample population displays sufficient variation in mode choice to be classified as multimodal all.

#### **4.3 Gender as a determinant of mode choice behavior**

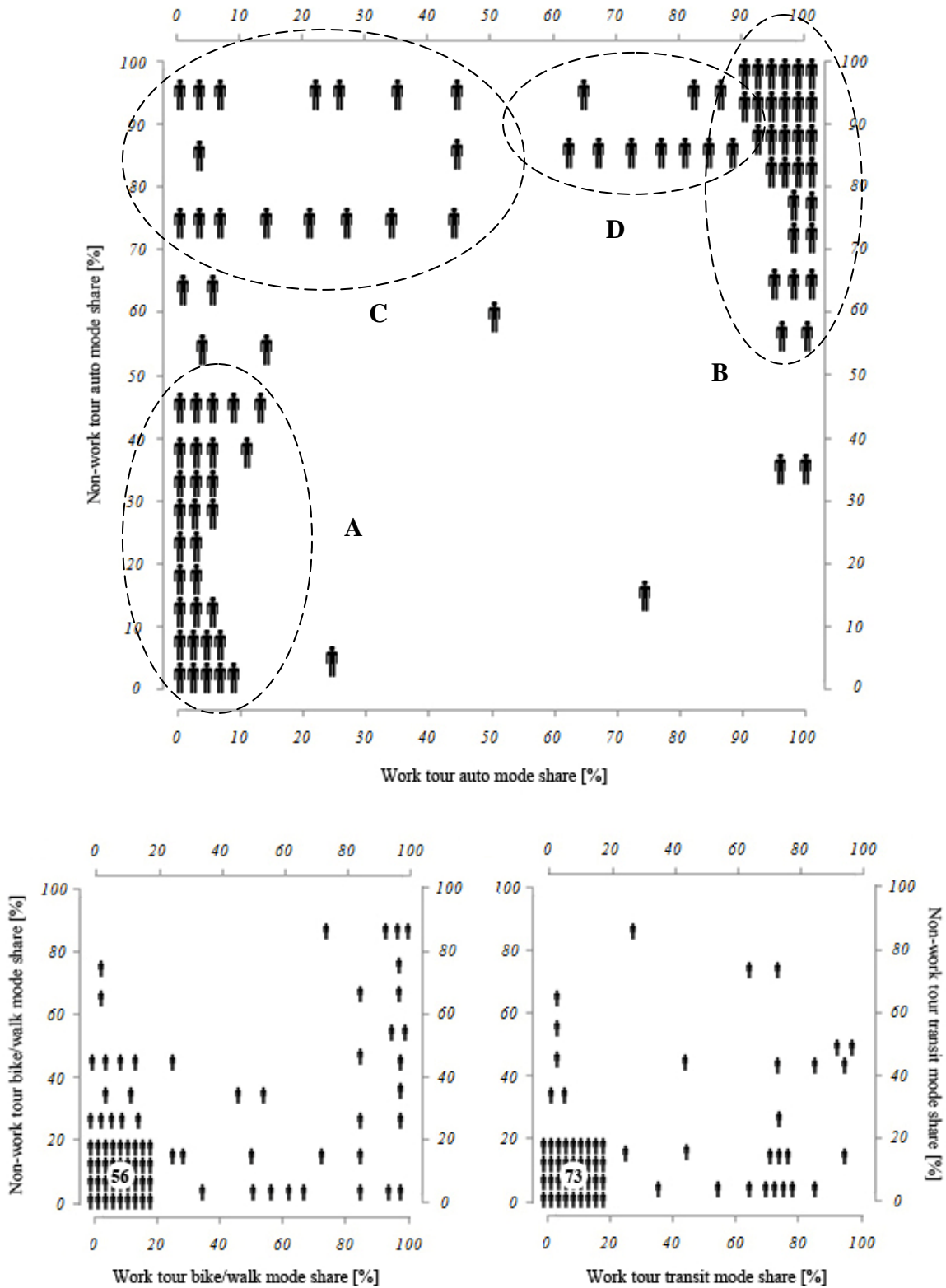
The second and third rows of Figure 2 present modality styles by gender. One can see that women are more likely to be multimodal, and they are, on average, less auto-oriented and more likely to use transit. These differences are equally pronounced across work and non-work tours. Women are more likely than men to be multimodal, irrespective of the nature of the tour. For work tours in specific, women display a greater incidence of being quasi-unimodal transit users or walkers/bikers.

#### **4.4 Modality style differences between work and non-work tours: polarization and correlation**

As suggested above, people may have different modality styles for work and non-work tours. To investigate the relationship between work and non-work modality styles for a given individual, we select 101 individuals who have reported a sufficient number of work and non-work tours and we plot the mode shares for the three main modes against each other. The results are shown in Figure 3 as a scatter plot, where each stick figure represents one individual. For the transit and bike/walk plots, there is a substantial number of individuals that have a near zero mode share for both work and non-work tours; these people are plotted in the lower left portion of the graph and we write the total number of individuals inside a white circle.

When comparing the distributions, one sees a strong polarization in the automobile data points. There are many people who use the car either very little, labeled “A”, or very much, labeled “B”, with a lower concentration of individuals elsewhere on the spectrum. The individuals in cluster B are heavily automobile-oriented, using the car for almost all tours, regardless of purpose. Of the 31 individuals with more than 90% mode share on commuting trips, only 2 individuals reported less than 50% auto mode share on non-work tours. On the other hand, 38 individuals take the car on less than 10% of their work tours, but their car use for non-work tours is more evenly spread out between 0% and 100%.

The plot also suggests a correlation between work and non-work auto use: Practically all individuals who occasionally or regularly used the automobile for work tours use it for 50% or more of their non-work tours: Of the 30 individuals in the center of the scatter plot, between approximately 10% and 90% auto



**Figure 3:** Scatter plot of individual mode shares for work and non-work tours. Each stick figure on the plot represents one individual in our sample, except for the bike/walk and transit plots where the number of individuals in the lowest quintile is written into the plot inside the white circle

use for work tours, 23 have an auto use for non-work tours of more than 50% (clusters “C” and “D”), lending reason to believe that somebody who is multimodal all is likely to be so both in work and non-work tours. The scatter plot supports the concept of three or four modality classes for auto use: quasi-unimodal auto users (B), multimodal auto users (D) and two groups with low auto use: one that uses the automobile mostly for non-work tours (C), and one that makes little use of the automobile altogether (A).

In the case of bike/walk and transit, the most distinctive feature of the plots is the large number of people in the bottom left corner who make piddling use of either mode (so large in fact that it prevented representation by individual stick figures). Apart from that block of individuals, we find a small cluster of people who do not use these modes for work tours, and who use them occasionally for non-work tours. Compared to the auto graph, fewer data points appear in the unimodal areas. The bike/walk group shows a correlation between work and non-work mode shares: There is a group of people in the top right corner that bikes and walks for almost all trip purposes. Most of them are classified as quasi-unimodal. Of the multimodal people who occasionally bike and walk to work (10% – 90%), none do it more than 50% for non-work tours. This reflects the specialized nature of these modes. Quasi-unimodal bikers and walkers, on the other hand, may be much more willing to adjust their destinations and trip chains in a way that their mobility needs can be fulfilled by their mode of choice.

#### **4.5 Discussion of modality results**

Although our analysis focused exclusively on mode choice, it is strongly intertwined with destination, activity chaining and travel time choice. A habitual auto user may have a different perception of space, travel times and the activity chaining options than, for example, a habitual transit user. Moreover, the auto user may find it difficult to think of activities in ways that would be required if using a bicycle or transit, and may perceive some of the “inconveniences” associated with these modes (e.g., timing activities to transit departures, using a bike with luggage) as obstacles that drive the choice probability of those alternatives close to zero *a priori*. On the other hand, the regular transit user may build an activity schedule around these constraints such that they are of no or little inconvenience.

From the point of view of travel demand modeling, if these interdependencies are to be introduced, it may no longer be permissible to assume that an individual chooses a mode, travel time or destination every time a trip is made, or that the full choice set is considered, but rather that habits and perceptions based on past behavior (in summary, the mobility style, which is not directly observable through common socio-economic variables) may influence observed behavior.

Our results from this section reveal that, averaged across all tours, more than a third of the individuals in our sample population can be classified as quasi-unimodal. However, consistency in choices does not necessarily imply that a choice is not being made at all, and evidence of quasi-unimodal behavior can also be attributed to modal availability and temporal stability of other controlling factors such as level-of-service attributes (Bamberg et al., 2010). At the other extreme, one should also not conclude that observed multimodality is always due to an objective optimization of mode choice. In some cases, the multimodal all group may include individuals from households where a car is shared among drivers in the household, and therefore multimodality is more an issue of availability. This conclusion was also reached by Kuhnimhof (2006) based on self-reported modality styles from a survey. These limitations to the descriptive analysis are addressed more thoroughly in the next section, where both availability and level-of-service attributes are explicitly accounted for.

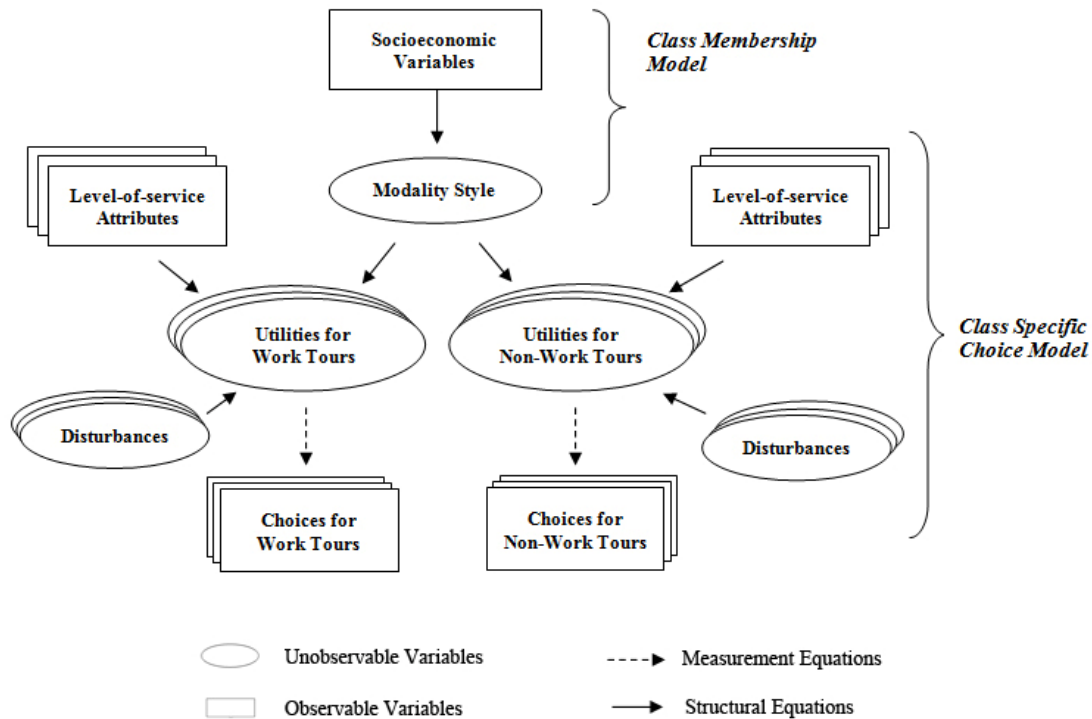
### **5. Stage II: Econometric Analysis – Capturing Modality Styles in a Mode Choice Model**

In this section we demonstrate how the idea of modality styles can be integrated into the framework of travel demand models through the use of behavioral mixtures models as captured by latent classes. The results from the modality analysis in the previous section suggest that different modality styles exist as

exhibited by different mode choice behavior. However, to test that these differences in choice behavior are the result of behavioral predispositions, it is necessary to ensure that these differing styles persist once transportation level-of-service variables are controlled for. We develop a model that incorporates modality styles as higher level individual orientations that influence ones modal choices across different trip purposes and over time. We first describe the general latent class model framework that we use, before delving into the details of the model specification. This is followed by a comparison with other latent class specifications, where we elaborate upon the reasons that lead us to choose our final specification. We close this section with a discussion of the estimation results for our preferred model, and how they compare with results for alternative model forms.

### 5.1 Framework

In developing a framework for our model, we adopt the behavioral mixtures approach, where a priori considerations based off our findings from the descriptive analysis are used to inform the mixture distributions. We argue that discrete modality styles exist, that these modality styles are indicative of higher-level orientations that influence choices across multiple dimensions, and consequentially individuals with different modality styles exhibit different mode choice behavior. The latent class framework is particularly appropriate given the discrete nature of heterogeneity hypothesized here (Gopinath, 1995). Figure 4 represents the framework of the general model form. Consistent with the usual notation, ellipses denote unobservable variables and rectangles denote observable variables, while dashed arrows represent measurement equations and solid arrows represent structural equations. The class membership model relates latent modality styles to observable socioeconomic variables. The class-specific choice model depicts the influence exerted by a single overarching modality style on an individual’s modal choices across multiple work and non-work tours over time (denoted by the stacked



*Figure 4: Model Framework*

shapes in the figure). Heterogeneity across modality style classes includes both the modes considered (choice set) and the values of taste parameters and alternative specific constants. The disturbances reflect unobserved factors that influence individual choices. The class membership and class-specific choice models together explicitly integrate the modality style construct with mode choice models.

The first piece to the latent class model is the class-specific choice model, which predicts the probability of choosing an alternative conditional on being in that class, and is written as:

$$P(i_{nt}|X_{nt}, s_n)$$

, where  $P(i_{nt}|X_{nt}, Z_n, s_n)$  is the probability that individual  $n$  chooses alternative  $i$  over observation  $t$ , conditional on the attributes of the alternatives for observation  $t$  and characteristics of the individual  $X_{nt}$ , and conditional on the individual having modality style  $s_n$ . As shown in Figure 4, we allow the class-specific mode choice probability model to vary for work and non-work tours. This conforms with typical travel demand modeling practice in which different models are estimated for different purposes. However, a critical difference here is that the purpose-specific models are linked via a single modality style that influences multiple work and non-work tours, thereby introducing correlation between behaviors across tour purposes. For example, a quasi-unimodal auto user has a strong proclivity for driving which impacts her modal preferences for not just work or non-work tours, but both.

The second piece to the latent class model is the class-membership model, which is denoted by:

$$P(s_n|X_n)$$

, where  $P(s_n|X_n)$  is the probability that individual  $n$  has modality style  $s_n$ , conditional on characteristics of the individual  $X_n$  (which are the same across multiple observations for the same individual). The number of modality styles is determined endogenously, by estimating models with different number of classes. Assuming  $S$  styles, the choice probability becomes:

$$P(i_{nt}|X_{nt}) = \left( \sum_{s=1}^S P(s|X_n) P(i_{nt}|X_{nt}, s) \right)$$

, where  $P(i_{nt}|X_{nt})$  is the probability that individual  $n$  selects mode  $i$  in observation  $t$ , equal to the sum over all modality styles  $s = 1, \dots, S$  of the class-specific conditional probability multiplied by the probability that individual  $n$  has that modality style. Since the modality style of each decision-maker is unknown, the two equations must be estimated simultaneously.

In writing the likelihood function, we capture the panel structure of the data in two ways: first the class-membership probability is specific to the individual and not the choice situation; and, second, error components are introduced to correlate errors across choices made by the same individual (consistent with the framework introduced by Revelt and Train, 1997). An individual's choice probabilities over different tours are conditionally independent, conditioned on the modality style of the individual (the classic latent class assumption) and on the error components (from the mixed logit portion of the model). Combining the class membership model, the class-specific choice model for work tours, the class-specific choice model for non-work tours, the error components, and the multiple modal choices observed for each person ( $t_w = 1, \dots, T_{nw}$  work tours and  $t_p = 1, \dots, T_{np}$  non-work tours), the likelihood function of the sample  $L$  is given by:

$$L = \prod_{n=1}^N \left( \int_{\eta} \sum_{s=1}^S \left( P(s|X_n) \prod_{t_w=1}^{T_{nw}} P(i_{nt_w}|X_{nt_w}, s, \eta) \prod_{t_p=1}^{T_{np}} P(i_{nt_p}|X_{nt_p}, s, \eta) \right) f(\eta) d\eta \right)$$

, where the error components are denoted by  $\eta$ , and their distributions by  $f(\eta)$ . All our models are estimated using Python Biogeme, an open source freeware designed for the estimation of discrete choice models (Bierlaire, 2003).

## 5.2 Data and Model specification

For the purposes of model development, we narrow our dataset to tours contained within Karlsruhe, since level-of-service attributes for all modes are unavailable for the city of Halle. In the case of work tours we consider both simple work-only tours without any additional stops, and tours on which the individual made additional stops on the way to work, on the way back, or both. However, for work tours with additional stops, we use the same level-of-service attributes in our mode choice models as those for the usual tour from home to work and back, and the presence or absence of intermediate stops is represented by a binary variable. This is the typical practice with activity-based models, where destination choice for intermediate stops is often predicated on mode choice (see, for example, Bradley et al., 2010). For instance, the location an individual chooses to stop on his way back from work to buy groceries might depend on whether he's walking, on the bus, or in a car. Therefore, it is suspect to compare different modes for the specific tour route, since a different tour might have been undertaken had a different mode been chosen. For these same reasons, in the case of non-work tours we limit our attention to only those tours with two constituent trips, one each to and from the main destination, with no additional stops along the way. Consideration of tours with intermediate stops would call for a model that predicts destination choice as well. The absence of land use data and level-of-service attributes for all possible tours, and not merely the tour that was made, preclude estimation of such a model, and therefore we exclude non-work tours with multiple stops. These restrictions reduce the dataset to 1445 work tours and 3359 non-work tours made between 117 individuals over the six-week observation period. For each tour, four main modes are defined: auto, transit, bike and walk.

In this section we present our final model specification, although in the next section we will take a step back to discuss the testing performed to arrive at this specification. Estimation requires defining both the class-membership model (explaining the individual's modality-style) and the class-specific mode choice models for work and non-work tours. The class-specific mode choice models are mixed logit models. Variables that enter the class-specific modal utility functions include travel time, access and egress time for transit, and a stop binary variable that captures the effect of additional stop(s) on a work tour on the utility of auto. Unfortunately, there was no cost data available for any of the modes, and so no price parameters were estimated in the model. The travel time parameter and alternative-specific constants are allowed to vary across classes. As class-specific parameters for the tour stop dummy variable and access/egress time for transit were not robust, these were constrained to be the same across classes.

In terms of the error structure for the class-specific choice models, error components are introduced (i) to capture unobservable correlation that accrues from the panel nature of our data (the errors are correlated across different instances of mode choice for the same individual); and (ii) to introduce flexible substitution patterns between alternatives. Different substitution patterns were tested, and correlation between bike and walk was the only one that was significant. Consequentially, error components representing correlation between other alternatives were dropped from the final model.

In addition to allowing the taste parameters to vary across classes, in some cases we also allow the available alternatives to vary across classes. The strongly polarized auto mode share scatter plot of Figure 3 forms a blueprint for the model. The choice set for work tours for one of the classes is restricted such that it consists only of auto, to reflect quasi-unimodal auto users. Since Figure 3 lends reason to believe that individuals display greater flexibility for non-work tours, none of the constraints are extended to non-work tours for this or any other class. Access to auto for work tours is denied to individuals belonging to another class, to reflect the presence of multimodal green users in our sample who are averse to driving to work, and are more open to alternative modes such as bicycling and transit. No choice set constraints are

imposed on individuals belonging to the third class, to allow the model to differentiate between consistency in choices based on the temporal stability of level-of-service attributes, and indifference to or ignorance of the same. Therefore, as suggested by Figure 3, we design the three classes to represent, respectively, quasi-unimodal auto, multimodal green, and multimodal all users.

Given the model structure described above, the equation for the utility function for each alternative is as follows:

$$U_{auto,nt} = \beta_{tt,s,p} \cdot tt_{auto,nt} + \beta_{stop} \cdot stop_{nt} + \sigma_{auto,p} \cdot \eta_{auto,n} + \varepsilon_{auto,nt}$$

$$U_{transit,nt} = ASC_{transit,s,p} + \beta_{tt,s,p} \cdot tt_{transit,nt} + \beta_{accegr,p} \cdot t_{accegr,nt} + \sigma_{transit,p} \cdot \eta_{transit,n} + \varepsilon_{transit,nt}$$

$$U_{bike,nt} = ASC_{bike,s,p} + \beta_{tt,s,p} \cdot tt_{bike,nt} + \sigma_{bike,p} \cdot \eta_{bike,n} + \sigma_{bikewalk,p} \cdot \eta_{bikewalk,n} + \varepsilon_{bike,nt}$$

$$U_{walk,nt} = ASC_{walk,s,p} + \beta_{tt,s,p} \cdot tt_{walk,nt} + \sigma_{walk,p} \cdot \eta_{walk,n} + \sigma_{bikewalk,p} \cdot \eta_{bikewalk,n} + \varepsilon_{walk,nt}$$

$U_i$	utility function for alternative $i$
$n$	denotes the individual decision-maker
$t$	denotes a specific choice instance
$s$	denotes a latent class, i.e. modality style
$p$	denotes a tour purpose, i.e. work or non-work
$ASC$	alternative-specific constants (estimated)
$\beta$	taste parameters (estimated)
$tt$	total travel time for auto, bike and walk, in-vehicle time for transit (minutes)
$t_{accegr}$	access and egress time for transit (minutes)
$stop$	binary variable equal to 1 when tour involved additional stop (applies to work tours only)
$\eta$	five error components, i.i.d. $N(0,1)$ across individuals, but constant across observations for the same individual
$\sigma$	error structure parameters (estimated), assumed to be the same across classes
$\varepsilon$	error components, i.i.d. $EV(0,1)$ across all individuals and observations

The other component of the latent class model, the class membership model, is specified as a multinomial logit model. Explanatory variables for the latent classes include outcomes from longer-term mobility decisions, including car and bicycle ownership, and transit season pass possession. Other explanatory variables are included to capture the life-cycle effect, including gender, parental status, and married status. Household income was not found to be significant, likely due to a combination of a large fraction of missing data for this variable and its correlation with the number of cars owned. The utilities for the three modality styles - quasi-unimodal auto (*qua*), multimodal green (*mmg*) and multimodal all (*mma*) - are then specified as follows:

$$C_{qua,n} = \epsilon_{qua,n}$$

$$C_{mmg,n} = CSC_{mmg} + \gamma_{mmg,numAuto} * numAuto_n + \gamma_{mmg,seasonPass} * seasonPass_n + \gamma_{mmg,numBike} * numBike_n + \gamma_{mmg,male} * male_n + \gamma_{mmg,parent} * parent_n + \gamma_{mmg,married} * married_n + \epsilon_{mmg,n}$$

$$C_{mma,n} = CSC_{mma} + \gamma_{mma,numAuto} * numAuto_n + \gamma_{mma,seasonPass} * seasonPass_n + \gamma_{mma,numBike} * numBike_n + \gamma_{mma,male} * male_n + \gamma_{mma,parent} * parent_n + \gamma_{mma,married} * married_n + \epsilon_{mma,n}$$

$C_i$	utility of modality style $i$
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$n$	denotes the individual decision-maker
$CSC$	class-specific constants (estimated)
$\gamma$	model parameters (estimated)
$numAuto$	number of cars owned by the household
$numBike$	number of bicycles owned by the household
$seasonPass$	binary variable equal to 1 if individual has a transit season pass
$male$	binary variable equal to 1 if individual is male
$parent$	binary variable equal to 1 if individual has children under the age of 18 living in the house
$married$	binary variable equal to 1 if individual is married and living with spouse
$\epsilon$	error components, i.i.d. $EV(0,1)$ across all individuals

### 5.3 Determining the final model specification

In determining the final model specification as described above, we estimated numerous models where we varied the utility specification, the number of classes, error structures, and the choice set assumptions. Here we briefly summarize this process and present key results in Table 1 for 6 different models. Estimating models with different numbers of classes is the standard procedure in latent class modeling to determine the number of classes. We found that the relatively small dataset could not support models with more than three classes, and so we report here results for one, two, and three latent classes. The first two models are single class models: Model 1 is a standard logit model (to serve as an overall point of reference) and Model 2 is a mixed logit model with error components (to capture correlation between alternatives and across choices made by the same individual). Models 3 and 4 have two classes and models 5 and 6 have three classes, and all of these models include the error component specification of Model 2 in order to capture basic correlations. For both the two and three-class models, we explored different specifications regarding the choice set, namely whether the choice set is constrained (i.e., alternatives are excluded from consideration for some classes) or whether the full choice set is available in all cases. As discussed above, heterogeneous choice sets are central to the idea of modality styles: individuals with differing modality styles are expected to display different modal predispositions, and these differences need to be reflected by the alternatives that enter the individual's decision protocol. In keeping with these ideas, Model 3 is a general two-class model with no constraints on the choice set, whereas Model 4 restricts the choice set for work tours for one of the two classes to consist solely of auto, to represent quasi-unimodal auto users explicitly. Analogously, Model 5 is the general three-class model with no restrictions on the choice set, while Model 6 constrains choice sets for different classes according to the structure detailed in the previous subsection. Other than the wrinkles of different numbers of classes and constraints or not on the choice set, all six models follow the general specification described in the previous subsection. To facilitate comparison of the models, Table 1 enumerates for each model its log-likelihood, the number of parameters estimated, and the corresponding values for the rho-bar-squared ( $\bar{\rho}^2$ ), the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC). The AIC is a function of  $\bar{\rho}^2$ , and the two statistics are equivalent measures of model fit.

Examining the statistical measures of fit in Table 1, with the exception of Model 4 the two and three-class models fare markedly better than either of the single class models. However, goodness-of-fit is not the only criterion on which to base a decision, and consideration must also be given to parameter estimates and the attendant behavioral interpretation. While Model 5 has the best statistical fit by any measure, counterintuitive signs on the parameter estimates for travel time for both work and non-work tours for one its three classes compels us to reject Model 5. The remaining models do not have such sign issues. Model 4 does not fare well statistically relative to Model 3 and Model 6, and so we remove Model 4 from consideration. In terms of comparing Model 3 and Model 6, Model 3 has a slightly better fit. However, the issue with Model 3 is that the behavioral differences among the two classes are not well-defined and

<i>Model</i>	<i>Classes</i>	<i>Description</i>	<i>Param.</i>	<i>LL</i>	$\bar{\rho}^2$	<i>BIC</i>	<i>AIC</i>
1	One	Logit	15	-4867.1	0.185	9861.4	9764.3
2	One	Mixed logit with error components	25	-3429.7	0.423	7071.3	6909.3
3	Two	Uniform choice sets	38	-3227.3	0.455	6759.7	6526.5
4	Two	Heterogeneous choice sets	32	-3469.1	0.416	7209.5	7002.3
5	Three	Uniform choice sets	53	<b>-3113.1</b>	<b>0.472</b>	<b>6658.6</b>	<b>6328.2</b>
6	Three	Heterogeneous choice sets	46	-3240.5	0.452	6870.9	6572.9

*Table 1: Summary statistics for different one, two and three-class models*

the classes are difficult to interpret. On the other hand, while Model 6 has a slightly poorer fit to the data, it has three well-defined and distinct classes that are consistent with our findings from the descriptive analysis. Therefore, based on both statistical analysis and behavioral interpretation, Model 6 is our preferred model. We present the detailed estimation results for this model in the next section.

#### 5.4 Detailed estimation results for the chosen latent class model

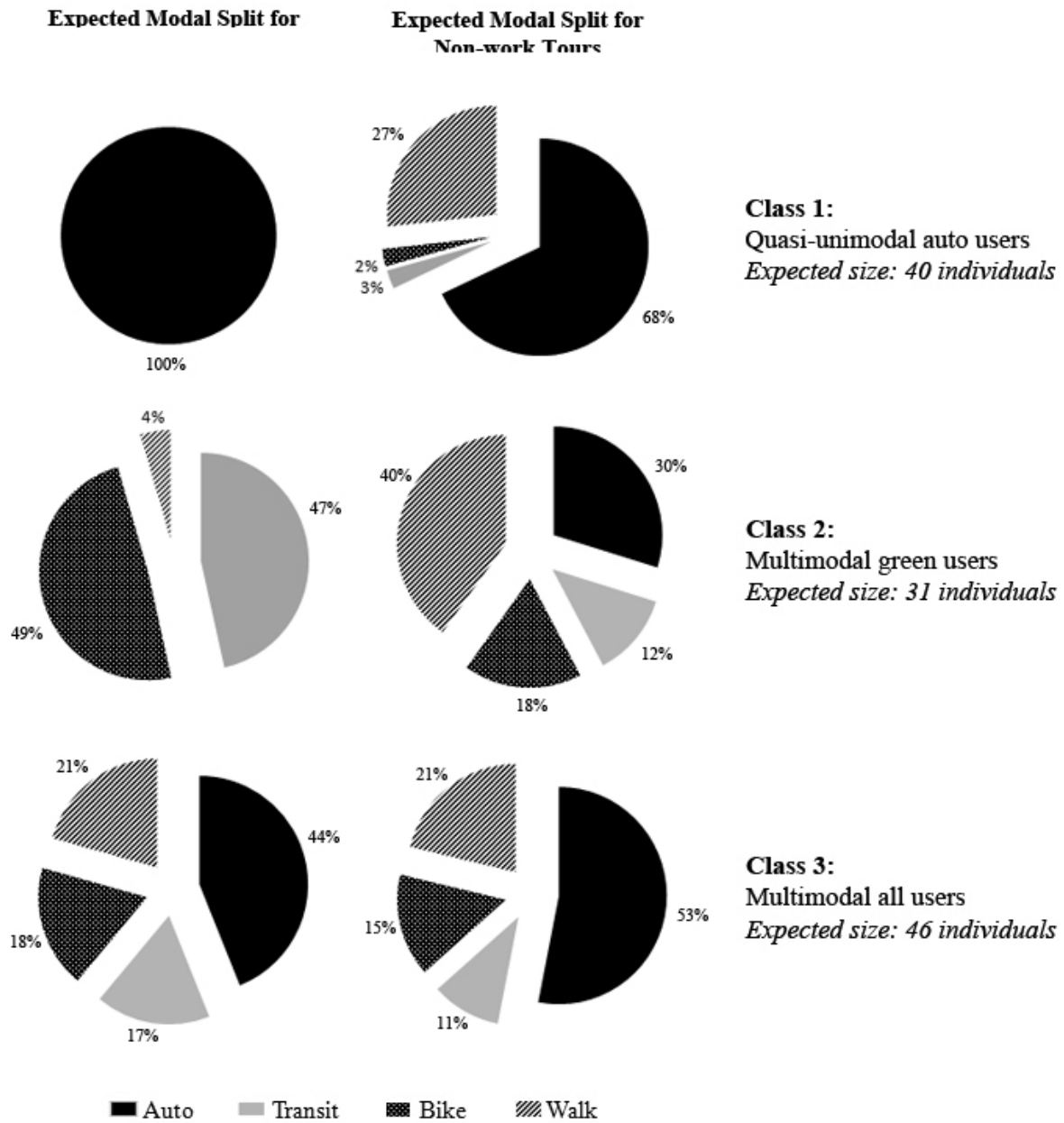
Table 2 presents detailed parameter estimates for both the class-membership and class-specific choice models for our chosen three-class behavioral mixtures model (Model 6). To reiterate the consequences of our choice set constraints, no parameters are estimated as part of the class-specific mode choice model for work tours for quasi-unimodal auto users. Similar reasons preclude estimation of parameters associated exclusively with the utility of auto for work tours for multimodal green users. Also recall that the transit access and egress time and the standard deviations for the error components have been constrained to be the same across classes for work and non-work tours.

In terms of parameter values, first we discuss parameters that do not vary across classes. The sign on transit access and egress time is negative and significant. Interestingly, individuals appear to be more sensitive to access and egress time for non-work tours than for work tours. For instance, a multimodal green user values a minute of access and egress time for work tours as roughly equal to a minute of travel time. For non-work tours however, a minute of access and egress time is worth three minutes of travel time. The stop dummy has a positive and significant value for multimodal all users which implies that a multimodal all user prefers to take a car for a work tour that entails an additional stop along the way. The correlation parameters are all highly significant for both work and non-work tours, indicating a high degree of correlation across tours made by the same individual, and an equally high degree of correlation between walk and bike.

In terms of behavioral differences across classes, we examine the estimates for alternative-specific constants and the parameter on travel time. Class 1, which consists of quasi-unimodal auto users, expectedly has the greatest sensitivity to travel time for non-work tours. Interestingly, quasi-unimodal auto users seemingly exhibit a strong willingness to walk for short distance non-work tours, reflected by a positive and significant alternative-specific constant for that mode and a relatively high sensitivity to travel time. Class 2, which comprises multimodal green users, has a greater sensitivity to travel time than Class 3, which consists of multimodal all users. The Wald-statistic confirms that the parameter estimates for travel time are significantly different across classes at a p-value of 0.01. The alternative-specific constants for Class 3 for both work and non-work tours suggest a bias towards the two motorized modes: auto and transit.

<i>Variable</i>	<i>Class 1 (quasi-unimodal auto)</i>		<i>Class 2 (multimodal green)</i>		<i>Class 3 (multimodal all)</i>	
	<i>coeff.</i>	<i>p-val</i>	<i>coeff.</i>	<i>p-val</i>	<i>coeff.</i>	<i>p-val</i>
<i>Class specific choice model for work tours</i>						
ASC Auto	-	-	-	-	0.000	-
ASC Transit	-	-	0.000	-	0.375	0.46
ASC Bike	-	-	-0.836	0.29	-1.230	0.00
ASC Walk	-	-	-2.480	0.01	-0.164	0.52
Travel time (minutes)	-	-	-0.090	0.00	-0.009	0.00
Transit access and egress time (minutes)	-	-	←		-0.101	0.07
Stop (binary variable), in auto alt.	-	-	-	-	0.602	0.02
<i>Error structure/correlation terms (class independent) for work tours</i>						
Std dev for auto error component	-	-	-	-	2.460	0.00
Std dev for transit error component	-	-	-	-	2.142	0.00
Std dev for bike error component	-	-	←		2.333	0.00
Std dev for walk error component	-	-	-	-	1.750	0.00
Std dev of bike & walk error component	-	-	-	-	1.560	0.00
<i>Class specific choice model for non-work tours</i>						
ASC Auto	0.000	-	0.000	-	0.000	-
ASC Transit	-2.122	0.00	0.770	0.00	-0.243	0.38
ASC Bike	-4.240	0.00	-0.373	0.08	-2.310	0.00
ASC Walk	1.464	0.00	2.510	0.00	-1.021	0.00
Travel time (minutes)	-0.0839	0.00	-0.052	0.00	-0.008	0.00
Transit access and egress time (minutes)	←				-0.182	0.00
<i>Error structure/correlation terms (class independent) for non-work tours</i>						
Std dev for auto error component	-	-	1.391	0.00	-	-
Std dev for transit error component	-	-	1.100	0.00	-	-
Std dev for bike error component	←		2.209	0.00	→	
Std dev for walk error component	-	-	1.244	0.00	-	-
Std dev of bike & walk error component	-	-	0.485	0.00	-	-
<i>Class membership model</i>						
Class-specific constant	0.000	-	1.730	0.18	0.204	0.84
Number of cars owned by household	-	-	-2.600	0.00	-0.255	0.64
Transit season pass (binary variable)	-	-	1.600	0.07	1.590	0.05
Number of bicycles owned by household	-	-	0.701	0.07	0.196	0.49
Male (binary variable)	-	-	-0.876	0.20	-0.656	0.22
Married (binary variable)	-	-	-0.926	0.26	-0.930	0.16
Parent (binary variable)	-	-	-0.232	0.82	1.100	0.14

**Table 2:** Estimation results for Model 6 (three-class model with constrained choice-sets)



*Figure 5: Sample enumeration results for Model 6 (three-class model with constrained choice-sets)*

Next, we look at the estimates for the class membership model. Demographic binary variables that correlate the different roles played by individuals within a household can be seen to exert a significant effect on modality styles. Males are likelier to be quasi-unimodal auto users than females. Single adults appear to be more inclined to bicycle or take transit than their married counterparts. However, parenthood decreases the probability of being multimodal green whilst simultaneously increasing the odds of being multimodal all. The class membership model further confirms that modality styles are strongly influenced by longer-term mobility decisions such as car and bicycle ownership, and individual transit season pass possession, with expected signs on all parameters. An individual who owns a transit season pass has little likelihood of being a quasi-unimodal auto user, but is interestingly indifferent between multimodal green and multimodal all, suggesting a strong transit orientation for the latter, also borne out by the estimates on the alternative-specific constants for that class. Auto and bicycle ownership wield significant influence on multimodal green users relative to the other two modality styles.

To further underscore behavioral differences between the three classes, a sample enumeration is carried out, and the results are illustrated in Figure 5. The class membership probabilities for each individual are summed to arrive at the expected size of the three modality style segments. The class-specific probability of choosing an alternative on a tour is weighed by the class membership probability for the respective individual, and the product is summed over all tours to arrive at the expected modal split for each of the three modality styles. Most notably, the expected size of the three classes is more or less the same, with multimodal all users forming the largest segment, comprising nearly 40% of the sample population. Figure 5 supports our inferences based on the parameter estimates, and these results are returned to later when we discuss implications for policy-makers.

## 5.5 Comparison with other modeling approaches for capturing heterogeneity

Here we compare how our three-class behavioral mixtures model compares against other ways of incorporating heterogeneity in choice models (without the use of attitudinal indicators), namely systematic taste heterogeneity (Model 7) and random taste heterogeneity (Model 8). Both are single class models and build on the framework of Model 2, the single-class model with error components. Table 3 lists parameter estimates for the two models.

Model 7 differs from Model 2 in that the coefficient on travel time is defined as a linear function of the three demographic binary variables denoting gender, marital status, and parenthood, to capture systematic heterogeneity in sensitivity to travel time. Furthermore, auto and bike ownership enter the utility function as linear parameters, to make for a fairer comparison with our preferred three-class behavioral mixtures model. Most of these socioeconomic variables are significant. However, a counterintuitive sign on the parameter for access and egress time for transit work tours questions the validity of the specification.

Model 8 captures random taste heterogeneity by assuming the coefficient on travel time  $\beta_{tt}$  to be lognormally distributed. We follow procedures developed by Bhat (2000) and Greene et al. (2006) that allow for systematic heterogeneity around the location and scale parameter of the lognormal distribution. This is achieved by specifying the two parameters as independent linear functions of observable socioeconomic variables. Again, demographic binary variables reflecting gender, marital status and parenthood all exert a significant influence on the distribution of the coefficient on travel time for both work and non-work tours. We omit p-values for the constant in the location parameter function, since the only meaningful test for the parameter would be against a value of negative infinity (Bhat, 2000).

Table 4 lists the summary statistics for these two models, along with Model 2 (as a baseline for comparison) and Model 6 (our preferred three-class behavioral mixtures model). Examining the model fit serves as a good starting point for a comparison. Introducing heterogeneity of any form beyond the basic correlations of Model 2 significantly improves model fit. Further, Model 8 provides strong evidence of the existence of both systematic and random heterogeneity. However, in terms of fit alone, the three-class

<i>Variable</i>	<i>Model 7</i>				<i>Model 8</i>			
	<i>Work</i>		<i>Non-work</i>		<i>Work</i>		<i>Non-work</i>	
	<i>coeff.</i>	<i>p-val</i>	<i>coeff.</i>	<i>p-val</i>	<i>coeff.</i>	<i>p-val</i>	<i>coeff.</i>	<i>p-val</i>
<i>Non-random parameters</i>								
ASC Auto	-	-	-	-	-	-	-	-
ASC Transit	0.954	0.04	0.806	0.00	2.720	0.00	0.942	0.00
ASC Bike	0.244	0.57	0.765	0.00	1.670	0.00	-0.007	0.00
ASC Walk	1.080	0.01	2.420	0.00	1.280	0.00	2.590	0.00
Transit access and egress time (minutes)	0.022	0.47	-0.122	0.00	-0.110	0.00	-0.096	0.00
Stop (binary variable), in auto alt.	-0.097	0.67	-	-	0.245	0.26	-	-
Number of cars owned by household, in auto alt.	1.520	0.00	1.230	0.00	2.110	0.00	1.370	0.00
Number of bicycles owned by household, in bike alt.	0.131	0.12	0.190	0.00	-0.091	0.00	0.236	0.00
<i>Error structure/correlation terms</i>								
Std dev for auto error component	3.111	0.00	1.578	0.00	3.180	0.00	1.634	0.00
Std dev for transit error component	1.314	0.00	1.689	0.00	2.300	0.00	0.604	0.00
Std dev for bike error component	2.529	0.00	2.980	0.00	2.162	0.00	2.252	0.00
Std dev for walk error component	0.763	0.01	0.171	0.01	0.251	0.11	0.135	0.07
Std dev of bike & walk error component	2.320	0.00	0.219	0.00	2.997	0.00	0.979	0.00
<i>Location parameter of the distribution of the coefficient on travel time</i>								
Constant	-0.037	0.00	-0.026	0.00	-6.250	-	-3.220	-
Male (binary variable)	0.012	0.00	0.004	0.14	-0.680	0.09	-0.461	0.00
Married (binary variable)	0.001	0.83	-0.014	0.00	-1.690	0.00	0.226	0.04
Parent (binary variable)	0.016	0.00	0.017	0.00	3.742	0.00	-0.988	0.00
<i>Scale parameter of the distribution of the coefficient on travel time</i>								
Constant	-	-	-	-	3.700	0.00	0.506	0.00
Male (binary variable)	-	-	-	-	-0.542	0.31	-0.658	0.00
Married (binary variable)	-	-	-	-	-0.608	0.14	0.419	0.00
Parent (binary variable)	-	-	-	-	0.836	0.28	0.658	0.00

**Table 3: Estimation results for alternative single-class models**

<i>Model</i>	<i>Classes</i>	<i>Description</i>	<i>Param.</i>	<i>LL</i>	$\bar{\rho}^2$	<i>BIC</i>	<i>AIC</i>
2	One	Mixed logit with error components	25	-3429.7	0.423	7071.3	6909.3
7	One	Mixed logit with error components and systematic heterogeneity	31	-3415.2	0.425	7093.3	6892.5
8	One	Mixed logit with error components and random parameters	39	-3356.2	0.433	7042.9	6790.3
6	Three	Heterogeneous choice sets	46	<b>-3240.5</b>	<b>0.452</b>	<b>6870.9</b>	<b>6572.9</b>

*Table 4: Summary statistics for alternative approaches to capture heterogeneity*

behavioral mixtures model betters both alternative models across all statistical measures. More importantly, Model 6 offers a much richer behavioral interpretation than Model 8. The random parameters approach offers little behavioral interpretation other than that taste parameters vary in the population, whereas the behavioral mixtures approach provides a behavioral underpinning to the correlation structure, which explicitly ties the unobserved heterogeneity to different modality styles. As we will discuss in the conclusion, this has policy implications.

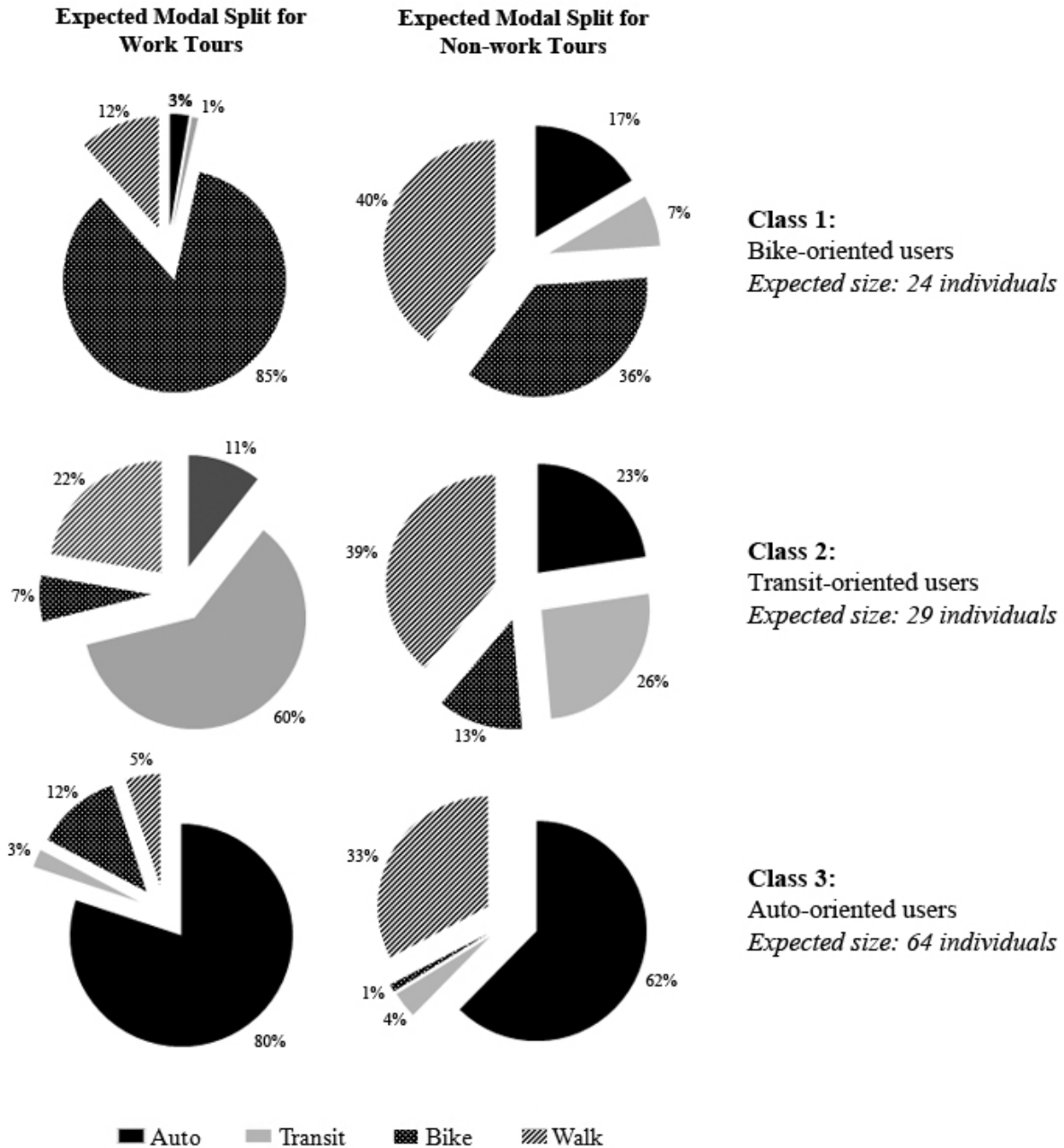
### 5.6 The case for longitudinal data

To explore whether distinct modality styles can be observed using more readily available cross-sectional travel-diary data, we estimate a two-day diary analogy of our behavioral mixture specification by treating observations taken on two different two-day periods for the same individual as being independent. We estimate a three-class model with unconstrained choice sets using this formulation (referred to as Model 9). We examine results from a sample enumeration, illustrated in Figure 6, to get a better indication of how the model compares with Model 6. In the two-day diary analogy, each of the three classes displays a unique modal orientation, particularly for work tours, with negligible mode shares for any of the other modes: Classes 1 and 3 are bike and auto-oriented, respectively, Class 2 shows a distinct, if somewhat weaker, bias for transit. The results seem to suggest that, under the two-day travel-diary assumption, the model is unable to differentiate between unimodal and multimodal behavior. Both the descriptive analysis and our preferred three-class behavioral mixtures model identified separate modality styles associated with quasi-unimodal auto users and multimodal all users of roughly equal sizes in the sample population. With the two-day travel-diary assumption, the model is unable to tell the two modality styles apart, resulting in a single auto-oriented class that is predicted to attract more than half of the sample population. This is not entirely unexpected, since an observation period of two days is likely not long enough to observe enough variation in mode choice to be able to discern multimodality. However, perhaps with a larger dataset, a richer picture of modality styles could be uncovered from shorter observation periods.

## 6. Conclusions

This paper builds a behavioral framework that captures the influence exerted by modality styles on two dimensions of individual travel behavior: mode choice for work tours and mode choice for non-work tours. Modality styles are seen as being embedded in the larger concept of an individual’s mobility style and, ultimately, lifestyle. We show that modality styles can not only be directly observed from a person’s modal choice behavior over a period of time, but that they can also be inferred through the means of mode choice models. The results are encouraging in that both the descriptive and the econometric analysis reveal that there are different groups in the population that are clearly distinguishable by their modality behavior. The descriptive analysis suggests the presence of “quasi-unimodal” individuals (35% of the

sample, most of them auto-oriented) who consistently use the same mode for the vast majority of their tours over the six weeks, and “multimodal” individuals who exhibit variation in their mode choices over the six weeks. The multimodal behavior is further distinguished by those whose multimodality includes auto (54% of the sample) and those whose does not (12% of the sample). In line with these findings, the



**Figure 6:** Sample enumeration results for Model 9, the three-class model with uniform choice-sets under the two-day travel diary assumption



econometric analysis indicates the presence of three distinct groups of roughly equal size: “quasi-unimodal auto” users with a strong bias for choosing auto (34% of the sample), “multimodal green” users whose auto use is minimal at best (26%), and “multimodal all” users who display a more balanced modal use (39%). Also, both the model and the modality analysis indicate that a person’s modality style is strongly correlated with long-term mobility decisions, such as vehicle ownership, and demographic characteristics, such as gender.

The three-class behavioral mixtures model is found to outperform the random parameters model in terms of statistical fit. Moreover, by providing a behavioral rationale to the covariance structure, it provides additional insight useful for policy-makers in how to market more sustainable transportation alternatives to different modality styles. Modality styles are a key aspect of individual travel behavior, as individuals with different modality styles likely respond differently to policies aimed at changing travel behavior. When considering different options, it is important to have an understanding of the distribution of modality styles in the population and of the possible responses. The class membership model is rich in interpretation, and serves as a harbinger of some of these potentially important implications for policy-makers. As an example, it is likely that policies aimed at achieving a mode shift from automobile to transit (e.g., through financial incentives to buy transit passes) might bear greater fruit if targeted specifically at multimodal all users. The influence of any such policy on quasi-unimodal auto users is expected to be little, even though that segment of the population might account for a majority of automobile trips. However, land use and residential zoning policies could take advantage of the fact that quasi-unimodal auto users display a strong willingness to walk for non-work tours through the design of more walkable auto-oriented suburban neighborhoods. Alternatively, attention could be given to initiatives that promote less driving through changes in destination or travel time, but do not aim at shifting modes.

Our research builds on previous research that examines the influence of lifestyle on travel behavior and multimodality by demonstrating how traditional travel demand models can be modified to reflect the influence of modality styles. One of the unique aspects of our research was that we were able to use data from the six-week *MOBIDRIVE* survey, which enabled us to observe and model modality styles in a way that would be difficult with standard 1-2 day activity diaries. Estimation and sample enumeration results for the three class model with unconstrained choice sets under the two-day travel diary assumption attest to these potential difficulties - an observation period of two days appears likely not long enough to discriminate between quasi-unimodal and multimodal behavior. While not surprising that longer periods of observation are likely needed to infer modality style, it does point to data availability issues and the need for travel data collection methods to move towards automated GPS-based survey methods to enable data collected over a longer horizon (e.g., see Stopher et al., 2008). Also note that the econometric results presented here were estimated from only 117 individuals and without the use of attitudinal data, so in this sense the data requirements were relatively low.

Sample enumeration results for our preferred three-class behavioral mixtures model indicate that 60% of the sample population does not appear to consider the full mode choice-set for all tours. This puts doubt on one of the basic assumptions of travel demand modeling, namely that all decision-makers are choosers, at all times. Further, the implications of modality styles extend well beyond mode choice, which we’ve focused on in this paper, and towards the broader travel demand modeling paradigm. Mobility styles (and with them, modality styles) influence other stages of travel demand modeling, in particular residential location, destination choice and mobility bundles (e.g., auto or transit season pass ownership).

Finally, the data used for our analysis were from two urban areas in Germany, where transit and non-motorized alternatives are, in general, more attractive than in many cities in the United States, and awareness of these alternatives is greater. Yet, we were still able to observe and infer clearly auto-oriented modality styles. We suspect that these groups would be represented significantly more strongly in the United States.

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## References

- Aarts, H., Verplanken, B., van Knippenberg, A. (1997), "**Habit and information use in travel mode choices**," *Acta Psychologica*, Vol. 96, pp. 1–14.
- Axhausen, K.W., Zimmermann, A., Schönfelder, S., Rindsfuser, G., and Haupt, T. (2002), "**Observing the rhythms of daily life: A six-week travel diary**," *Transportation*, Vol. 29, pp. 95-124.
- Bamberg, S., Aarø, T., and Schmidt, P. (2003), "**Choice of travel mode in the theory of planned behavior: The roles of past behavior, habit, and reasoned action**," *Basic and Applied Social Psychology*, Vol. 25, No. 3, pp. 175-187.
- Ben-Akiva, M., D. Bolduc and M. Bradley (1993), "**Estimation of Travel Choice Models with Randomly Distributed Values of Time**," *Transportation Research Record*, Vol. 1413, pp. 88-97.
- Ben-Akiva, M., and Boccara, B. (1995), "**Discrete choice models with latent choice sets**," *International Journal of Research in Marketing*, Vol. 12, pp. 9-24.
- Ben-Akiva, M., Walker, J., Bernardino, A., Gopinath, D., Morikawa, T., and Polydoropoulou, A. (2002), "**Integration of choice and latent variable models**," In: Mahmassani, H. (ed) *In perpetual motion: Travel behaviour research opportunities and application challenges*. Elsevier, Amsterdam, pp. 431–470.
- Bhat C, and Guo J (2006), "**A comprehensive analysis of built environment characteristics on household residential choice and auto ownership levels**," In: *Presented at the 85th Annual Meeting of the Transportation Research Board*, Washington DC.
- Bhat, C. R. (2000), "**Incorporating observed and unobserved heterogeneity in urban work travel mode choice modeling**," *Transportation Science*, Vol. 34, No. 2, pp. 228-238.
- Bierlaire, M. (2003), "**BIOGEME: A free package for the estimation of discrete choice models**," *Proceedings of the 3rd Swiss Transportation Research Conference*, Ascona, Switzerland.
- Boarnet, M.G., and Crane, R. (2001), "**Travel by design: The influence of urban form on travel**," Oxford: Oxford University Press.
- Bowman, J. L. (1998), "**The day activity schedule approach to travel demand analysis**," *PhD dissertation*, Massachusetts Institute of Technology.
- Bradley, M., Bowman, J. L., and Griesenbeck, B. (2010), "**SACSIM: An applied activity-based model system with fine-level spatial and temporal resolution**," *Journal of Choice Modelling*, Vol. 3, No. 1, pp. 5-31.
- Cantillo, V., and Ortúzar, J. de D. (2005), "**A semi-compensatory discrete choice model with explicit attribute thresholds of perception**," *Transportation Research Part B: Methodological*, Vol. 39, No. 7, pp. 641-657.

- Cascetta, E., and A. Papola (2001), “**Random utility models with implicit availability/perception of choice alternatives for the simulation of travel demand,**” *Transportation Research Part C: Emerging Technologies*, Vol. 9, No. 4, pp. 249-263.
- Cervero, R., and Duncan, M. (2002), “**Residential self selection and rail commuting: A nested logit analysis,**” University of California Transportation Center, Berkeley, CA.
- Chamberlain, G. (1980), “**Analysis of Covariance with Qualitative Data,**” *The Review of Economic Studies*, Vol. 47, pp. 225–238.
- Choo, S. and Mokhtarian, P. (2004), “**What type of vehicle do people drive? The role of attitude and lifestyle in influencing vehicle type choice,**” *Transportation Research Part A*, Vol. 38, No. 3, 201-222.
- Cirillo, C., and Axhausen, K.W. (2006), “**Evidence on the distribution of values of travel time savings from a six-week diary,**” *Transportation Research Part A: Policy and Practice*, Vol. 50, No. 5, pp. 444-457.
- Eluru, N., Pinjari, A. R., Pendyala, R. M., and Bhat, C. R. (2010a), “**An econometric multi-dimensional choice model of activity-travel behavior,**” *Transportation Letters: The International Journal of Transportation Research*, Vol. 2, pp. 217-230.
- Eluru, N., Bhat, C. R., Pendyala, R. M., and Konduri, K. C. (2010b), “**A joint flexible econometric model system of household residential location and vehicle fleet composition/usage choices,**” *Transportation*, Vol. 37, pp. 603–626.
- Fosgerau, M. (2005), “**Investigating the distribution of the value of travel time savings,**” *Transportation Research Part B: Methodological*, Vol.40, No. 8, pp. 688-707.
- Gaudry, M., and M. Dagenais (1979), “**The Dogit Model,**” *Transportation Research Part B: Methodological*, Vol. 13, No. 2, pp. 105-111.
- Gopinath, D. A. (1995), “**Modeling heterogeneity in discrete choice processes: application to travel demand,**” *PhD dissertation*, Massachusetts Institute of Technology.
- Greene, W. H., Hensher, D. A., and Rose, J. (2006), “**Accounting for heterogeneity in the variance of unobserved effects in mixed logit models,**” *Transportation Research Part B: Methodological*, Vol. 40, No. 1, pp. 75-92.
- Hensher, D.A., and Greene, W.H. (2003), “**Mixed logit models: state of practice,**” *Transportation*, Vol. 30, No. 2, pp. 133–176.
- Hess, S. (2005), “**Advanced discrete choice models with applications to transport demand,**” *PhD dissertation*, Imperial College London.
- Hess, S., M. Bierlaire and J. W. Polak (2005), “**Estimation of value of travel-time savings using mixed logit models,**” *Transportation Research Part A: Policy and Practice*, Vol. 39, Nos. 2-3, pp. 221–236.
- Hess, S., Ben-Akiva, M., Gopinath, D., and Walker, J. (2009), “**Taste heterogeneity, correlation and elasticities in latent class choice models,**” *Compendium of Papers, 88th Annual Meeting of the Transportation Research Board*. Washington, DC: Transportation Research Board.
- Hess, S., Rose, J. M. (2006), “**Effects of distributional assumptions on conditional estimates from mixed logit models,**” *ITLS working paper*, Institute for Transport and Logistics Studies, University of Sydney, Sydney, Australia.

- Johansson, M. V., Heldt, T., and Johansson, P. (2006), "**The effects of attitudes and personality traits on mode choice**," *Transportation Research Part A: Policy and Practice*, Vol. 40, No. 6, pp. 507–525.
- Kitamura, R. (1988), "**Life-style and travel demand**," *Transportation Research Board Special Report 220*, pp. 149-189. Washington, DC: Transportation Research Board.
- Kitamura, R., Mokhtarian, P.L. and Laidet, L. (1997), "**A micro-analysis of land use and travel in five neighborhoods in the San Francisco Bay Area**," *Transportation*, Vol. 24, pp. 125-158.
- Krizek, K., and Waddell, P. (2002), "**Analysis of lifestyle choices: Neighborhood type, travel patterns and activity participation**," *Transportation Research Record*, Vol. 1807, pp. 119-128.
- Kuhnimhof, T., Chlond, B. and von der Ruhren, S. (2006), "**The Users of Transport Modes And Multimodal Travel Behavior – Steps Towards Understanding Travelers’ Options and Choices**," *Compendium of Papers, 85th Annual Meeting of the Transportation Research Board*. Washington, DC: Transportation Research Board.
- Kuhnimhof, T. (2009), "**Measuring and modeling multimodal mode use in the longitudinal section**," *Compendium of Papers, 88th Annual Meeting of the Transportation Research Board*. Washington, DC: Transportation Research Board.
- Lanzendorf, M. (2002), "**Mobility styles and travel behavior: Application of a lifestyle approach to leisure travel**," *Transportation Research Record*, Vol. 1807, pp. 163-173.
- Manski, C. (1977), "**The structure of random utility models**," *Theory and Decision*, Vol. 8, No. 3, pp. 229–254.
- McFadden, D., Train, K. (2000), "**Mixed MNL models for discrete response**," *Journal of Applied Econometrics*, Vol. 15, pp. 447-470.
- Ohnmacht, T., Götz, K, and Schad, H. (2009), "**Leisure mobility styles in Swiss conurbations: construction and empirical analysis**," *Transportation*, Vol. 36, pp. 243-265.
- Ory, D. T., Mokhtarian, P. L. (2009), "Modeling the structural relationships among short-distance travel amounts, perceptions, affections, and desires," *Transportation Research Part A: Policy and Practice*, Vol. 43, No. 1, pp. 26-43.
- Outwater, Maren L., S. Castleberry, Y. Shiftan, M. Ben-Akiva, Y. S. Zhou, and A. Kuppam (2003), "**Attitudinal market segmentation approach to mode choice and ridership forecasting: Structural equation modeling**," *Transportation Research Record*, Vol. 1854, pp. 32-42.
- Outwater, Maren L., Spitz, G., Lobb, J., Campbell, M., Pendyala, R., Sana, B., and Woodford, W. (2010), "**TCRP H-37 Characteristics of premium transit services that affect mode choice: Summary of phase I**," TRB 2011 Annual Meeting.
- Pas, E. (1988), "**Weekly travel-activity behavior**," *Transportation*, Vol. 15, pp. 89-109.
- Pinjari, A. R., Pendyala, R. M., Bhat, C. R., and Waddell, P. A. (2007), "**Modeling residential sorting effects to understand the impact of the built environment on commute mode choice**," *Transportation*, Vol. 34, pp. 557-573.
- Revelt, D. and K. Train (1998), "**Mixed logit with repeated choices**," *Review of Economics and Statistics*, Vol. 80, pp. 647–657.
- Revelt, D. and K. Train (2000), "**Customer-specific taste parameters and mixed logit**," *Working paper No. E00-274*, Department of Economics, University of California, Berkeley.

- Salomon, I., and Ben-Akiva, M. (1982), "**Life style segmentation in travel demand analysis,**" *Transportation Research Record*, Vol. 879, pp. 37-45.
- Salomon, I., and Ben-Akiva, M. (1983), "**The use of the life-style concept in travel demand models,**" *Environment and Planning*, Vol. 15, No. 5, pp. 623-638.
- Schwanen, T., and Mokhtarian, P. (2005), "**What affects commute mode choice: neighborhood physical structure or preferences toward neighborhoods?**" *Journal of Transport Geography*, Vol. 13, pp. 83-99.
- Srinivasan, S. and Ferreira, J. (2002), "**Travel behavior at the household level: understanding linkages with residential choice,**" *Transportation Research Part D: Transport and Environment*, Vol. 7, No. 3, pp. 225-242.
- Stopher, P.R., Kockelman, K., Greaves, S.P., and Clifford, E. (2008), "**Reducing burden and sample sizes in multiday household travel surveys,**" *Transportation Research Record*, No. 2064, pp. 12-18.
- Swait, J., and Ben-Akiva, M. (1986), "**Empirical test of a constrained discrete-choice model,**" *Behavioral Research for Transport Policy*, VNU Science Press, Utrecht, The Netherlands.
- Swait, J., and Ben-Akiva, M. (1987), "**Incorporating random constraints in discrete models of choice set generation,**" *Transportation Research Part B: Methodological*, Vol. 21, No. 2, pp. 91-102.
- Swait, J. (2009), "**Choice models based on mixed discrete/continuous PDFs,**" *Transportation Research Part B: Methodological*, Vol. 43, No. 7, pp. 766-783.
- Thøgersen, J. (2006), "**Understanding repetitive travel mode choices in a stable context: A panel study approach,**" *Transportation Research Part A: Policy and Practice*, Vol. 40, No. 8, pp. 621-638.
- Train, K. E. (2009), "**Discrete choice models with simulation,**" Cambridge University Press, Cambridge.
- Tversky, A. (1972), "**Elimination by aspects: A theory of choice,**" *Psychological Review*, 79, pp. 281-299.
- Vovsha, P., and Petersen, E. (2009), "**Model for person and household mobility attributes,**" *Transportation Research Record*, Vol. 2132, pp. 95-105.
- Walker, J., and Li, J. (2006), "**Latent lifestyle preferences and household location decisions,**" *Journal of Geographical Systems*, Vol. 9, No. 1, pp. 77-101.
- Walker, J.L., and Ben-Akiva, M. (2011) "**Advances in discrete choice: mixture models,**" In: de Palma, A., Lindsey, R., Quinet, E., and Vickerman, R. (eds) *A Handbook Of Transport Economics*. Edward Elgar Publishing.
- Wirthlin Worldwide, and FJCanon (2000). "**Enhancing the visibility and image of transit in the United States and Canada,**" *TCRP Report 63*, Transit Cooperative Research Program, Transportation Research Board, Washington, D.C.
- Wood, W., Quinn, J.M., and Kashy, D.A. (2002), "**Habits in everyday life: Thought, emotion, and action,**" *Journal of Personality and Social Psychology*, Vol. 83, No.6, pp. 1281–1297.