Exploration of Short-Term Vehicle Utilization Choices in Households with Multiple Vehicle Types

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With the growing concerns of energy sustainability, greenhouse gas emissions, and climate change, there is an increasing interest in understanding vehicle ownership and utilization decisions better so that effective policies can be implemented to reduce the negative impacts of private automobile usage. Although there is a rich body of literature on the long-term decisions of vehicle ownership and the composition of vehicles, the short-term choices of which vehicle to use from the household's vehicle holdings and what distance will be traveled to access opportunities, as well as the interrelationship between the two, are less understood. The purpose of this study was to contribute to the literature on short-term vehicle utilization decisions with the use of data collected in 2009 from the National Household Travel Survey. A latent class segmentation model was estimated with alternate interrelationship structures as the latent classes. Within each latent class, the choices were modeled consistently with the interrelationship structure through the introduction of the first choice as an explanatory variable in the model of the second choice. Additionally, scale was introduced to account for differences in the choices and interrelationships across regions. Most of the model estimation results were behaviorally plausible and consistent with expectations. A significant finding was that interrelationships in both latent classes were insignificant. It was also found that the latent model, even with the insignificant interrelationships, outperformed the alternate model formulations in terms of model fit. This finding shows that the latent segments may capture unobserved heterogeneity beyond the interrelationships.

In the United States, the personal automobile is by far the most dominant mode of transportation used to meet the mobility needs of individuals and households. The personal automobile is also associated with negative implications for natural and built environments. With the growing concerns of energy consumption, greenhouse gas emissions, and climate change, transportation professionals are constantly seeking ways to alter personal automobile ownership and usage patterns to promote sustainable mobility. There is a need to better understand vehicle ownership and utilization decisions so that effective transportation policies can be formulated.

Several choice dimensions characterize personal automobile ownership and usage, and these dimensions span different time scales. On a longer-term horizon—typically spanning multiple years—households make choices of vehicle ownership (how many vehicles), the composition of vehicles (the make, model, and year of each vehicle), and the evolution of vehicles (if and when to replace each vehicle). There is a rich body of literature on understanding longer-term choices, including the number of vehicles owned in a household and the composition of vehicle holdings (*1–3*); see Anowar et al. for a detailed review (*4*). Several studies have studied the role of such factors as socioeconomic and demographic variables, land use variables, and psychological factors to explain the heterogeneity in longer-term vehicle ownership and utilization choices (*5–9*).

The short-term choices, which typically operate within a day, include the choice of vehicle from the household vehicle holdings and the choice of the distance traveled to pursue activity and travel needs. It is important to study the short-term decisions because they have direct implications for fuel consumption and emissions. Although there is a tremendous amount of research into the longer-term choices, the research on the shorter-term choices is limited and lacking. In most studies, short-term vehicle utilization choices are considered at an aggregate level (e.g., the household level) over long time periods (e.g., annually) (*3, 10*). However, such an aggregation fails to account for household-level trade-offs and interactions and ignores the role of daily activity–travel engagement choices on short-term choices.

Additionally, there are potential interrelationships between the two short-term choices (vehicle type and distance). In the first interrelationship, the choice of the vehicle affects the distance traveled. This interrelationship represents the decision process in which an individual makes a choice of vehicle from his or her household vehicle holdings, and, subsequently, the choice of vehicle, along with other considerations, influences how far the individual travels to pursue activities. In the alternate interrelationship, distance affects the choice of vehicle. This interrelationship represents the decision process in which an individual first makes a choice of which destinations to access and then makes a choice of which vehicle to choose from the household vehicles on the basis of distance and other considerations. The interrelationship in which the choice of vehicle type affects the distance is referred to as the "VTD interrelationship" in this paper; the interrelationship in which the distance affects the choice of vehicle type is referred to as the "DVT interrelationship" in this paper.

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The direction of the interrelationship between the short-term vehicle utilization choices has implications for the effectiveness of transportation policies aimed at reducing energy consumption and greenhouse gas emissions. For example, if high-density, mixed-use built environments are being considered to alter energy consumption and emissions and a significant interrelationship was found in which individuals traveling smaller distances preferred larger vehicles, then a land use policy that promoted density may not be effective because the short distance to the destinations afforded by the policy may mean that individuals would use their households' larger vehicles. This choice would negate the positive gains attributable to shorter travel distances.

Recently, researchers have attempted to address the knowledge gap by conducting disaggregate analyses of short-term vehicle and distance decisions (*11–15*). Although these studies explore the choice dimensions at a disaggregate unit of analysis, there are some limitations. The studies either do not consider the interrelationships or assume a single interrelationship to hold for the entire population (*14, 15, 11, 12*); in reality, different interrelationship structures are plausible for different segments of the population. Therefore, there is a need for modeling frameworks that can accommodate different interrelationship structures for different segments of the population simultaneously to accurately describe the underlying decision-making process.

The primary objective of this study is to add to the literature on the disaggregate analysis of short-term vehicle utilization decisions. The study attempts to explore the factors that influence the vehicle and distance decisions and accommodate the interrelationships between the choices. The study also attempts to explore differences in the short-term vehicle utilization choices across different regions, characterized by varying degrees of automobile dependency and transit usage.

The modeling approach used in the study is based on the concept of the latent class segmentation framework (*16–18*). A latent class segmentation framework theorizes that individual decision makers can be classified into latent (unobserved) groups on the basis of a variety of exogenous factors, including socioeconomic, demographic, and environmental factors related to the decision maker. On the basis of the latent group to which a decision maker belongs, the framework allows the choice dimensions of interest to be modeled. The proposed formulation of the latent class segmentation framework can not only model the vehicle type and distance dimensions simultaneously but also accommodate the different interrelationships (namely, VTD and DVT). The proposed model assumes a different interrelationship structure for each of the latent segments. Further, the proposed latent segmentation model can accommodate unobserved heterogeneity specific to an urban region in the sample by specifying scale parameters in the vehicle choice and distance components of the model.

Data from the 2009 National Household Travel Survey (NHTS) were used in this study (*19*). The choice of vehicle in households with a single vehicle is an obvious one, but the choice of vehicle in households with multiple vehicles involves an interesting process. Therefore, the focus of the empirical exploration was on understanding the short-term vehicle utilization decisions of individuals in households with multiple vehicles. Further, vehicles of the same body type were not differentiated in the study because (*a*) it was assumed that individuals did not differentiate between multiple vehicles of the same body type because they likely offered the same level of comfort and convenience and (*b*) the difference in the emissions and energy implications of vehicles belonging to the same body type was likely small. Therefore, consistent with this assumption, the analysis was limited to households with multiple vehicle types because the choice of vehicle from different body types had more pronounced implications for energy and emissions.

The rest of the paper is organized as follows. In the next section, the proposed latent segmentation method is presented. In the following section, the data used in the study and the sample composition are described. In the fourth section, the results are presented, followed by conclusions in the fifth section.

METHODOLOGY

The proposed latent class segmentation model is presented in this section. The model formulation comprises (*a*) latent segmentation, (*b*) vehicle type choice, and (*c*) distance traveled. The latent segmentation component is formulated as a binary logit model, with the interrelationship structures as the choice alternatives. Individuals are probabilistically allocated to one of the latent segments on the basis of a variety of exogenous variables. Once assigned to a latent segment, vehicle type choice and distance are modeled, consistent with the interrelationship structure, by introducing the first choice as an explanatory variable in the model of the second choice. The proposed formulation is capable of exploring different interrelationships for different segments of the population. This capability is in contrast to earlier studies, which have assumed a single structure to hold for the entire population (*11, 12*).

The choice of vehicle type was a discrete variable. Therefore, the vehicle type choice component was modeled through a multinomial logit formulation, and the vehicle types from the household's vehicle holdings were the alternatives. The distance traveled was a continuous variable. Therefore, the distance traveled component was modeled through a linear regression formulation. Let q denote the individual decision maker ($q = 1, 2, \ldots, Q$), i denote the index for the latent segments ($i = 1$ or 2), and v denote the index for the vehicle type choice alternatives ($v = 1, 2, \ldots, V$). The three components—latent segmentation, vehicle type choice, and distance traveled—can then be formulated as shown in Equations 1 to 3, respectively.

$$u^*_{qi} = \alpha x_{qi} + \varepsilon_{qi} \tag{1}$$

$$u^*_{qiv} = \beta_i x_{qiv} + \varepsilon_{qiv} \tag{2}$$

$$y_{qid} = \gamma_i x_{qid} + \varepsilon_{qid} \tag{3}$$

where

u^*_{qi} = utility derived by qth individual in selecting the ith latent segment,
u^*_{qiv} = utility derived by qth individual in selecting vehicle type v in the ith latent segment,
y_{qi} = distance traveled by the individual in the ith latent segment,
x_{qi}, x_{qiv}, and x_{qid} = explanatory variables,
α, β_i, and γ_i = vector of unknown parameters associated with the explanatory variables, and
ε_{qi}, ε_{qiv}, and ε_{qid} = error terms.

The error term ε_{qi} is assumed to follow a standard Type 1 extreme value distribution. The error term ε_{qiv} also follows a Type 1 extreme value distribution, with a location parameter of zero and a scale (δ_{irq})

that varies with the latent segment (i) and region (r_q) to which the individual belongs. The error term ε_{qid} is assumed to follow a normal distribution, with a mean value of zero and a standard deviation (σ_{ir_q}) that also varies with the latent segment (i) and region (r_q) to which the individual belongs. The nonconstant scale and the standard deviation parameters are specified to accommodate the unknown heterogeneity in the choices across the different regions. The error terms for each of the model components are also assumed to be independent. The two scale parameters in the models are parameterized as follows:

$$\delta_{ir_q} = \exp\left(\theta_{r_q} x_{r_q}\right) \qquad \text{and} \qquad \sigma_{ir_q} = \frac{\sigma}{\exp\left(\vartheta_{r_q} x_{r_q}\right)}$$

where

- σ = scale for one selected region,
- x_{r_q} = vector of explanatory variables associated with the region to which the individual belongs (r_q),
- θ_{r_q} = vector of coefficients associated with the explanatory variables entering the parameterization equation for scale δ_{ir_q}, and
- ϑ_{r_q} = vector of coefficients associated with the explanatory variables entering the parameterization equation for scale σ_{ir_q}.

The parameters $\exp(\theta_{r_q} x_{r_q})$ and $\exp(\vartheta_{r_q} x_{r_q})$ are set to one for a selected region for the sake of empirical identification.

With the above as preliminaries, the probability (P_{qi}) that individual q will select latent segment i is given below in Equation 4:

$$P_{qi} = \frac{\exp\left(\alpha_i x_{qi}\right)}{\sum_{j=1}^{I} \exp\left(\alpha_i x_{qj}\right)} \tag{4}$$

where j is a temporary index used in the summation of the exponential term across all latent segments.

The probability associated with individual q in latent segment i selecting vehicle type choice v is given in Equation 5:

$$P_{qiv} = \frac{\exp\left(\dfrac{\beta_i x_{qiv}}{\delta_{ir_q}}\right)}{\sum_{j=1}^{V} \exp\left(\dfrac{\beta_i x_{qij}}{\delta_{ir_q}}\right)} \tag{5}$$

where j is a temporary index used in the summation of the exponential term across all vehicle type alternatives.

For the distance logged variable, the probability that individual q selects value y_{qid} is given as

$$P_{qid} = \frac{1}{\sigma_{ir_q}} \varphi\left[\frac{\left(y_{qid} - \gamma_i x_{qid}\right)}{\sigma_{ir_q}}\right] \tag{6}$$

where φ represents the standard normal probability density function. The probability (P) of jointly observing the vehicle type choice and the distance traveled observations can be expressed as follows:

$$P_q = \sum_{i=1}^{2} P_{qi} \prod_{j=1}^{V} \left(P_{qij}\right)^{\rho_j} \left(P_{qid}\right) \tag{7}$$

where ρ_j is a choice indicator and assumes a value of one if a particular vehicle type alternative j is selected, and a value of zero otherwise. The total log likelihood (L) for the sample can be expressed as

$$L = \sum_{q=1}^{Q} \ln\left(P_q\right) \tag{8}$$

The log likelihood function was coded in GAUSS matrix programming language, and the unknown parameters α, β_i, γ_i, θ_{r_q}, σ, and ϑ_{r_q} were estimated through the maximum likelihood estimation technique.

DATA DESCRIPTION AND SAMPLE COMPOSITION

Data from the 2009 NHTS were used in this study. NHTS is a cross-sectional survey that collects information about the travel characteristics of a nationally representative sample of households in the United States. The collected characteristics include household- and person-level socioeconomic and demographic information, vehicle holdings data, and information about household vehicles used for different trips. The data contained in the NHTS allow vehicle utilization decisions to be explored at different temporal resolutions, including day level and same day. To identify the appropriate temporal resolution for the analysis, the data set was explored to understand what percentage of individuals switched vehicles within a day. It was found that only a small percentage of people (5.01%) switched vehicles during the day; this finding indicated that vehicle choice might not be a same-day phenomenon for most people. Therefore, a day-level exploration was pursued in this study.

As noted earlier, only households with multiple vehicle types were considered in the analysis because the choice of vehicle and the distance logged in such households can have important implications for energy and emissions on the basis of vehicle type. Further, this treatment also allowed the trade-offs and compromises associated with the selection of vehicle from the household vehicle holdings to be understood. The analysis was conducted at a person-level and limited to only adults who had a valid driver's license.

One of the objectives of the study was to explore the differences in short-term vehicle usage decisions in cities with varying degrees of automobile dependency and usage. The cities of New York, Washington, D.C., and Los Angeles, California, were selected from the data set because of the extremes of automobile dependency and transit usage patterns experienced in those cities. New York had low auto dependency and was more transit friendly, and Los Angeles was the opposite, with more auto dependency and fewer transit options. Washington, D.C., fell somewhere between the two extremes.

After the imposition of the restrictions and the elimination of records with missing entries, the subsample for analysis consisted of 8,426 persons from 5,486 households. Table 1 provides some summary statistics for the subsample. In 24% of the cases, all household vehicles were utilized on the survey day; in the remaining 76% of the households, only a subset of the vehicles owned were used on any given day. This observation indicated that individuals faced a choice at the start of the day of what vehicle to select from the household vehicle holdings on the basis of the individual's activity–travel needs. Even in households in which all vehicle holdings were used, it was likely that an individual negotiated with other household members on what vehicle to use on any given day. In the table, from

TABLE 1 Summary Statistics for Subsample

Variable	New York	Los Angeles	Washington, D.C.	Three Regions
Number of survey respondents considered in analysis	3,071	3,732	1,623	8,426
Percentage of males	48.3	50.9	49.2	49.6
Percentage with at least bachelor's degree education	45.9	39.0	44.5	42.6
Workers (%)	69.3	66.5	68.6	67.9
Age distribution (%)				
18–25	7.4	9.4	6.7	8.1
26–39	13.1	15.7	16.3	14.9
40–54	40.7	37.2	40.4	39.1
55–64	22.7	21.0	20.3	21.5
Over 65	16.0	16.7	16.3	16.4
Average number of people	3.3	3.3	3.2	3.3
Average number of workers	1.6	1.6	1.5	1.6
Average number of drivers	2.5	2.5	2.4	2.5
Average number of adults	2.5	2.5	2.3	2.5
Vehicle utilization distribution (%)				
All vehicles	26.7	24.1	19.1	24.1
Subset of vehicles	73.3	75.9	80.9	75.9
Average daily distance traveled (mi)				
Auto	18.5	17.0	25.4	19.1
Van	5.4	4.3	6.2	5.1
SUV	14.8	12.1	11.6	13.0
Truck	4.2	6.5	9.0	6.1
Distribution of vehicle type used (%)				
Auto	43.2	43.9	43.1	44.0
Van	13.3	11.2	13.9	12.0
SUV	34.5	28.9	25.8	30.0
Truck	9.1	16.0	17.3	14.0
Distribution of trip rates by purpose				
Home	1.4	1.4	1.4	1.4
Work	0.5	0.6	0.5	0.5
School	0.1	0.1	0.1	0.1
Maintenance	1.1	1.0	1.1	1.1
Discretionary	0.4	0.4	0.3	0.4
Pick up	0.1	0.2	0.1	0.1
Drop off	0.2	0.2	0.2	0.2
Other	0.2	0.2	0.3	0.2

New York to Washington, D.C., the percentage of households in which all vehicles owned by the household were used decreases. This finding appears counterintuitive; it would be expected that with the abundance of transit options in New York, households would be less likely to use all vehicles owned than households would in Los Angeles. It is plausible that the households that own multiple vehicles in the New York region are the ones that have adopted a mobility lifestyle that requires them to drive to meet their activity–travel needs. This observation further lends credibility to the second objective of the study: exploring differences in the choices across the three regions.

The vehicle types in the original NHTS consisted of nine categories, which were consolidated into four categories—auto, van, SUV, and truck—on the basis of a similarity in body type. A similar percentage of autos were used across the three regions (about 44%). However, there were significant differences in the percentages of other vehicle types used. Trucks were preferred, when available, in Los Angeles and Washington, D.C., more than in New York. SUVs, when available, were preferred most in New York, followed by Los Angeles and Washington, D.C. These observations further pointed to the importance of studying differences across different regions. The trip rates (about 4.1 trips per person) and the distributions across purposes were similar across the three regions. The subsample consisted of an even percentage of males and females. Most of the respondents were workers and in their middle age, between 40 and 54 years. The average household size was about 3.3, with about 2.5 adults per household, and most of the adults were licensed drivers.

MODEL ESTIMATION RESULTS

A latent class segmentation model was estimated on the basis of 2009 NHTS data from New York, Washington, D.C., and Los Angeles to explore the two short-term vehicle utilization decisions: vehicle type and distance. The latent segments were specified to reflect the two interrelationship structures: VTD and DVT. Within any latent segment, the first choice dimension was entered as an explanatory variable in the model of the second choice dimension. A statistically significant coefficient associated with the first choice dimension provided evidence in support of a significant interrelationship. Although the interrelationship structure was used to name and describe the latent segments, the segments might have captured additional heterogeneity and regularities beyond the interrelationships. Therefore, in assessing the proposed latent class segmentation approach, it was not sufficient to consider the significance of the interrelationships alone. A comprehensive evaluation of alternate model formulations, including the latent segmentation model, was warranted to select a model that best explained the underlying short-term vehicle utilization choices.

In the latent component of the proposed model, the DVT interrelationship was chosen as the reference alternative. In the vehicle type choice component, the truck was chosen as the baseline alternative. A host of household- and person-level socioeconomic and demographic characteristics and daily activity–travel attributes were used as explanatory variables in the different model components. Additionally, unobserved heterogeneity across the regions was captured through the specification of indicator variables, interaction variables, and, more importantly, the introduction of scale in the models of vehicle type choice and distance.

Model Estimation Summary

In this study, six models were estimated. The models, along with the model estimation summary statistics, are shown in Table 2. All the models were statistically significant and provided behaviorally plausible results. However, on closer inspection with model fit statistics, which included log-likelihood values, the Akaike information criterion, and the Bayesian information criterion, the independent DVT model (Model 2) offered the poorest fit, and the scaled version of the latent class segmentation model (Model 6) offered the best fit. This finding indicated that a model formulation that assumed a single interrelationship structure to represent the behavior of the entire population might not be appropriate and that different structures might be needed to accurately represent the behavior of different segments of the population. Also, the scaled versions of the model formulations (Models 2, 4, and 6) always performed better than the model formulations without scale (Models 1, 3, and 5). This finding suggested that when combining data from different regions, scale should be included to capture the region-specific unobserved heterogeneity in behavior. Overall, the scaled version of the latent segmentation model offered the best fit, and the estimation results for this model are discussed in the remainder of this section.

TABLE 3 Model Estimation Results for Latent Segmentation Component

Description	Coefficient	*t*-Statistic
Constant	−1.6433	−13.9
Indicator for New York	−0.1511	−1.7
Male	0.4474	6.5
Age ≥ 26 and ≤ 39	0.3225	2.7
Age ≥ 40 and ≤ 54	0.5025	5.3
Age ≥ 55 and ≤ 64	0.3144	3.0
Flexible work schedule	0.1623	2.1
No fixed workplace	0.6790	2.6
Multiple jobs	0.2446	2.1
Part-time employment	−0.1823	−1.8
Professional, managerial, or technical occupation	0.3248	4.3
Home in urban area	−0.3759	−4.6

Estimation Results for the Latent Segment Model

The model estimation results for the latent segmentation component are presented in Table 3. As noted earlier, the reference alternative is the DVT interrelationship. There was a general preference for the DVT structure, as can be seen from the negative constant value. Male respondents and respondents between ages 26 and 64 preferred the VTD structure. Also, people with flexibility in their work schedules—as evidenced by no fixed workplace, a flexible work schedule, and multiple jobs—favored the VTD interrelationship. Respondents who were employed part-time and respondents who resided in urban areas were found to prefer the DVT interrelationship. Regional differences were also explored in the latent segmentation component through the use of indicator variables, and significant differences were observed for the New York region, which showed a preference for the DVT structure.

Estimation Results for the Interrelationship Structures

Table 4 presents the results for the short-term vehicle utilization choice dimensions in which the VTD interrelationship structure holds.

TABLE 2 Model Estimation Summary

Model Description	LL	Number of Observations	Number of Parameters	AIC	BIC
1. Independent model in which vehicle type choice affects distance	−102,461.8	8,426.0	104.0	205,131.7	205,863.8
2. Independent model in which vehicle type choice affects distance with scale parameters to capture differences across regions	−51,170.1	8,426.0	81.0	102,502.2	103,072.3
3. Independent model in which distance affects vehicle type choice	−102,467.7	8,426.0	105.0	205,145.5	205,884.6
4. Independent model in which distance affects vehicle type choice with scale parameters to capture differences across regions	−51,171.0	8,426.0	82.0	102,506.0	103,083.2
5. Latent segmentation model	−46,509.1	8,426.0	128.0	93,274.2	94,175.2
6. Latent segmentation model with scale parameters to capture differences across regions	−46,467.4	8,426.0	140.0	93,214.7	94,200.2

NOTE: LL = log likelihood; AIC = Akaike information criterion; BIC = Bayesian information criterion.

TABLE 4 Model Estimation Results for VTD Latent Segment

	Auto		Van		SUV		Distance (mi)	
Variable Description	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.
Constant	1.6930	6.3	0.0244	0.1	0.0891	0.3	113.5836	9.7
Socioeconomic and demographic characteristics								
Male	–1.1993	–4.5	–1.6871	–4.2	–1.3320	–4.4	na	na
Age ≥ 18 and ≤ 25	0.6620	2.8	na	na	na	na	na	na
Age ≥ 26 and ≤ 39	na	na	na	na	–0.2785	–1.6	na	na
Age ≥ 40 and ≤ 54	na	na	–0.3263	–1.6	na	na	na	na
Age ≥ 65	na	na	na	na	na	na	22.3999	2.9
At least a bachelor’s degree education	0.3968	2.2	0.4847	1.9	0.3997	2.0	na	na
Self-employed	–0.2701	–1.7	na	na	na	na	na	na
Part-time employment	na	na	na	na	0.3649	1.9	na	na
Manufacturing, construction, maintenance, or farming occupation	–0.3512	–1.8	na	na	na	na	na	na
Income ≥ \$50,000 and < \$75,000	na	na	0.4891	1.7	na	na	na	na
Income ≥ \$75,000 and < \$100,000	0.5131	2.3	0.5549	1.7	0.5946	2.4	na	na
Income ≥ \$100,000	na	na	na	na	na	na	9.3141	2.1
Home in urban area	na	na	na	na	0.2866	1.9	na	na
Number of people	na	na	na	na	na	na	–3.5046	–2.1
Number of workers	–0.1520	–2.2	na	na	–0.3480	–3.2	na	na
Number of drivers	na	na	na	na	0.2397	2.5	na	na
Travel day is a weekday	na	na	na	na	na	na	–19.6918	–3.7
Vehicle age ≤ 5 years	na	na	–0.4775	–2.3	na	na	19.8631	4.5
Activity–travel characteristics								
Presence of a work trip	0.4148	2.8	na	na	na	na	na	na
Presence of a discretionary trip	na	na	0.4760	2.2	na	na	na	na
Presence of a pickup trip	na	na	0.4681	1.9	na	na	na	na
Presence of a drop-off trip	na	na	na	na	na	na	7.4271	1.6
Average trip occupancy	na	na	0.4689	4.1	0.3261	3.6	13.7755	5.6
Interrelationship variable								
Auto selected	na	na	na	na	na	na	–9.3568	–1.4
Van selected	na	na	na	na	na	na	–7.6593	–0.8
SUV selected	na	na	na	na	na	na	–5.9487	–0.8
Regional characteristics								
Indicator for New York	–0.5893	–3.3	na	na	na	na	–13.7190	–1.9
Indicator for Los Angeles	–0.6828	–4.1	na	na	na	na	–23.6973	–3.7
Scale for Los Angeles	–0.4595	–2.0	–0.4595	–2.0	–0.4595	–2.0	–0.2495	–5.4
Scale for New York	–0.2859	–1.2	–0.2859	–1.2	–0.2859	–1.2	–0.1113	–2.3

NOTE: Coeff. = coefficient; *t*-stat. = *t*-statistic; na = not applicable.

Tables 5 and 6 present the results for the choice dimensions in which the DVT interrelationship structure holds.

Role of Interrelationship

The coefficients for the interrelationships provided plausible signs. Increasing distance positively affected the choice of auto and van and decreased the probability of selecting SUV in the DVT structure (Table 6). In the VTD structure, the choice of vehicle type had a negative influence on the distance traveled across all vehicle types, compared with trucks; the highest negative coefficient was for auto, followed by van, and then SUV (Table 4). However, none of these coefficients were significant at the 95% level of confidence. The insignificance of the interrelationship was an important finding and shed light on the underlying choice process. It is likely that vehicle type and utilization are not short-term choices that are evaluated and optimized on a daily basis. In other words, vehicle choice may be a household decision in which individuals are allocated a vehicle from the household vehicle holdings on the basis of the individuals’ assumed roles and other considerations (see Tables 4 through 6 for the range of explanatory variables) and not on the basis of the distance the individuals have to travel, and vice versa. This finding was also consistent with a recent study by Nam et al., which found that nearly 59% of households in the United States did not efficiently allocate vehicles and that the reallocation of vehicles among household members could cut their fuel consumption by nearly 5.2% (*13*).

As mentioned earlier, the latent segments were named on the basis of the interrelationships for convenience but potentially captured additional heterogeneity in the shorter-term vehicle choice dimensions. Therefore, the insignificance of the interrelationships alone should not be used to infer the significance of the latent class segmentation approach. Indeed, the model fit statistics also provided evidence in support of this notion and showed that the scaled latent segmentation model best fit the data; the log likelihood value (–46,467.4) was almost half the value of the independent model with the VTD structure (–102,461.8). A closer examination is warranted to identify the characteristics of the latent segments beyond the interrelationship

TABLE 5 Model Estimation Results for DVT Latent Segment: Socioeconomic, Demographic, and Activity–Travel Characteristics

	Auto		Van		SUV		Distance (mi)	
Variable Description	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.
Constant	1.2985	5.7	0.6510	2.6	0.2432	1.0	14.1489	9.5
Socioeconomic and demographic characteristics								
Male	–2.2922	–11.7	–2.8389	–11.4	–2.3173	–11.5	1.5262	3.1
Age ≥ 18 and ≤ 25	0.7374	4.8	–0.9965	–3.7	na	na	na	na
Age ≥ 26 and ≤ 39	–0.3660	–3.1	na	na	na	na	1.4105	1.9
Age ≥ 40 and ≤ 54	–0.3831	–4.0	na	na	na	na	1.0057	1.8
Age ≥ 55 and ≤ 64	–0.2205	–2.3	na	na	na	na	na	na
At least a bachelor's degree education	0.1168	1.7	na	na	na	na	na	na
Self-employed	–0.2349	–2.1	na	na	na	na	na	na
Flexible work schedule	0.2622	3.4	na	na	na	na	na	na
Part-time employment	0.3512	2.0	0.6235	2.8	0.3106	1.6	–2.6895	–4.0
Sales and service occupation	na	na	na	na	na	na	1.4117	2.0
Clerical and administrative support occupation	na	na	na	na	0.3215	2.4		
Manufacturing, construction, maintenance, or farming occupation	–0.7580	–4.2	–0.4791	–2.0	–0.5236	–2.8	3.2566	3.5
Professional, managerial, or technical occupation	na	na	na	na	0.1366	1.6	2.9982	4.8
Income ≥ \$75,000 and < \$100,000\$	na	na	na	na	na	na	1.0280	1.6
Income ≥ \$100,000	na	na	na	na	na	na	2.2422	4.0
Home in urban area	na	na	na	na	na	na	–4.6087	–7.1
Number of people	na	na	0.1012	2.5	na	na	–1.1609	–4.8
Number of drivers	na	na	na	na	na	na	0.7975	2.2
Number of adults	0.0649	1.6	na	na	na	na	na	na
Travel day is a weekday	na	na	na	na	na	na	1.2953	2.4
Vehicle age ≤ 5 years	na	na	na	na	0.9237	5.3	2.8635	4.8
Vehicle age between 5 and 10 years	–0.2854	–3.1	na	na	0.4475	2.5	1.2514	2.0
Vehicle age between 10 and 15 years	0.2714	2.2	na	na	0.4366	2.1	na	na
Activity–travel characteristics								
Presence of a work trip	na	na	–0.3910	–3.0	na	na	12.2400	20.1
Presence of a school trip	1.6931	2.8	1.1736	1.8	1.4658	2.4	5.8342	7.5
Presence of a maintenance trip	na	na	na	na	0.2669	3.6	5.3307	11.0
Presence of a discretionary trip	0.1634	2.3	na	na	na	na	8.1451	15.7
Presence of a pickup trip	0.4075	1.9	0.7051	2.8	0.6025	2.7	4.8175	6.0
Presence of a drop-off trip	na	na	na	na	na	na	4.0237	7.4
Average trip occupancy	0.2699	2.9	0.7457	6.2	0.5487	5.1	2.0348	6.4

TABLE 6 Model Estimation Results for DVT Latent Segment: Interrelationship and Regional Characteristics

	Auto		Van		SUV		Distance (mi)	
Variable Description	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.
Interrelationship								
Distance traveled	0.0009	0.3	0.0006	0.1	–0.0004	–0.1	na	na
Regional characteristics								
Indicator for New York	na	na	na	na	na	na	–5.1807	–5.1
Indicator for Los Angeles	0.1719	2.1	na	na	na	na	–6.4402	–6.9
Scale for Los Angeles	0.1563	1.7	0.1563	1.7	0.1563	1.7	–0.1976	–5.3
Scale for New York	–0.1636	–1.7	–0.1636	–1.7	–0.1636	–1.7	–0.0432	–1.0
Male respondent in New York	–0.2733	–2.4	na	na	na	na	na	na
Respondent living in Los Angeles and travel day is a weekday	0.1505	1.8	na	na	na	na	na	na
Respondent age ≥ 18 and ≤ 25 in New York	na	na	na	na	na	na	2.2338	1.5
Respondent household income ≥ \$100,000 in Washington, D.C.	na	na	na	na	na	na	–2.9975	–2.4

TABLE 7 Choices Predicted in Latent Segmentation Model

Choice Dimension	All Regions	New York	Los Angeles	Washington, D.C.
Vehicle type choice affects distance traveled				
Percentage of individuals allocated	22.0	20.9	21.7	24.9
Average distance	106.4	107.8	98.1	122.8
Share of auto (%)	50.0	51.0	46.2	56.8
Share of van (%)	10.1	10.4	10.1	9.8
Share of SUV (%)	27.0	29.5	28.3	19.1
Share of truck (%)	12.9	9.2	15.3	14.3
Distance affects vehicle type choice traveled				
Percentage of individuals allocated	78.0	79.1	78.3	75.1
Average distance	25.7	26.0	23.5	30.1
Share of auto (%)	41.7	40.8	43.5	39.2
Share of van (%)	13.1	13.8	11.7	14.8
Share of SUV (%)	31.2	35.5	28.9	28.1
Share of truck (%)	14.1	9.9	15.9	17.9

structures. Table 7 provides the predicted probabilities and distance values of the choice dimensions for the VTD and DVT latent structures. There are clear differences in the predicted probabilities and distances between the two latent segments. The VTD latent segment is characterized by longer daily distances traveled and a higher percentage of auto vehicle choices. The DVT latent segment is characterized by shorter daily distances traveled, a smaller share of auto use, and a greater share of SUV use.

Differences Across Regions

One of the objectives of the study was to explore differences in the shorter-term vehicle choices across regions. In addition to capturing the differences through the introduction of dummy indicators, scale parameters were introduced in the vehicle type choice and distance models to isolate the impacts of unobserved heterogeneity across regions. The parameters $\exp(\theta_{r_q} x_{r_q})$ and $\exp(\vartheta_{r_q} x_{r_q})$ for the Washington, D.C., region were assumed to be equal to one for empirical identification, and the parameters for Los Angeles and New York were estimated. The model estimation results of the regional effects for the VTD and DVT interrelationships are presented in Tables 4 and 6, respectively.

The indicator variables for New York and Los Angeles were significant in both choice dimensions for the VTD structure. In the DVT structure, the New York indicator variable was significant only for the distance choice, but the Los Angeles indicator was significant both in the vehicle type choice and distance dimensions. The direction of the influence of the Los Angeles indicator on the vehicle type choice dimension varied between the VTD and DVT structures.

The scale parameters for Los Angeles and New York were found to be significant in the VTD structure, except for the scale parameter corresponding to New York on the vehicle type choice dimension, which was only marginally significant. In the DVT structure, only the scale parameter for Los Angeles on the distance dimension was found to be significant. In addition to the indicators for the regions, differential impacts of explanatory variables, including socioeconomic and demographic characteristics, were tested through the introduction of interaction variables. Although no interaction variables turned out to be significant in the VTD structure, several variables turned out to be significant in the DVT structure. Specifically, there was a smaller preference for males in New York to select the auto vehicle type. Also, respondents from Los Angeles who were traveling on a weekday preferred to use the auto vehicle type. The interaction variables were also found to influence the distance dimension for persons living in households with incomes greater than or equal to $100,000 who preferred to travel shorter distances.

Role of Socioeconomic and Demographic Characteristics

A variety of socioeconomic and demographic characteristics were used to explain the heterogeneity in the vehicle type choice and distance dimensions in the two structures (as shown in the socioeconomic and demographic characteristics portions of Tables 4 and 5). Of the person-level variables, gender, age, level of education, employment status, work arrangement, and occupation were found to influence the short-term choices. Of the household-level variables, income, home location, household composition, travel day, and vehicle characteristics were found to be significant. There were significant differences in the influence of the different variables in the VTD and DVT structures; this finding further pointed to the value of the latent segmentation approach.

Role of Activity–Travel Characteristics

A host of attributes related to the activity–travel engagement patterns were explored to capture the potential influence of activity and travel pursuits on short-term vehicle utilization choices (as shown in the activity–travel characteristics portions of Tables 4 and 5). Across both structures, the distance traveled increased as the number of accompanying passengers increased. This result was likely attributable to the extra activities individuals may pursue to satisfy the needs of the accompanying passengers. The presence of different types of activities also influenced the choice of vehicle type and distance in both structures. However, the influence of different types of trips was lower in the VTD structure than in the DVT structure. The presence of work, school, maintenance, discretionary, pickup, and drop-off activities influenced the choice of both vehicle type and distance in the DVT structure. In the VTD structure, only the presence of work, discretionary, pickup, and drop-off activities affected the short-term choices. The presence of a pickup activity was found to positively influence the choice of the van vehicle type, compared with other vehicle types, in both structures. This finding was plausible because pickup activities generally involve kids or other household members with mobility barriers, so there may be a preference to choose a van for comfort.

CONCLUSIONS

The travel behavior literature is replete with examples of longer-term vehicle ownership and vehicle holding choices. However, very limited research explores the shorter-term vehicle usage decisions, including the choice of vehicle from the household vehicle holdings and the distance traveled in the chosen vehicle. A good understanding of the shorter-term vehicle usage decisions is needed to accurately track the usage of each vehicle and subsequently assess the implications for energy consumed and emissions generated. This research attempts to contribute to the literature on short-term vehicle utilization choices (namely, vehicle type choice and distance traveled) and account for the potential interrelationships between the choices. Further, the study also explores potential differences in the choices across different regions with varying levels of auto dependency and transit availability.

A latent class segmentation model was estimated on the basis of data from the 2009 wave of the NHTS. Additionally, scale was introduced into the model formulation to capture unobserved heterogeneity in the choices across different regions. In addition to the scaled version of the latent class segmentation model, five models were estimated with different specifications of scale and latent segments.

The scaled version of the latent segmentation model performed best in terms of model fit parameters. The model estimation results were plausible and consistent with expectations. A significant finding from the study was that the interrelationships across the vehicle type choice and distance dimensions were insignificant. Despite the insignificance, the scaled latent model outperformed the other model formulations considered in the analysis. This observation lent credence to the notion that the latent segments may capture unobserved heterogeneity beyond the interrelationships that were used to name them and lead to a better model fit. The findings further suggested that allowing parameters to vary across groups enabled a better representation of the underlying behavior and subsequently resulted in more accurate estimations and inferences. The study also found differences in the choices across the regions, as evidenced by significant parameter values for the region indicators, significant interaction variables with the region indicators, and significant scale parameters in the vehicle type choice and distance models.

The findings in this study are insightful and contribute to a better understanding of short-term vehicle choices. The limitations of the current work open avenues for future research and inquiry. First, in the current study, no significant interrelationships were found between the choice dimensions when the analysis was performed at a day level. However, in Konduri et al., significant interrelationships were found when the analysis was performed at a tour level (*11*). Therefore, questions still abound about the appropriate scale for studying the short-term choices, and a temporal analysis that used a multiday data set would provide insights into the temporal scale appropriate for the analysis of short-term vehicle choices. Second, there may be common unobserved attributes that affect the vehicle type choice and distance dimensions simultaneously. The exploration of complex error structures within the latent segmentation model framework is another interesting line of inquiry for future research. Last, vehicle choice may not be a person-level decision but a household-level decision. The exploration of vehicle choice as a household-level decision that involves negotiation between household members, their characteristics, and their activity–travel needs will be another interesting endeavor.

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