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ARE MILLENNIALS MORE MULTIMODAL? A LATENT-CLASS CLUSTER ANALYSIS WITH ATTITUDES AND PREFERENCES AMONG MILLENNIAL AND GENERATION X COMMUTERS IN CALIFORNIA

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Submitted for publication in *Transportation*

June 2018

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ABSTRACT

Millennials tend to use a variety of travel modes more often than older birth cohorts. Two potential explanations for this phenomenon prevail in the literature. According to the first explanation, millennials often choose travel multimodality at least in part because of the effects of the economic crisis, which affected young adults more severely than their older counterparts. Another explanation points to the fact that millennials may have fundamentally different preferences from those of older birth cohorts. This paper presents an examination of millennials' travel behavior as compared to the preceding Generation X, based on a survey of 1,069 California commuters. It shows that millennials adopt multimodality more often than Gen Xers, on average. However, the analysis also points to substantial heterogeneity among millennials and indicates that, perhaps contrary to expectations and the stereotype in the media, the majority of millennials are monomodal drivers in California. The paper contributes to the literature on millennials' mobility in several ways. First, it rigorously classifies various forms of travel multimodality (on a monthly basis and distinctively taking trip purpose into account) through the analysis of a rich dataset that includes individual attitudes and preferences; second, it explores gradual changes of multimodality across age and generation; and third, it analyzes the effects of various demographic, built environment, and attitudinal attributes on the adoption of multimodality.

Keywords: Millennials, Travel multimodality, Latent class analysis, Attitudes and preferences, Shared mobility

1. INTRODUCTION

The millennial generation, which includes those who were born from the early 1980s to the late 1990s (Dimock, 2018), has travel patterns that differ from those of preceding generations when they were at the same age. Millennials wait longer to obtain a driver's license, own fewer cars, drive less, and make more trips by alternative or emerging modes such as car sharing and on-demand ride services (Delbosc & Currie, 2013; Kuhnimhof et al., 2012; Kuhnimhof, Zumkeller, & Chlond, 2013a, 2013b; Millard-Ball et al., 2005; Circella et al., 2018). Scholars have speculated about the possible causes for their unique travel patterns and coalesced around three dominant hypotheses. First, researchers point to the effects of economic hardship on today's young adults and the fact that life course events such as independent living from parents, marriage, and childbearing are delayed compared to previous years, while pursuing higher education has increased. According to this theory, lack of economic resources (especially in the past few years) has prevented millennials from owning and driving personal vehicles and moving onto the next stage in the lifecycle (e.g. starting their own household and having children), at which people usually make more trips (Blumenberg, Ralph, Smart, & Taylor, 2016; Delbosc & Currie, 2013; Klein & Smart, 2017; McDonald, 2015). Instead, millennials choose cities where they can find affordable rental units and travel without cars.

Second, researchers also assert that the increasing share of college graduates among young adults and their delay in experiencing life course events are manifestations of long-term social trends. One factor behind these trends is the transition towards knowledge-based economies that demand highly educated labor and agglomeration economies (Millsap, 2018). As an effect of such trends, millennials are the most educated generation in US history, while on average the amount of their debt from student loans is higher than that of previous generations (Fry, Parker, & Rohal, 2014; Taylor, Fry, & Oates, 2014). Together with delaying marriage and childbearing, millennials neither can afford to buy nor need their own home until later in their lives (Census, 2011), or simply prefer smaller housing units, so they tend to choose urban neighborhoods and travel more with non-car travel modes (Scheiner, Chatterjee, & Heinen, 2016). Moreover, scholars point out that work arrangements and commute trips are changing as part of the transformations in the economy, including an increase in zero-hour contracts and home-based workers (Chatterjee et al. 2018; Marsden, Dales, Jones, Seagriff, & Spurling, 2018; Mateyka, Rapino, & Landivar, 2012). These changes bear implications for travel behavior in general and mode choice in particular, and they do so more for young adults, who are starting to build their careers in the evolving job market of the moment.

Third, scholars, according to reports in the academic journals and popular media, note that changes in attitudes and preferences and the adoption of information and communication technologies (ICT) may play a key role in affecting millennials' choices. They observe that millennials have pragmatic attitudes towards car ownership, are more conscious of the negative externalities of driving, are more informed about environmental and public health issues, prefer closer access to vibrant parts of cities, and are more willing to substitute virtual contacts for physical trips (Couture & Handbury, 2017; Delbosc & Currie, 2014; Hopkins, 2016; Puhe & Schippl, 2014; Raymond, Dill, & Lee, 2018; Smith & Page, 2016; Taylor, Doherty, Parker, & Krishnamurthy, 2014; Vij, Carrel, & Walker, 2013). Since these explanations have different implications for planning and policy, it is important to assess the contribution of various factors to current travel patterns of millennials and understand what these mean for possible changes to their travel in the near future (Delbosc & Ralph, 2017; Polzin, Chu, & Godfrey, 2014).

One less studied aspect of millennials' travel behavior is their use of multiple travel modes in a given period, or multimodality (Kuhnimhof, Chlond, & von der Ruhren, 2006; Nobis, 2007). By multimodality, scholars imply travel patterns that present some balance among various modes (e.g., half of trips made by driving and the other half by non-motorized modes), instead of relying on a single mode. While previous studies focused on various dimensions of millennial travel separately, the lens of multimodality helps researchers understand the unique patterns of millennial travel in more comprehensive ways (Ralph, 2016). In addition, understanding trends in multimodality could reveal how millennials might respond to policy interventions. Multimodal travelers are found to be better informed about and more sensitive to level-of-service attributes of various modes than habitual users of certain modes (Heinen & Ogilvie, 2016; Van Exel & Rietveld, 2009). These characteristics of multimodals may lead them to choose the mode that best matches their needs, which may differ by circumstance. Certainly, understanding how many millennials are multimodal travelers is of importance in that it informs the development of travel demand management (TDM) strategies for this birth cohort.

A few studies have analyzed millennials' multimodality. According to these studies, millennials represent several distinctive traveler groups based on daily travel patterns and longer-term mobility choices. By analyzing the 2009 National Household Travel Survey (NHTS), Ralph (2016) suggested that four groups of travelers could be identified: *drivers*, *long-distance trekkers*, *multimodals*, and *carless.* Among these groups, multimodals made more than half of their trips by walking, biking, and public transit; were less likely to have a driver's license and access to household vehicles; but traveled more frequently than the first two groups who traveled almost exclusively in automobiles. Unlike the popular depiction in the mass media, only 3.6% of those aged between 16 and 36 fit into this category in the 2009 NHTS. With a simpler measure of travel multimodality, Buehler and Hamre (2014) found that younger people tended to travel more by walking, biking, and using public transit than their older counterparts. The authors also showed that the longer the measurement period, the higher the proportion of users that would be categorized as multimodal travelers in the population. For example, while only 22.1% of respondents in the 2009 NHTS data used more than one mode on the surveyed day, the share of "multimodal travelers" increased to 72% if its definition includes users that adopted different modes on different days of the same week. Thus, identifying multimodal travelers based only on daily travel patterns may omit a substantial portion of the population, who may be (nearly) as responsive to policies and interventions as daily multimodals (Buehler & Hamre, 2014; Molin, Mokhtarian, & Kroesen, 2016; Van Exel & Rietveld, 2009; Schlich & Axhausen, 2003). While the aforementioned studies analyzed one or more cross-sectional datasets separately, Vij and his colleagues (Vij, Gorripaty, & Walker, 2017) estimated *pooled* models using two repeated cross-sectional datasets to see if (in the aggregate) young and older adults prefer multimodality more over time. Using two regional travel survey datasets in the San Francisco Bay Area in 2000 and 2012, they reported that "Car Preferring Multimodals" increased their shares in the population while "Complete Car Dependents" decreased in the 2000s. Interestingly, in their study, the trend of increasing multimodals was not limited to young adults, but present in all age groups. In contrast, Heinen and Mattioli (2017) documented (at the aggregate level) decreasing trends in multimodality in England from 1995 to 2015 by analyzing the Great Britain National Travel Survey, a nationally representative cross-sectional dataset that is collected annually. The study found that those who were between 16 and 30 (in all years) always tended to exhibit more multimodal travel behavior than those who were older than 30. However, on average, the level of multimodality of the young adults decreased in these two decades (while those of the older groups had remained stable at their *lower* levels).

Researchers have developed a variety of multimodality definitions and indices, most of which have not been applied to studies with a focus on millennials. Buehler and Hamre (2014) classified all individuals into three traveler groups: (a) those who use only automobiles, (b) those who use both automobiles and several alternatives (walking, biking, and public transit), and (c) those who use only these non-automobile modes. Although intuitive and convenient, this approach fails to capture the continuous degree of mono/multimodality that each traveler might have and its multidimensionality. Heinen and her colleagues (Heinen, 2018; Heinen & Chatterjee, 2015; Heinen & Mattiolo, 2017; Scheiner, Chatterjee, and Heinen , 2016) tested several continuous measures, each of which focused on specific aspects of multimodality. For example, the share of trips made with the most frequently used mode captures individuals' degree of concentration on a single mode, but does not take into account the distribution of use across other modes. In contrast, the *Herfindahl-Hirschman Index (HHI)* and *Shannon's Entropy* index measure how concentrated or dispersed individuals' use patterns are across multiple modes, but do not consider what their primary mode is.

Other researchers have attempted to measure the multidimensional nature of multimodality. Diana and Mokhtarian (2009) classified survey respondents from France and the US into four traveler types, using a k-means cluster analysis on objective, subjective, and desired levels of travel by various modes. Ralph (2016) employed a latent profile analysis in which she included seven indicators of mobility choices for various time horizons, from daily travel patterns to medium-term commitments such as driver's license, car ownership, and annual miles driven. Molin et al. (2016) avoided arbitrarily weighting indicators of various time horizons by employing monthly frequencies of various modes in their latent-class cluster analysis. Vij et al. (2017) employed a latent-class choice model to estimate unobserved modal preferences of individuals, which they define as "behavioral predisposition towards a certain travel mode or set of travel modes that an individual habitually uses" (p. 242). In brief, although a wide range of measurement techniques is available in the literature, researchers of millennials' travel behavior have not employed many of them yet. In particular, more complex approaches that capture the multidimensional nature of travel modality have been rarely used.

The objectives of this paper are two-fold. First, we examine various types of multimodality and their relative shares in a sample of millennials and members of Generation X by employing a rich set of variables, including individual attitudes and the use of shared mobility services – these variables are rarely available in conventional travel-diary data. Second, we analyze the effects of various individual attributes, such as socioeconomics and demographics, attitudes and preferences, and residential location, on the likelihood of belonging to certain traveler groups. The organization of the paper is as follows: Section 2 describes the dataset and variables used in the study. Section 3 discusses the methodological approach and Section 4 offers detailed findings; Section 5 provides implications of the main findings, suggestions for policies and interventions, and future research directions.

2. DATA AND VARIABLES

In this paper, we analyze the California Millennials Dataset, which includes information on travel behavior, attitudes and preferences (e.g., urban/suburban lifestyles, ICT use, and emerging modes such as Uber/Lyft), residential and work/school locations, past and planned/anticipated changes in living arrangements, and sociodemographic and economic attributes of young adults (millennials) and members of the preceding Generation X. As part of a multi-year research endeavor involving a panel, in 2015 we collected a first wave of data consisting of 2,400 individuals across six regions of California and three neighborhood types (urban, suburban, and rural), using a quota sampling approach. That is, with weights, the sample allows analyses that are representative of the two generations in California. We developed the weights by applying a combination of cell weights and the iterative proportional fitting (IPF) algorithm. In this process, we used targets for gender, race and ethnicity, student/worker status, presence of children in the household, and household income from the 2015 US Census American Community Survey 5-year estimates (Circella et al., 2017a; Circella et al., 2017b; Circella et al., 2016). This paper uses the weighted sample.

To capture various patterns of travel multimodality, we employed a subsample of 1,069 cases who regularly commute either to work or school, and constructed several indicator variables from their frequency of using various transportation modes for *commute* and *leisure/shopping/social* (henceforth, "non-commute") trips. For commute trips, we asked the frequency of using various modes for one-way trips. Unlike previous studies, we analyze multimodality in a way that takes into account trip purposes, because reports and statistics suggest that millennials' mode choice may differ from that of older birth cohorts only for trips with certain purposes, e.g., non-commute (Jaffe, 2013, 2014). Note that this study examines the travel patterns of a sample of commuters, whose mode choice behaviors may differ from those of non-commuters. After all, commute trips usually take place in similar circumstances, so commuters may well develop habits of choosing a certain (set of) mode(s). Their habits may also affect their mode choices for non-commute trips and their overall multimodality.

The original raw data include frequencies of using 13 travel modes reported on a 7-point ordinal scale, separately for the two categories of trip purposes. For each of the 26 mode/purpose combinations, individuals marked a choice that ranges from "Not available" to "5 or more times a week." Since the survey asked individuals to report retrospectively how often they "typically" use various travel modes, they may have inaccurately reported their frequencies (Stopher, FitzGerald, & Xu, 2007). For analysis, we grouped the 26 variables into nine indicators based on similarity and uniqueness of modes and purposes, developing "monthly" frequencies for four groups of modes for commute trips and five groups of modes for non-commutes. The four groups of modes common to both commute and non-commute trips are: *car as a driver*, *car as a passenger* (including taxi and ridehailing services for commute trips, which are classified separately for non-commute trips), *public transit* (including both bus and rail options), and *active modes* (including walking, biking and skateboarding). An additional group of modes was included for non-commutes, measuring the use of *emerging transportation modes* (ride-hailing services such as Uber/Lyft and carsharing services such as Zipcar/Car2Go) (refer to Appendix 1). To obtain the monthly frequencies for these nine groups, we summed proxy values that capture the monthly frequencies of the raw modes that belong to each group (refer to Appendix 2). Given that many studies analyzed the NHTS datasets, which lack information on use of various modes for more than a day (Buehler & Hamre, 2014; Ralph, 2016), our indicators capturing monthly use of various travel modes are expected to reveal unexplored patterns of multimodality, which may substantially differ from those measured only on one day.

We used three groups of explanatory variables in the model: sociodemographic traits and economic characteristics, attitudes and preferences, and built environment attributes. For attitudes and preferences, the dataset contains individuals' level of agreement with 66 statements on a 5-point Likert-type scale from "Strongly disagree" to "Strongly agree". We conducted a factor analysis and identified 17 factors as the best solution, leaving 14 stand-alone statements that were not included in the final factor solution (but were retained for further analysis), based on multiple criteria including interpretability (Circella et al., 2017b; refer to Appendix 3). For built environment attributes, the California Millennials Dataset contains individuals' home addresses, which we geocoded using the Google Maps Application Programming Interface (API). Using these geocoded locations, we extracted information on land use and transportation systems from external sources. The Smart Location Database of the US Environmental Protection Agency provides a wide range of land use variables, which we factor analyzed to obtain composite indexes capturing activity intensity and land-use balance. For the level of service by public transit, we collected the *transit connectivity index*, i.e. a composite index that takes into account bus routes and train stations within walking distance for each census block group, from alltransit.cnt.org (CNT, 2016). In addition, we used the five neighborhood types that Salon (2015) developed based on the land use characteristics of individual census tracts throughout California. While her typology included *central city*, *urban*, *suburban*, *rural in urban*, and *rural*, we rename the fourth type *exurban* based on the census tracts' geographical locations and land-use patterns.

3. METHODS

In this paper, we employ latent profile analysis to *probabilistically* assign individuals to traveler groups, each of which is characterized by relatively similar mode use patterns, while maximizing the heterogeneity of these patterns across groups. This analytical approach has several advantages over simpler methods for identifying multimodal travel behaviors. First, we attempt to measure multimodality in its entirety, instead of developing a *single* (composite) index. We believe that travel multimodality cannot be easily reduced to a mono-dimensional measure such as HHI or Shannon's Entropy. The same values for these indexes may refer to travel behaviors which are very different from each other, and each of which could be the target of unique sets of policies and interventions. Instead, we classify individuals into *latent classes* based on multiple indicators, all of which depict the unique mode use patterns of each class.

Second, unlike deterministic classification schemes (Buehler & Hamre, 2014; Diana & Mokhtarian, 2009; Kuhnimhof et al., 2006; Nobis, 2007), latent profile analysis estimates individuals' probabilities of belonging to various latent classes. Each of these classes shows its own profile consisting of average frequencies of use of various modes. Specifically, they are the group-specific probability-weighted averages of indicator variables (the nine mode use frequencies) across the sample. In brief, the latent profile analysis better captures the heterogeneity of multimodal travel behaviors by creating an unobservable construct consisting of multiple modality styles, each of which characterizes a given individual to varying degrees (i.e., with varying probabilities). Third, as for the effects of various factors (i.e., active covariates) on the individuals' probabilities of belonging to various latent classes, the latent profile analysis simultaneously estimates these effects while classifying individuals into various classes. Several researchers, to date, have deterministically identified traveler groups and then assigned individuals to these groups in a separate stage (Buehler & Hamre, 2014; Nobis, 2007; Ralph, 2016). However, their methods (1) do not use information available in the active covariates to help estimate the probability of belonging to a given group, and (2) do not guarantee to maximize the heterogeneity between groups.

Regarding estimation, the latent class profile analysis consists of two sub-models which are estimated simultaneously. Equation (1) presents the entire model (Vermunt and Magidson, 2002; adapted from Molin, Mokhtarian, and Kroesen, 2016). One sub-model estimates the probability of an individual i (with covariates $\boldsymbol{x}_i$) belonging to a latent class c, and it employs a multinomial logit model. The other submodel estimates the class-specific means and standard deviations of the nine indicators, y_{ij} (j = 1, 2, …, 9) or arrayed in the vector $\boldsymbol{y}_i$ (the frequencies of using various travel modes for two purposes), and it assumes a normal distribution for those indicators. The results consist of two sets of parameter estimates: the class-specific coefficients of the active covariates, and the class-specific means and standard deviations of the indicators. That is, whether a given covariate accounts for the probability of individual commuters belonging to a certain class is determined by its statistical significance in the multinomial logit model setting. We used M*plus* 8.1 for model estimation (Muthén & Muthén, 2017).

$$P(\boldsymbol{y}_i|\boldsymbol{x}_i) = \sum_{c=1}^{C} P(c|\boldsymbol{x}_i) \prod_{j=1}^{9} P(y_{ij}|c) \tag{1}$$

A potential issue with the application of latent profile analysis to the nine indicators described in Section 2 lies in the local independence assumption, which assumes independence among indicators conditional on class membership. That is, for a given latent class, its members' frequencies of use of a certain mode should not explain, or predict, those for other modes. However, we found violations of this assumption: e.g., driving for work/school is statistically correlated with taking public transit for work/school for the same traveler class. Thus, we allowed bivariate residual correlations between indicators of different groups of modes for the same trip purposes. Also, in some cases, we allowed the indicators of the same group of modes for different trip purposes to be correlated (e.g., use of public transit for commute and non-commute trips) (Higgins & Kanaroglou, 2016). Figure 1 presents the relationships among the latent construct of mobility styles, the indicators, and the active and inactive covariates, and Appendix 4 includes the pairs of mode/purpose combinations whose residuals are allowed to be correlated in the model.

4. RESULTS

After testing several alternatives, we chose the four-class solution as best, based on several goodness of fit measures and interpretability. Information criteria help determine the best among models with varying specifications (e.g., differing numbers of latent classes). Mplus reports several such criteria, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and sample-size adjusted BIC (for formulas, see Akaike, 1987; Schwartz, 1978; Sclove, 1987). Low values for these criteria are associated with better model fit. However, because the values of these criteria kept decreasing as the number of latent classes increased, we considered the tradeoffs between model fit and interpretability of the model results to determine the number of latent classes in the final model. Additional consideration was given to discarding model solutions that included very small classes (containing only a few cases in the sample). Figure 2 displays the frequency profiles for the use of various modes by the four traveler groups.

4.1. Four Traveler Groups

We identified four traveler groups, having different frequencies of use of various travel modes for two trip purposes. In this section, we briefly introduce the multimodal travel patterns and socioeconomic attributes of these classes: monomodal drivers (including 84.2% of cases in the weighted sample), carpoolers (4.9%), active travelers (7.7%), and transit riders (3.1%). To understand the distinctive traits of each traveler group, we use both active and inactive covariates. Note that class-specific (probability-weighted) summary statistics in Table 1 need to be understood in the context of the small sample size in this study (N=1,069), which is subject to large sampling errors, compared to large-sized samples.

Containing the vast majority of cases, ***monomodal drivers*** drive for most of their commute (16.1 times per month) and non-commute (12.8 times per month) trips. Monomodal drivers own the most vehicles and have the greatest access to their household's vehicles (available 92.7% of the time). The majority of monomodal drivers are full-time workers (73.1%), usually with either an associate's or bachelor's degree (37.8% and 36.3%, respectively), and their commute distance is the second longest (8.99 miles), following carpoolers (9.39 miles). Many monomodal drivers tend to live with their partners and children, and have average household incomes between $60,000 and $120,000. The members of this group are older on average, are likely to perceive that a car is more than a tool, and more often reside in suburban or exurban neighborhoods. As expected, they drive the most (144 miles per week), which is three times the average driving distance for transit riders.

Carpoolers drive occasionally; however, they commute more often as a passenger in a car driven by someone else, either via carpool, a taxi, or on-demand ride services (17.98 times per month, or more than four times a week). For non-commute trips, they tend to drive instead of having others drive for them (10.47 versus 6.92 times per month). Carpoolers have the longest commutes among all groups (9.39 miles one-way), and they likely work full time. Many carpoolers earn household incomes more than $120,000 a year, and they live in a large household with many working adults. While a majority of carpoolers have a driver's license (80.7%) and a car available most (71.6%) of the time on average, these values are lower than those of monomodal drivers (at 95.7% and 92.7%, respectively). Carpoolers feel more constrained to drive, for reasons such as their inflexible schedules or destinations not served by public transit. Not surprisingly, most carpoolers rate cars either "good" or "very good" as their means of transportation, but overall, they are less averse to alternative travel modes, public transit and active modes, than monomodal drivers. Carpoolers' household composition, somewhat limited car availability, and attitudes appear to explain their weekly vehicle-miles driven (VMD), which are 20 percent fewer than those of monomodal drivers.

Active travelers travel most frequently by walking, biking or skateboarding for both commute (19.64 times per month) and non-commute (13.37 times per month) purposes. Many active travelers do not hold a driver's license (i.e., only 71.4% of them are licensed), they own few household vehicles (0.59 per adult), and report lower car availability (50.7%) than the two car-oriented groups. Active travelers reveal the most pragmatic attitudes towards cars; they do not feel they are constrained in terms of scheduling trips or choosing travel modes; and they view active modes more positively than those in the other classes. Three of every four members of this group are millennials (74.0%), and their share of urban residents is the highest (43.1%) among the four groups (followed by the transit riders group, at 36.7%).

As the smallest among the four traveler groups (including only 3.1% of the 1,069 cases, or 33 travelers in the weighted sample), ***transit riders*** use public transit almost every day for commute (22.24 times per month) and non-commute (22.96 times per month) trips. For non-commute trips, they often travel by active modes, possibly as an access or egress mode for public transit, because they lack access to a car (e.g., only 56.4% of the members of this class hold a driver's license, and their household vehicles are available only 41.8% of the time on average). Not surprisingly, this group has the largest share of transit pass holders (73.6%). Moreover, the transit rider class has adopted emerging transportation services (e.g., carsharing or ridehailing) more than the other classes, using these services more than once a week. Their total numbers of commute and non-commute trips are the highest among all classes, implying that either their trip rates are the highest or (more likely) they tend to use multiple modes for a single tour.

Transit riders contain the largest share of college graduates and current students (27.7% of this group being either part-time or full-time students). While college/graduate students in certain areas (e.g., college towns) or other countries (e.g., European countries, as discussed in Buehler, Pucher, Merom, & Bauman (2011)) may choose walking more than other modes to reach their place of study, many students in our sample, which covers the entire state of California, appear to live in locations that are not within a walkable distance from their school. On average, they have the lowest annual household income (55.4% of this group earns $60,000 or less). Also, this group shows the strongest support for environmental policies that would regulate driving. Counterintuitively, transit riders are not particularly pro-exercise, suggesting that their choice of public transit is not to increase their level of daily physical activity but to meet their travel needs. Members of this class accept public transit as either a "good" or "very good" means of travel, and on average they live in neighborhoods with high development density, mixed land use, and decent transit levels-of-service. Many transit riders reside in neighborhoods located either in or close to the central core of cities (e.g., downtown Los Angeles and San Francisco). As a result, they drive fewer miles (64 miles per week, on average) than the members of the two car-oriented classes, monomodal drivers and carpoolers.

4.2. Class Membership Model

In addition to depicting the four classes of travelers based on summary statistics, we attempt to understand the factors affecting the probabilities of individuals belonging to these groups. Table 2 presents the estimates of active covariates that are statistically significant in the membership model. Here, the reference group is monomodal drivers (which is therefore omitted in the table), so we interpret the coefficients for the other groups in comparison to monomodal drivers. We test two hypotheses by including covariates that relate to millennials' limited economic resources and delayed life course events, as well as to their different preferences from the older cohorts. Moreover, we analyze the separate effects of the built environment, which most studies neglected.

Economic factors and related living arrangements affect class membership in various ways. First, not surprisingly, those without a driver's license are more likely to be carpoolers, active travelers, or transit riders than monomodal drivers. Having fewer cars per adult in the household is associated with belonging to carpoolers or active travelers. Those who do not have children living at home are more likely to be active travelers, suggesting they are less burdened by childcare and housework duties, which may make driving convenient or necessary. Interestingly, those who are students, either part-time or full-time, are less likely to be active travelers. Instead, it is a short commute distance that increases one's probability of belonging to the active traveler class. In the meantime, those with higher educational credentials are associated with a higher likelihood of using public transit. However, these factors do not present the full picture of millennials' multimodality. We also find separate associations of individual ***attitudes and preferences*** with class membership. In particular, those who think of a car as a mere "tool" (to reach a destination) rather than a desirable object in its own right are more likely to be active travelers than monomodal drivers. Those who share concerns over the environmental impacts of driving tend to travel more by public transit. Consistent with class-specific (probability-weighted) summary statistics in Table 1, those who do not see themselves constrained regarding trip schedules and mode choice tend to travel more by active modes or public transportation (the opposite is true for carpoolers, who feel constrained).

Land use attributes of one's place of residence help account for multimodality. Activity intensity, a composite measure extracted from a factor analysis on variables such as population and employment density in the place of residence, increases the likelihood of an individual being a public transit user. Dense neighborhoods, mostly located in or close to the central city, usually offer a transit-conducive environment and are well served by public transit. In comparison, we did not find statistical significance for land-use balance, a composite index measuring the balance between housing and employment. This finding suggests that the intensity of activities in a given neighborhood induces its residents to use alternative modes, while land-use balance in itself does not. After all, the same balance value (e.g, 1 to 1 between residential and commercial) may represent very different built environments (e.g., inner city or sprawled suburbs). We see the transit service quality measure is not significant because of its high correlation with the density measure.

To determine the relative importance of covariates based on the magnitude of their coefficients, we computed standardized coefficients, which take the standard deviation of individual covariates into account. Appendix 5 presents those coefficients, whose values can be directly compared across covariates (i.e., across rows). For standard coefficients in each class (i.e., in each column), we identified the most important covariates, one in each direction (i.e., those with the largest absolute value). These covariates contribute to one's utility of belonging (or not belonging) to each class the most. As for the carpooler class, the number of commute days per week is the most important determinant encouraging belonging to the class, and cars per adult in the household is the most critical covariate discouraging belonging to the class. Those with more commute days may find it to be more cost-efficient / less-burdensome to organize carpooling, and those with better access to household vehicles may be less likely to commute by carpooling. As for the active traveler class, one's perception of active travel modes (the degree of liking them as a personal means of travel) is the most decisive positive covariate, and one's commute distance is the most important negative one. As for the transit rider class, perception of public transit is the most critical positive covariate, and pro-exercise attitudes follow as the most important negative covariate. As we discussed above, we do not believe transit riders are against getting exercise, but instead, we interpret that they choose public transit for other reasons, not for the increase in their level of physical activity. In this context, we also checked the third most important covariate for the transit rider class, which is one's driver license holding (negatively associated).

4.3. Generational Effects

To evaluate the effects of being a member of a certain generation on the adoption of multimodality, we control for one's age as an inactive covariate in the latent profile analysis, to investigate *subtler* differences among individuals belonging to the various groups (i.e., how they differ within and across generations). In fact, many studies attempted to measure generational effects by including a set of binary variables that indicate whether individuals are millennials or members of preceding generations in multiple regression models (Buehler & Hamre, 2014; McDonald, 2015). This approach may be effective for checking the existence of such effects, especially with panel or repeated cross-sectional datasets; however, it cannot reveal specific sources of the effects unless a rich set of qualitative attributes is also included. In contrast, we hypothesize that individuals' sociodemographic and economic conditions, living arrangements, and attitudes and preferences affect the type and intensity of travel multimodality. For instance, two same-aged people may travel in different ways because of the aforementioned factors being different (e.g., married or not), and two people with different ages may be very similar in their multimodal patterns, because of these factors being similar (e.g., similar preferences for urban lifestyles and active modes).

Figure 3 displays the share of each traveler group by age (note that the y-axis starts at 68 percent to clearly present the variation in the composition by age). Since we do not have sufficient cases for each age, we calculate five-year moving averages. As expected (in view of their large share), monomodal drivers dominate all age groups from 18-22 to 46-50; however, we see gradual changes, or even fluctuations, in the shares of the four traveler groups by age. The proportion of active travelers tends to decrease up to the age of 41 and slightly increase again after that age (probably because of the reduction in household obligations as children become older). Transit riders first peak in the early and mid 30s, gradually decrease to 0.7% at about 40 years old, and rebound among individuals in their mid to late 40s. Given that Figure 3 presents a one-time snapshot of the population, not a trajectory that follows the same individuals over time, young transit riders and older transit riders may differ in their characteristics. The largest proportion of active travelers are observed around an age of 29 years. In sum, treating one's age as an inactive covariate in the latent-class cluster analysis helps reveal nuanced, continuous, distributions of heterogeneity in multimodality by age, while we use individual attitudes and preferences, in addition to sociodemographics, to characterize the mobility styles of the members of the various latent classes. Still, how many millennials will continue to have multimodal travel patterns (as opposed to travel patterns more similar to those of the current older adults) as they age is an open question, which cannot be answered with the analysis of cross-sectional data.

5. CONCLUSIONS

This study employs a latent-class model and a comprehensive set of variables to identify varying patterns of travel multimodality and the relationships of these patterns to individual attributes. By doing so, we reveal multiple classes of multimodal travelers. Our results suggest possible changes in the mode use patterns of millennials in coming years, which can inform policies to help millennials stay multimodal.

Unlike popular images of multimodal millennials in the media, our study (Figure 3) shows that the majority of millennials in California are monomodal drivers, which is consistent with findings in a recent study that covers the entire US (Ralph, 2016). In contrast to the monomodal drivers, the three multimodal traveler classes have lower driver's licensure rates and limited car availability, as a result choose driving less often for commutes and leisure trips, and even though they drive occasionally, drive far fewer miles on a weekly basis. These traveler classes differ by several individual characteristics including household income, presence of children, and personal preferences. Not surprisingly, active travelers and transit riders more often reside in urban neighborhoods with high activity intensity, where public transit and non-motorized modes are viable alternatives. That is, land use facilitates, or inhibits, multimodality. Related to this, the combined share of the three multimodal travelers diminishes and that of monomodal drivers increases among individuals between 36 and 41 years old, ages at which people undergo marriage and childbearing, achieve increases in their earnings, and often relocate to the suburbs. Thus, to encourage individuals to maintain environmentally-beneficial behaviors and higher levels of travel multimodality, planners may take two approaches. First, they can spearhead plans for affordable residential alternatives (with decent public school quality) in the central parts of cities for those who *prefer* urban lifestyles, but also want to buy a home and raise children. Second, they can design and plan some suburbs with urban amenities (e.g., dense residential and commercial developments) for those who choose to relocate, to support more sustainable travel behavior.

This study presents a weighted analysis estimated with a relatively small sample from California. The travel patterns of the travelers included in this sample may differ from those in other regions or countries (for comparison see Heinen & Chatterjee (2015) for Great Britain, Molin et al.(2016) for the Dutch, and Kuhnimhof et al. (2012) for Germany). However, in view of California's position as a US leader in green energy production, greenhouse gas emissions reduction, and promotion of sustainable land use and transportation patterns, these results point to the difficulties in achieving sustainability goals at an aggregate level, even when the policy climate is favorable toward doing so. On the other hand, on average in California, proportionally more millennials belong to these three traveler groups than do the members of Generation X. Also, the membership model confirms that not only economic factors but also attitudes and preferences explain the likelihood of an individual to adopt travel multimodality (as shown in Table 2). Thus, the current shares of the four traveler groups by cohort are likely to change in the future as millennials age and experience life course events (even if at a more delayed time in life), assuming they maintain their current attitudes and preferences (e.g., they continue to be more supportive of environmental policies and take more pragmatic approaches to car ownership and driving than older adults).

As for effective policies and interventions to encourage multimodality, studies suggest focusing on the *dynamic* nature of multimodality, which helps identify windows of opportunity during which individuals adjust their travel patterns to new social and physical environments (Scheiner et al., 2016). We find this strategy highly relevant to young adults in California, because many of those belonging to the active traveler and transit rider classes in this study appear to be in transition to full-fledged adulthood. Many active travelers work part time, live close to their schools or workplaces, and do not live with their own children. Many of them earn incomes in the middle bracket, but live with low access to household vehicles in part because their lifestyles or urban locations may not demand frequent use of cars. Similarly, many transit riders are students either full-time or part-time while not making high incomes, but they do not necessarily perceive cars as merely a tool to get around (i.e., their demand for driving may be suppressed to some extent for now). Thus, when these young adults transition to next phases in the life cycle (e.g., relocation to less dense neighborhoods with low support for alternative modes), planners and policymakers should help them make an informed decision on mode choice by providing information on, and incentives for the use of, feasible alternatives in new circumstances (as well as improving the quality of such alternatives). By doing so, millennials may be both willing and able to keep being multimodal for a longer period of time.

This study analyzes cross-sectional data, which do not portray historic trends, so it cannot estimate the extent to which today's millennials will behave in coming years in the same way today's Gen Xers do. While researchers attempted to understand generational differences by examining panel and repeated cross-sectional data (i.e., comparing millennials and Gen Xers at the same age) (Chatterjee et al., 2018), these data lack attitudes and preferences, factors behind different travel behaviors and mobility choices of different generations. To overcome this limitation, we are completing a second round of data collection with a larger sample, which includes some of the same individuals from the first survey as well as new respondents included to refresh the panel. With the two waves collected at a two-and-a-half-year interval, we plan to investigate the *dynamic* nature of multimodal travel patterns of the same individuals by employing a latent transition model. By the time of the second survey, these individuals are likely in a different life stage, they may have different attitudes and preferences, and the environments in which they live may have changed, while the quality of emerging transportation technologies and services may have substantially evolved in the meantime. Examining the ways that these various types of changes affect the travel multimodality of these individuals will help us better understand behavioral changes and produce practical insights for planning and policy.

Note that our final sample does not include non-commuting millennials (and Gen Xers). Given that non-commuters have zero commute trips by any travel mode, the latent-class cluster analysis is likely to assign many of them to a single class, while in fact there are some variations in mode choice (for non-commute trips) among them. Our chosen approach, taken to avoid insufficient differentiation across latent classes, has limitations: First, we cannot generalize the main findings of the study to non-commuters. Second, since work arrangements are changing over time (e.g., recent increases in flexible arrangements such as zero-hour contracts and telework (Le Vine, Polak, & Humphrey, 2017)), current commuters may behave differently from commuters in the previous and future years. Thus, any direct comparison between the current group of commuters and commuters in previous (or future) years regarding their travel behaviors requires careful approaches (note that this study does not attempt to do so because of the cross-sectional data). However, we believe it is worthwhile for future research to examine the extent to which millennials' commute (and non-commute) travel patterns are associated with their wider adoption of non-traditional work arrangements.

6. ACKNOWLEDGEMENTS

The survey design, its administration, and data processing for the generation of the California Millennials Dataset were funded by the National Center for Sustainable Transportation (NCST), housed at the University of California at Davis, which receives funding from the USDOT and Caltrans through the University Transportation Centers program. We would like to thank Susan Handy, Lew Fulton, Farzad Alemi, Kate Tiedeman, and Rosaria Berliner for their support and contributions to this project. The comments of three anonymous peer reviewers helped to improve the paper. A previous version of this research was presented at the 97th Transportation Research Board Annual Meeting on January 9, 2018 in Washington, DC. On behalf of all authors, the corresponding author states that there is no conflict of interest.

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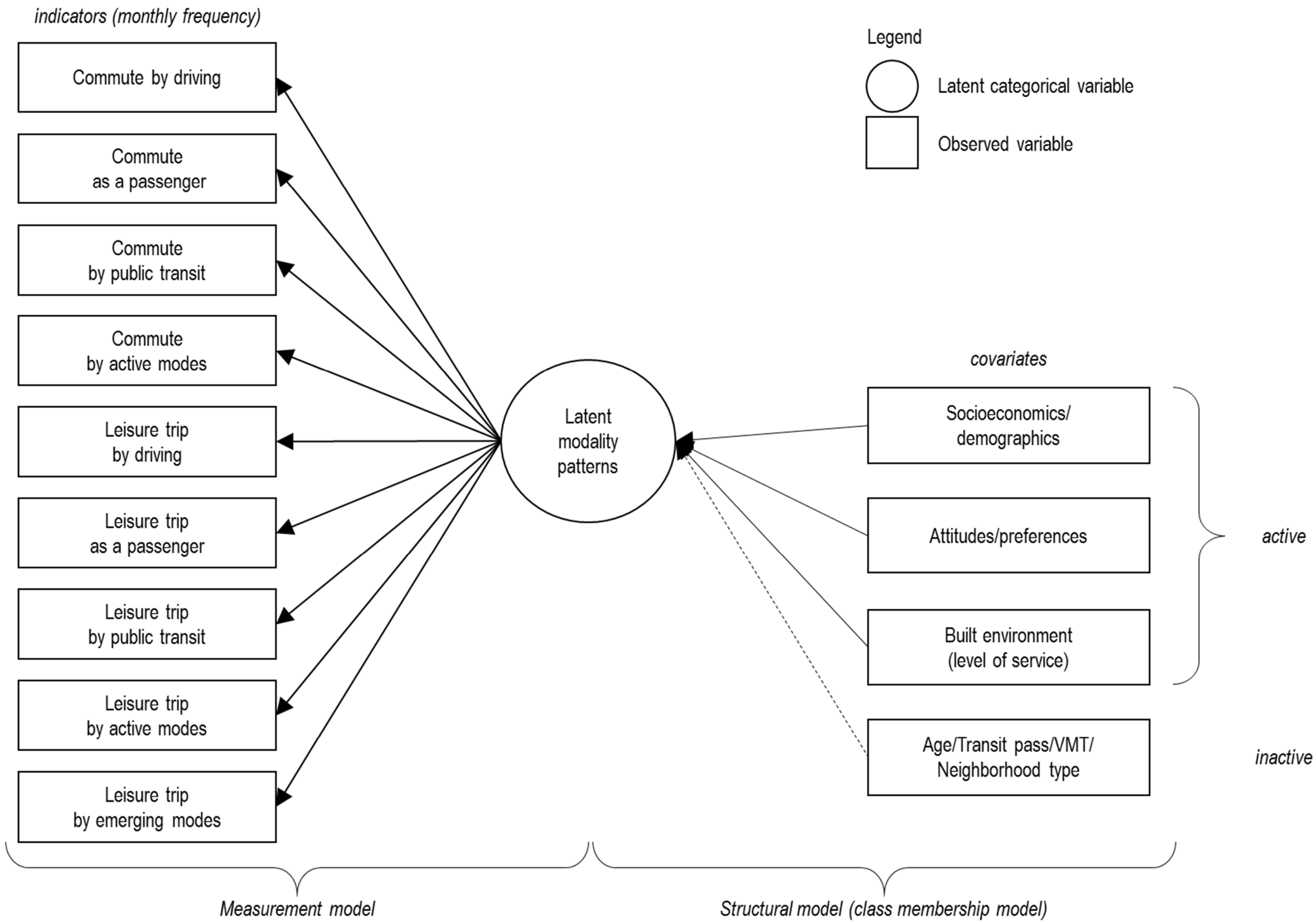

FIGURE 1 Graphical Representation of the Latent Profile Analysis with Covariates (Source: modified from Fig.1. in a previous study (Molin et al., 2016))

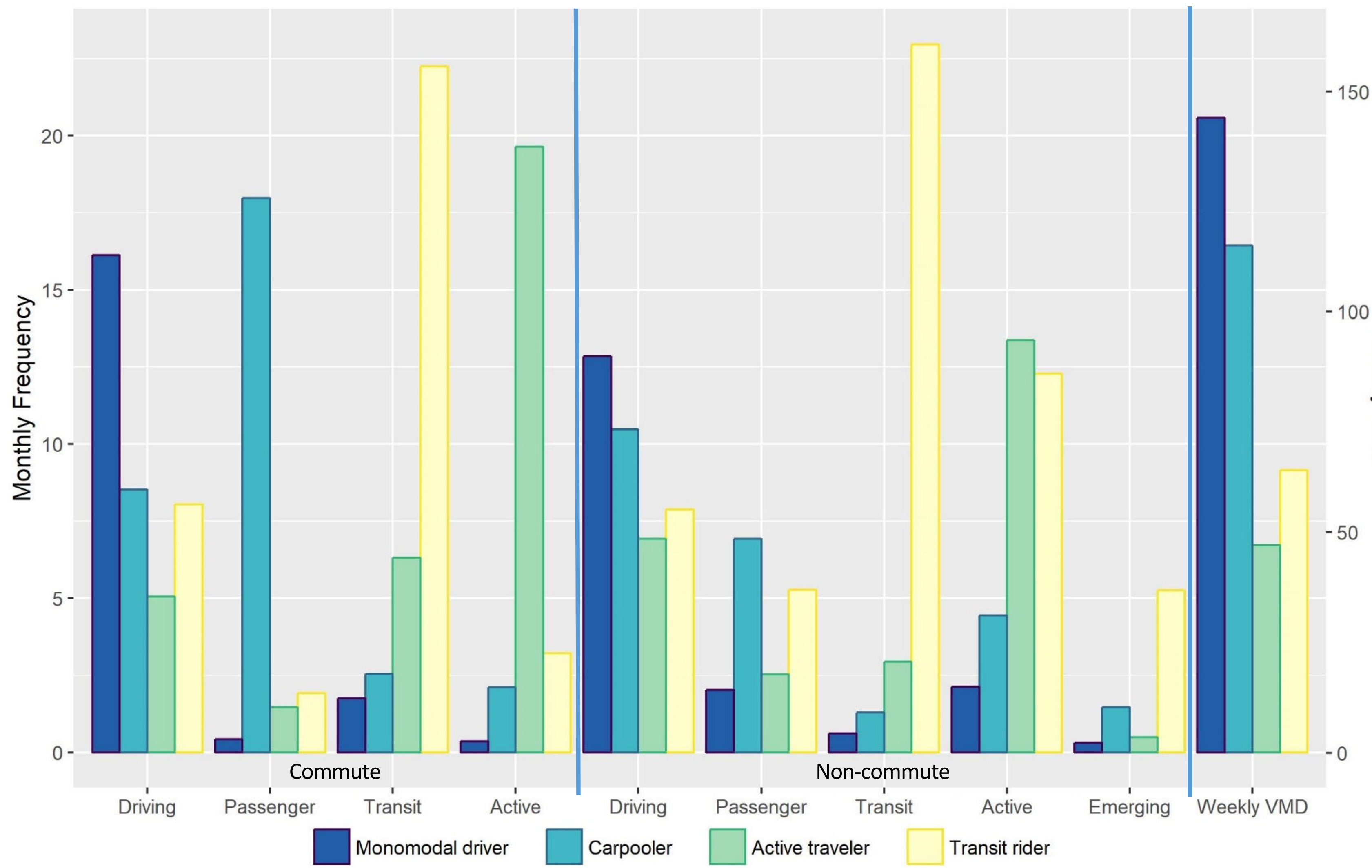

FIGURE 2 Monthly Frequencies of Use of Travel Modes and Weekly Vehicle Miles Driven (VMD) by Class

Note: The right y-axis applies only to the last set of bars (i.e., those bars above the x label of "Weekly VMD").

TABLE 1 Sample Characteristics for the Indicators and Covariates, by Traveler Group (Sample Size N=1,069)

	Monomodal driver	Carpooler	Active traveler	Transit rider
Class size (n) †	900	52	82	33
Class share (%)	84.2%	4.9%	7.7%	3.1%
Frequency per month				
For commute trips				
Car as a driver	**16.11**	8.53	5.06	8.04
Car as a passenger	0.43	**17.98**	1.45	1.92
Public transit	1.76	2.54	6.32	**22.24**
Active modes	0.35	2.10	**19.64**	3.21
Total	18.65	31.16	32.47	**35.41**
For leisure trips				
Car as a driver	**12.84**	10.47	6.93	7.87
Car as a passenger	2.02	**6.92**	2.54	5.28
Public transit	0.61	1.29	2.94	**22.96**
Active modes	2.13	4.44	**13.37**	12.28
Emerging modes	0.31	1.46	0.49	**5.25**
Total	17.92	24.58	26.26	**53.64**
Active covariates				
Travel patterns and mobility choices				
Commute days per week	4.49	**4.76**	4.57	4.26
Commute distance (mile)	8.99	**9.39**	3.73	5.46
Telecommuting frequency				
No	73.8%	70.7%	75.4%	**75.9%**
Less than once a week	17.4%	18.9%	**19.6%**	14.3%
At least once a week	8.8%	**10.4%**	5.1%	9.8%
Having a driver's license	**95.7%**	80.7%	71.4%	56.4%
Cars per household adult	**0.93**	0.74	0.59	0.64
Household composition				
Household size*	3.14	**3.42**	2.93	3.02
Living with parents*	19.9%	**32.3%**	29.3%	21.6%
Living with partner*	**64.7%**	63.5%	41.4%	40.4%
Living with own children	50.4%	41.7%	26.3%	**52.2%**
Work/study status				
Full-time student	8.3%	18.8%	6.4%	**20.8%**
Part-time student	1.3%	0.3%	0.2%	**6.9%**
Full-time worker	**73.1%**	66.7%	52.1%	63.4%
Part-time worker	16.7%	13.4%	**39.5%**	8.9%
Only doing unpaid work	0.6%	0.7%	**1.9%**	0.0%
Educational attainment				
Decline to answer	0.1%	0.0%	**3.2%**	0.0%
Up to highschool	9.3%	14.5%	**20.8%**	14.4%
Associate's degree	37.8%	**47.5%**	37.1%	28.2%
Bachelor's degree	**36.3%**	22.6%	21.8%	28.1%
Graduate degree	16.4%	15.3%	17.2%	**29.4%**
Household income*				
Decline to answer	5.2%	3.2%	**7.1%**	4.8%

~$60,000	35.1%	39.6%	38.6%	**55.4%**
$60,001~$120,000	35.4%	30.2%	**36.7%**	23.3%
More than $120,000	24.2%	**27.0%**	17.6%	16.4%
Attitudes and perceptions (factor scores)				
Car as a tool	-0.059	-0.075	**0.220**	-0.080
Pro environmental policies	0.056	0.273	0.592	**1.149**
Time/mode constrained	0.177	**0.296**	-0.568	-0.415
Pro exercise	**0.142**	0.068	0.057	-0.638
Personal vehicles				
Very bad	0.1%	**3.5%**	2.9%	0.0%
Bad	1.7%	2.1%	4.3%	**17.5%**
Neutral	12.8%	3.0%	**35.1%**	16.3%
Good	40.5%	34.1%	42.0%	**44.6%**
Very good	44.9%	**57.2%**	15.7%	21.6%
Public transportation				
Very bad	**14.0%**	10.6%	5.4%	0.0%
Bad	**25.4%**	23.0%	13.8%	2.8%
Neutral	**34.4%**	24.0%	17.4%	11.5%
Good	23.2%	28.4%	50.8%	**71.5%**
Very good	3.0%	13.9%	12.5%	**14.3%**
Active transportation				
Very bad	**12.1%**	6.6%	0.7%	5.3%
Bad	15.4%	**23.2%**	2.7%	4.7%
Neutral	**31.5%**	23.2%	11.2%	28.2%
Good	31.9%	32.0%	**50.7%**	38.2%
Very good	9.0%	15.1%	**34.7%**	23.6%
Land use attributes				
Activity intensity	0.114	0.206	0.506	**0.662**
Landuse diversity*	0.222	0.033	0.301	**0.320**
Transit service quality*	10.557	13.786	16.870	**19.459**
Inactive covariates				
Demographics				
Age	**34.27**	33.70	30.00	33.76
Proportion of millennials	51.6%	47.0%	**74.0%**	56.8%
Mobility choice				
Having a transit pass	11.3%	7.5%	33.3%	**73.6%**
Self-reported weekly VMD	**144**	115	47	64
Car availability [(a)]	**92.7%**	71.6%	50.7%	41.8%
Residential neighborhood type				
Central city	1.7%	2.3%	8.8%	**12.3%**
Urban	22.1%	24.1%	**43.1%**	36.7%
Suburban	**46.8%**	45.8%	33.4%	34.1%
Exurban	**20.7%**	19.0%	10.0%	11.6%
Rural	8.7%	**8.9%**	4.8%	5.4%

Notes: **Bold** values indicate the highest value for each row; * indicates a covariate dropped from the final specification due to statistical insignificance; † The counts of individual classes do not sum to the total due to rounding errors; and [(a)] measures a self-reported car availability (0-100%), i.e. the percentage of time an individual has access to a private vehicle.

TABLE 2 Class Membership Model (N = 1,069; Reference: Monomodal Drivers (84.2%))

Covariates	Carpooler		Active traveler		Transit rider	
Share	4.9%		7.7%		3.1%	
Travel pattern and mobility choices						
Natural log of commute distance	0.053		-1.052	***	-0.297	
# commute days per week	0.326	**	0.154		0.188	
Telecommute (reference: no telecommute)						
Less than once a week	0.451		0.081		0.135	
At least once a week	0.896		-2.073	**	0.260	
Has a drivers' license	-1.489	***	-1.264	**	-2.878	***
Cars per adult in the household	-1.342	**	-1.948	***	-0.722	
Household characteristics						
Living with own children	-0.124		-0.985	**	1.226	**
Student status (reference: not a student)						
Full-time student	0.570		-1.289	**	0.864	
Part-time student	-1.822		-4.004	***	1.904	
Educational attainment (reference: up to high school)						
Some college	0.068		0.004		-0.091	
Bachelor's degree	-0.422		-0.752		0.278	
Graduate degree	-0.037		0.364		1.718	**
Attitudes and preferences						
Car as a tool	-0.063		0.434	**	-0.400	
Pro-environmental	0.131		0.231		0.763	**
Time / mode constrained	0.322	*	-0.559	***	-0.400	*
Pro-exercise	-0.118		0.064		-0.901	***
Overall rating for cars	0.319		-0.737	***	-0.059	
Overall rating for public transit	0.262		0.033		1.105	***
Overall rating for active modes	-0.026		0.857	***	0.175	
Land-use attributes						
Activity intensity	0.051		0.003		0.990	**

Notes: * significant at the 10% level, ** significant at the 5% level, and *** significant at the 1% level; [a] denotes a single-item response (and not a factor score) for this attitudinal variable.

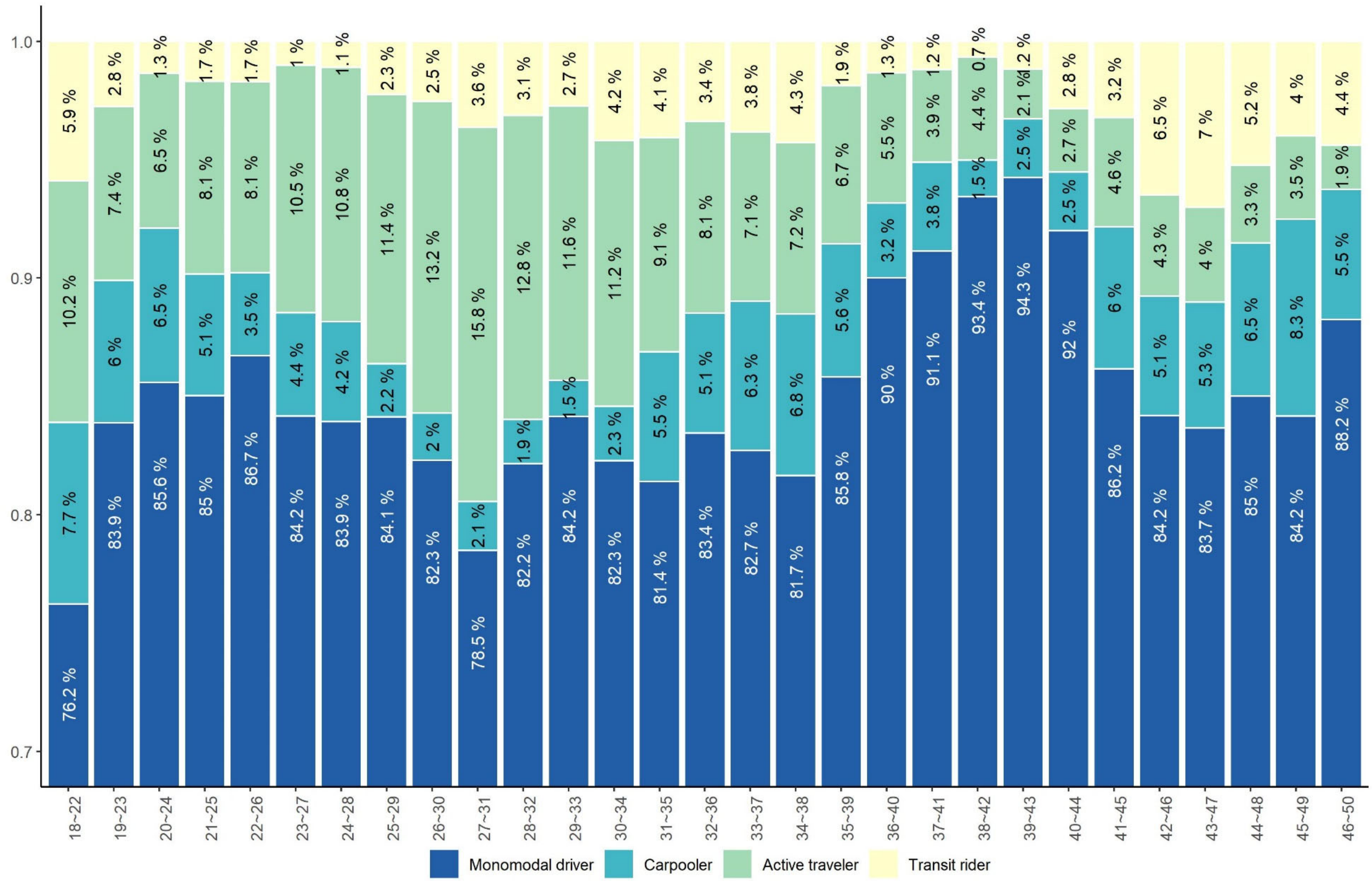

FIGURE 3 Shares of Four Traveler Classes by Age Group

Notes: Each bar presents the traveler group shares for cases within the specified five-year age range, with each bar advancing the five-year window by one year. Vertical axis truncated to clarify differences.

APPENDIX 1. Modes in the Survey and Classified Modes for Analysis

Mode in the survey (in the order in the survey)	Classified mode	
	Commutes	Non-commutes
Drive alone	Car as a driver	Car as a driver
Carpool or vanpool, as a driver	Car as a driver	Car as a driver
Carpool or vanpool, as a passenger	Car as a passenger	Car as a passenger
Drive a vehicle from a carsharing program (e.g. Zipcar)	*(Not asked)*	Emerging modes
Motorcycle or motor-scooter	Car as a driver	Car as a driver
Work/school-provided bus or shuttle	Public transit	*(Not asked)*
Public bus	Public transit	Public transit
Light rail/tram/subway (e.g. BART, LA Metro)	Public transit	Public transit
Commuter train (e.g. Amtrak, Caltrain, Metrolink)	Public transit	Public transit
Taxi	Car as a passenger	Car as a passenger
Uber/Lyft (or other on-demand ride services)	Car as a passenger	Emerging modes
Bike or e-bike	Active modes	Active modes
Skateboard, scooter, skates	Active modes	Active modes
Walk	Active modes	Active modes

Notes: In the survey, the use of carsharing was not asked for commute trips, and work/school-provided bus or shuttle was not asked for non-commute trips.

APPENDIX 2. Proxy Values for the Monthly Frequency

Option in the survey	Proxy for the monthly frequency
Not available (not asked for non-commute trips)	0
Available but I never use it ("Never" for non-commute trips)	0
Less than once a month	0.5
1-3 times a month	2
1-2 times a week	6
3-4 times a week	14
5 or more times a week	20

Notes: Since non-commute trips often take place outside of one's own neighborhood, respondents do not have the option of "Not available" for each of the 13 raw modes for non-commute trips. Also, one month is assumed to have four weeks, for the purposes of computing the monthly frequencies.

APPENDIX 3. Factors and Heaviest-Loading Statements

Factors	loadings
Car as a tool	
The functionality of a car is more important to me than its brand	0.579
To me, a car is just a way to get from place to place	0.480
Pro-environmental	
We should raise the price of gasoline to reduce the negative impacts on the environment	0.937
We should raise the price of gasoline to provide funding for better public transportation	0.841
The government should put restrictions on car travel in order to reduce congestion	0.331
Time / mode constrained	
My schedule makes it hard or impossible for me to use public transportation	0.580
I am too busy to do many things I'd like to do	0.443
Most of the time, I have no reasonable alternative to driving	0.388
Pro-exercise	
The importance of exercise is overrated	-0.822
Getting regular exercise is very important to me	0.587

Notes: Statements whose loadings are smaller than 0.3 are omitted here. For more details, refer to Circella et al. (2017b)

APPENDIX 4. Bivariate Residual Correlation Estimates

mode/purpose 1	mode/purpose 2	correlation estimate	two-tailed p-value	sig.
Commute by driving	Commute by public transit	-15.415	0.000	***
Commute by driving	Leisure trip by driving	28.012	0.000	***
Commute by driving	Leisure trip by public transit	-1.537	0.019	**
Commute by driving	Leisure trip by emerging modes	1.897	0.056	*
Commute as a passenger	Commute by public transit	2.427	0.033	**
Commute as a passenger	Commute by active modes	1.165	0.075	*
Commute as a passenger	Leisure trip as a passenger	0.820	0.015	**
Commute as a passenger	Leisure trip by public transit	0.514	0.017	**
Commute as a passenger	Leisure trip by emerging modes	0.531	0.011	**
Commute by public transit	Leisure trip by driving	-11.993	0.000	***
Commute by public transit	Leisure trip by public transit	3.867	0.001	***
Commute by active modes	Leisure trip by public transit	1.340	0.011	**
Commute by active modes	Leisure trip by active modes	2.682	0.001	***
Leisure trip by driving	Leisure trip by emerging modes	2.098	0.009	***
Leisure trip as a passenger	Leisure trip by active modes	1.802	0.051	*
Leisure trip as a passenger	Leisure trip by emerging modes	1.530	0.013	**
Leisure trip by public transit	Leisure trip by active modes	1.887	0.000	***
Leisure trip by active modes	Leisure trip by emerging modes	1.591	0.017	**

Notes: All possible pairs of bivariate residual correlations were tested and only those pairs that were statistically significant at 90% confidence or higher are included. (*** indicates significant at the 99% confidence level, ** at the 95% confidence level, and * at the 90% confidence level)

APPENDIX 5. Standardized Coefficients of the Class Membership Model

Covariates	Carpooler		Active traveler		Transit rider	
Share	4.9%		7.7%		3.1%	
Travel pattern and mobility choices						
Natural log of commute distance	0.049		-0.967	***	-0.273	
# commute days per week	0.421	**	0.199		0.243	
Telecommute (reference: no telecommute)						
Less than once a week	0.171		0.031		0.051	
At least once a week	0.252		-0.583	**	0.073	
Has a drivers' license	-0.407	***	-0.345	**	-0.786	***
Cars per adult in the household	-0.504	**	-0.732	***	-0.271	
Household characteristics						
Living with own children	-0.062		-0.492	**	0.613	**
Student status (reference: not a student)						
Full-time student	0.163		-0.370	**	0.248	
Part-time student	-0.212		-0.466	***	0.222	
Educational attainment (reference: up to high school)						
Some college	0.033		0.002		-0.044	
Bachelor's degree	-0.200		-0.357		0.132	
Graduate degree	-0.014		0.136		0.643	**
Attitudes and preferences						
Car as a tool	-0.063		0.432	**	-0.398	
Pro-environmental	0.135		0.238		0.785	**
Time / mode constrained	0.330	*	-0.573	***	-0.410	*
Pro-exercise	-0.110		0.060		-0.840	***
Overall rating for cars	0.259		-0.597	***	-0.048	
Overall rating for public transit	0.285		0.036		1.204	***
Overall rating for active modes	-0.030		0.992	***	0.202	
Land-use attributes						
Activity intensity	0.040		0.002		0.770	**

Notes: * significant at the 10% level, ** significant at the 5% level, and *** significant at the 1% level; (a) denotes a single-item response (and not a factor score) for this attitudinal variable.