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

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ABSTRACT

With growing concerns of energy sustainability, greenhouse gas emissions, and climate change issues, there is an increasing interest in better understanding the vehicle ownership and utilization decisions so that effective policies can be implemented to reduce the negative impacts of private automobile usage. While there is a rich body of literature regarding long-term decisions of vehicle ownership and composition of vehicles, the short-term vehicle utilization decisions of choice of vehicle from a household's vehicle holdings and distance traveled to access opportunities and the interrelationship between the two dimensions is less understood. The study attempts to contribute to the literature on short-term vehicle utilization decisions using data form the National Household Travel Survey (NHTS) collected in 2009. A latent class segmentation model was estimated with alternate interrelationship structures as the latent classes. Within each latent class, the choices were modeled consistent with the interrelationship structure by introducing first choice as an explanatory variable in the model of 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 from the study was that interrelationships in both latent classes turned out to be insignificant. It was also found that latent model even with the insignificant interrelationships outperformed alternate model formulations in terms of model fit. The finding shows that the latent segments may potentially be capturing unobserved heterogeneity beyond the interrelationships and hence the better model fit.

INTRODUCTION

In the US, personal automobile is by far the most dominant mode of transportation for meeting the mobility needs of individuals and households. Personal automobile is also associated with a number of negative implications on natural and built environments. With growing concerns of energy consumption, greenhouse gas emissions, and climate change concerns, transportation professionals are constantly seeking ways to alter personal automobile ownership and usage patterns in an effort to promote sustainable mobility patterns. In this regard, there is a need to better understand the vehicle ownership and utilization decisions so that effective transportation policies can be formulated.

There are a number of choice dimensions that characterize the personal automobile ownership and usage spanning different time scales. Operating on a longer-term horizon – typically spanning multiple years, households make choices of vehicle ownership (how many vehicles), composition of vehicles (what make, model, and year of each vehicle) and evolution of vehicles (if/when to replace each vehicle). There is a rich body of literature on understanding different longer-term choices including the number of vehicles owned in a household (*1*), and composition of vehicle holdings (*2*-*3*); see Anowar et al. (*4*) for a detailed review. Further, there are also a number of studies that have studied the role of different factors including socio-economic and demographic variables (*5*), land use variables (*6*-*7*), and psychological factors (*8*-*9*) for explaining the heterogeneity in longer-term vehicle ownership and utilization choices.

On the other end of the time scale are the short-term choices typically operating within a day including choice of vehicle from the household vehicle holdings and distance traveled to pursue activity and travel needs. It is important to study the short-term decisions because they have direct implications for the fuel consumed and the emissions generated. While 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. household-level) over long time periods (e.g. annually) (*3*, *10*). However, such an aggregation fails to account for household-level tradeoffs and interactions, and ignores the role of daily activity-travel engagement choices on short term choices.

Additionally, there are potential interrelationships at play between the two short-term choices: vehicle choice and distance. In the first interrelationship, the choice of the vehicle affects the distance traveled. This interrelationship represents the decision process where an individual makes a choice of vehicle from their household vehicle holdings and subsequently the choice of vehicle along with other considerations influence how far one travels to pursue activities. In the alternate interrelationship, distance affects choice of vehicle. This interrelationship represents the decision process where an individual makes a choice of which destinations to access first and then makes a choice of which vehicle to choose from the household vehicles based on the distance and other considerations. The direction of the interrelationship between the short-term vehicle utilization choices has implications for effectiveness of transportation policies aimed at reducing the energy consumption and greenhouse emissions. For example, if high density mixed use built environments are being considered to alter the energy consumption and emissions. And let us say that a significant interrelationship was found wherein individuals traveling smaller distances prefer larger vehicles. Then land use policy promoting density may not be effective because short distance to destinations afforded by the policy may mean that individuals prefer the larger vehicle from the household vehicles potentially. This would in turn negate the positive gains due to shorter travel distances.

Recently researchers have attempted to address the knowledge gap by conducting disaggregate analysis of short-term vehicle choice and distance decisions (*11-15*). While these studies explore the choice dimensions at a disaggregate unit of analysis there are some limitations. The studies either do not consider the interrelationships (*14-15*) or they assume a single interrelationship to hold for the entire population (*11-12*) when in reality it is possible that 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 population simultaneously to accurately describe the underlying decision-making process.

The primary objective of this study is to add to literature on disaggregate analysis of short-term vehicle utilization decisions that is less understood. The study attempts to explore the different factors influencing the vehicle choice and distance decisions while also accommodating the interrelationship structures 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 latent class segmentation framework (*16-18*). A latent class segmentation framework theorizes that individual decision-makers can be classified into latent (unobserved) groups based on a variety of exogenous factors including socio-economic, demographic and environment factors related to the decision-maker. Based on the latent group to which a decision-maker belongs, the framework then allows for modeling the choice dimension(s) of interest. The proposed formulation of the latent class segmentation framework is not only capable of modeling the vehicle type choice and distance dimensions simultaneously, it can also accommodate the different interrelationship structures (namely vehicle type choice affecting distance and distance affecting vehicle type choice). 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) was used in this study (*19*). The choice of vehicle in households with a single vehicle is an obvious one whereas the choice of vehicles in households with multiple vehicles involves a choice process that is interesting. Therefore, the focus of the empirical exploration is 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 1) it was assumed that individuals do not differentiate between multiple vehicles of the same body type because they likely offer the same level of comfort, and convenience and 2) the emissions and energy implications across vehicles belonging to the body type is also 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 has more pronounced implications for energy and emissions.

The rest of the paper is organized as follows. In the next section the proposed latent segmentation methodology is presented. In the following section, the data used in the study and the sample composition is described. In the fourth section, 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 of three components: 1) latent segmentation, 2) vehicle type choice, and 3) 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 based on 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 first choice as an explanatory variable in the model of second choice. It can be seen that the proposed formulation is capable of exploring different interrelationship structures for different segments of the population – this is in contrast to earlier studies which assume a single structure to hold for the entire population (*11-12*).

The vehicle type choice is a discrete variable. Therefore, vehicle type choice component was modeled using a multinomial logit formulation with vehicle types from the household's vehicle holdings as the alternatives. On the other hand, distance traveled is a continuous variable. Therefore, distance traveled component was modeled using 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 1) latent segmentation, 2) vehicle type choice, and 3) distance traveled can then be formulated as shown in Equations 1 through 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}^{*}represents the utility derived by the q^{th} individual for selecting the i^{th} latent segment, u_{qiv}^{*} represents the utility derived by q^{th} individual by selecting vehicle type alternative v in the i^{th} latent segment, and y_{qi} represents distance travelled by the individual in the i^{th} latent segment. x_{qi}, x_{qiv}, x_{qid} represent the explanatory variables and $\alpha, \beta_i, \gamma_i$ represent the vector of unknown parameters associated with the explanatory variables. Further, the error term ε_{qi} is assumed to follow a standard type I extreme value distribution. The error term ε_{qiv} also follows a type I extreme value distribution with a location parameter 0 and scale (δ_{ir_q}) varying 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 zero and a standard deviation (σ_{ir_q}) also varying with latent segment (i) and region (r_q) to which the individual belongs. The non-constant scale and standard deviation parameters are specified to accommodate the unknown heterogeneity in the choices across the different regions. The error term for each of the model components are also assumed to be independent. The two scale parameters in the models are parameterized as follows: $\delta_{ir_q} = \exp(\theta_{r_q} x_{r_q})$ and $\sigma_{ir_q} = {}^{\sigma}\!/_{\exp(\vartheta_{r_q} x_{r_q})}$ where σ corresponds to scale for one selected region. The parameters $\exp(\theta_{r_q} x_{r_q})$ and $\exp(\vartheta_{r_q} x_{r_q})$ are set to 1 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 as shown below in Equation 4:

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

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

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

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

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

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

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

where ρ_j is a choice indicator and assumes a value 1 if a particular vehicle type alternative j is selected and 0 otherwise. The total log-likelihood for the sample can be expressed as shown in Equation 8.

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

The log-likelihood function was coded in GAUSS matrix programming language and the unknown parameters: $\alpha, \beta_i, \gamma_i, \theta_{r_q}, \sigma$ and ϑ_{r_q}were estimated using the maximum likelihood estimation technique.

DATA DESCRIPTION AND SAMPLE COMPOSITION

Data from 2009 National Household Travel Survey was used in this study. NHTS is a cross-sectional survey collecting information about the travel characteristics of a nationally representative sample of households in the US including household- and person-level socio-economic and demographic information, vehicle holdings data, and information about household used for different trips. Data contained in the NHTS allows for exploring vehicle utilization decisions at different temporal resolutions including day-level and within-day. In an effort to identify the appropriate temporal resolution for the analysis, the dataset was explored to understand what percentage of individuals switch vehicles within a day. It was found that only a small percentage of people (5.01 percent) switch vehicles during the day, indicating that vehicle choice may not be a within-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 based on the vehicle type. Further, this treatment also allows one to understand the tradeoffs and compromises associated with the selection of vehicle from the household vehicle holdings. The analysis was conducted at a person-level and limited to only adults who have a valid driver's license.

One of the objectives of the study was to explore differences in short-term vehicle usage decisions across cities with varying degrees of automobile dependency and usage. The cities of New York, Washington DC, and Los Angeles were selected from the dataset owing to the extremes of automobile dependency and transit usage patterns experienced in these cities. New York has low auto dependency and more transit friendly and Los Angeles is the opposite with more auto dependency and fewer transit options and Washington DC falls somewhere in between the two extremes. From this point forward New York, Los Angeles, and Washington DC will be referred to using the abbreviations NY, LA, DC respectively.

After imposing the restrictions and eliminating records with missing entries, the subsample for analysis consisted of 8,426 persons belonging to 5,486 different households. Table 1 provides some summary statistics for the subsample. It can be seen that in 24 percent of the cases, all household vehicles are utilized on the survey day whereas in the remaining 75 percent of the households, only a subset of the vehicles owned are used on any given day. This observation indicates that individuals face a choice at the start of day of what vehicle to select from the household vehicle holdings based on their planned activity-travel engagement needs. Even in households where all vehicle holdings are used, it is likely that an individual negotiates with other household members on what vehicle to use on any given day. It is interesting to note that across NY, LA, and DC, the percentage of households where all vehicles owned by the household are used is decreasing. It appears counterintuitive because one would expect that with the abundance of transit options in NY, households would not use all vehicles owned compared to LA. It is plausible that households that own multiple vehicles in the NY 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 namely exploring differences in the choices across the three regions.

The vehicle types in the original NHTS consisted of 9 different categories which were consolidated into four categories namely: Auto, Van, Sports Utility Vehicle (SUV), and Trucks based on similarity in body types. It can be seen that a similar percentage of Auto are used across the three regions (about 44 percent). However, there are significant differences in the percentages of other vehicle types that are used. Trucks are preferred when available in LA and DC more than in NY. Similarly, SUV when available is preferred most in NY followed by LA and DC. These observations further point to the importance of studying differences across different regions. The trip rates (about 4.1 trips per person) and distribution across purposes are similar across the three regions. The subsample consists of an even percentage of males and females. Most of the respondents are workers and in their middle age between 40 and 54 years. Average households size is about 3.3 with about 2.5 adults per household and most of the adults are also licensed drivers.

MODEL ESTIMATION RESULTS

A latent class segmentation model was estimated using 2009 NHTS data from NY, DC and LA to explore the short-term vehicle utilization decisions: vehicle type choice and distance. The latent segments were specified to reflect the two interrelationship structures namely: vehicle type choice affecting distance and distance affecting vehicle type choice. 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 provides evidence in support of a significant interrelationship. It must be noted that while the interrelationship structure is used to name and describe the latent segments, the segments may potentially capture additional heterogeneity and regularities beyond the interrelationships. Therefore in assessing the proposed latent class segmentation approach, it is not sufficient to consider the significance of the interrelationships alone. A comprehensive evaluation of alternate model formulations including the latent segmentation model is warranted to select a model that best explains the underlying short-term vehicle utilization choices.

In the latent component of the proposed model, the interrelationship where distance affects vehicle type choice was chosen as the reference alternative. On the other hand in the vehicle type choice component, Truck vehicle type was chosen as the baseline alternative. A host of household- and person-level socio-economic and demographic characteristics and daily activity-travel engagement 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 through the introduction of scale in the models of the vehicle type choice and distance.

Model Estimation Summary

In this study, a total of six different models were estimated. The models along with model estimation summary statistics are shown in Table 2. All models were statistically significant and provided behaviorally plausible results. However, upon closer inspection using model fit statistics including log-likelihood values, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC), it was observed that the independent model where distance affects vehicle type choice (Model 2) offered the poorest fit and scaled version of the latent class segmentation model (Model 6) offered the best fit. This indicates that a model formulation that assumes a single interrelationship structure to represent the behaviors of the entire population may not be appropriate and that different structures may be needed to accurately represent the behaviors different segments of the population. Also, it was interesting to note that scaled version of the model formulation (Model 2, Model 4, Model 6) always performed better than a model formulation without scale (Model 1, Model 3, Model 5 respectively). This suggests that when combining data from different regions, scale should be included to capture the region specific unobserved heterogeneity in behaviors. Overall, the scaled version of the latent segmentation model offered the best fit and estimation results for this model are discussed in the remainder of this section. The structure where vehicle type choice affects distance will hereon be referred to as VTD and the alternative model structure where distance affects vehicle type choice will hereon be referred to as DVT

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. In general, there is a general preference for the DVT structure as can be seen from the negative constant value. It can be seen that, male respondents and respondents between ages 26 and 64 prefer the VTD structure. It is also interesting to note that people with flexibility in their work schedule as evidenced by no fixed work place, flexible work schedule, and multiple jobs favored the VTD interrelationship structure. Respondents who were employed part-time and those who reside 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 NY region with a preference for the DVT structure.

Estimation Results for the Interrelationship Structures

Table 4 presents results for the short-term vehicle utilization choice dimensions where VTD interrelationship structure holds. Tables 5a and 5b present the results for the choice dimensions where DVT interrelationship structure holds.

Role of Interrelationship

The coefficients for the interrelationships provide plausible signs with increasing distance positively affecting the choice of Auto and Van, and decreasing the probability of selecting SUV in the DVT structure (Table 5b). On the other hand in the VTD structure, the choice of vehicle type has a negative influence on the distance traveled across all vehicle types compared to Truck with the highest negative coefficient for Auto, followed by Van, and SUV (Table 4). However, none of these coefficients were significant at the 95 percent level of confidence. The insignificance of the interrelationship is an important finding and sheds light on the underlying choice process. It is likely that vehicle type choice and utilization are not short-term choices which are evaluated and optimized on a daily basis. In other words, vehicle choice may be a household decision wherein individuals may be allocated a vehicle from the household vehicle holdings based on their assumed roles and other considerations (see Tables 4 through 5b for the range of explanatory variables) and not based on the distance they have to travel and vice-versa. This finding is also consistent with a recent study by Nam et al. (*13*) who found that nearly 59 percent of households in the US do not efficiently allocate vehicles and that reallocating vehicles among household members can cut their fuel consumption by nearly 5.2 percent.

As mentioned earlier, the latent segments were named based on the interrelationships for convenience but they potentially capture additional heterogeneity in the shorter-term vehicle choice dimensions. Therefore, insignificance of the interrelationships alone shouldn't be used to infer the significance of latent class segmentation approach. Indeed, the model fit statistics also provide evidence in support of this notion by showing that the scaled latent segmentation model best fits the data; the log-likelihood value is (-46467.4) is almost half the value of the independent model with the VTD structure (-102461.8). A closer examination is warranted to identify characteristics of the latent segments beyond the interrelationship structures. Table 6 provides predicted probabilities and distance values of the choice dimensions for the VTD and DVT latent structures. It can be seen that there are clear differences in the predicted probabilities and distances between the two latent segments. VTD latent segment is clearly characterized by longer daily distances traveled and higher Auto vehicle type choice. On the other hand the DVT latent segment is characterized by shorter daily distances traveled and smaller shares of Auto vehicle type use and higher share of SUV usage.

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 DC region were assumed to be equal to 1 for empirical identification and the parameters for LA and NY were estimated. Model estimation results for the regional effects for the VTD and DVT interrelationships are presented in Tables 4 and 5b respectively.

It can be seen that indicator variables for the NY and LA are significant in both choice dimensions for the VTD structure. However, in the DVT structure NY indicator variable was significant only for distance choice whereas the LA indicator was significant in both vehicle type choice and distance dimensions. It is interesting to note that the direction of influence of the LA indicator on the vehicle type choice dimension varies across the VTD and DVT structures.

Scale parameters for LA and NY were found to be significant in the VTD structure except for the scale parameter corresponding to NY on the vehicle type choice dimension which was only marginally significant. In the DVT structure, only the scale parameter for LA on the distance dimension was found to be significant. In addition to the indicators for the regions, differential impacts of explanatory variables including socio-economic and demographic characteristics were tested through the introduction of interaction variables. While no interaction variables turned out to be significant in the VTD structure, a number of variables turned out to be significant in the DVT structure. Specifically there was a lower preference for males in NY to select the Auto vehicle type. Also, respondents who were from LA and traveling on a weekday preferred to use the Auto vehicle type. Interaction variables were also found to be influence the distance dimension with persons living in households with income greater than or equal to $100K preferring to travel shorter distances.

Role of Socio-economic and Demographic Characteristics

A variety of socio-economic and demographic characteristics were used to explain the heterogeneity in the vehicle type choice and distance dimensions across the two structures (as shown in Socio-economic and Demographic Characteristics portions of Tables 4 and 5a). Among the person-level variables, gender, age, level of education, employment status, work arrangement, and occupation were found to influence the short-term choices. Among the household-level variables, income, home location, household composition, travel day, and vehicle characteristics were found to be significant. It is interesting to note that there are significant differences in the influence of the different variables in the VTD and DVT structures further pointing 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 potential influence of activity and travel pursuits on the short-term vehicle utilization choices (as shown in Activity-Travel Characteristics portions of Tables 4 and 5a). It was observed that across both structures, the distance traveled increases as the number of accompanying passengers' increases. This is likely due to the extra activities individuals may be pursuing to satisfy the needs of the accompanying passengers. The presence of different types of activity purposes 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 compared to the DVT structure. Presence of work, school, maintenance, discretionary, pickup, and drop-off activities influenced the choice of both vehicle type choice and distance in the DVT structure. On the other hand in the VTD structure, only presence of work activity, discretionary activity, pickup activity and drop-off activity affected the short-term choices. Presence of pick up activity was found to positively influence the choice of Van vehicle type compared to other vehicle types in both structures. This is plausible because pick up activities generally involve kids or other household members with mobility barriers so there may be a preference to choose a Van for comfort reasons.

CONCLUSIONS

The travel behavior literature is replete with examples of longer-term vehicle ownership and vehicle holding choices. However, there is very limited research exploring the shorter-term vehicle usage decisions including the choice of vehicle from the vehicle holdings and the distance traveled by 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 on 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 while also accounting 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 using data from the 2009 wave of the NHTS. Additionally, scale was introduced in 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 other models were estimated with different specifications of scale and latent segments.

It was found that the scaled version of latent segmentation model performed the 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, it was interesting to note that the scaled latent model outperforms other model formulations considered in the analysis. This observation lends credence to the notion that the latent segments may potentially be capturing unobserved heterogeneity beyond the interrelationships that were used to name them and hence the better model fit. The findings further suggest that allowing parameters to vary across groups allows for a better representation of underlying behaviors which subsequently will result in more accurate estimation and inferences. The study also found differences in the choices across the regions as evidenced by the significant parameter values for the region indicators, significant interaction variables with the region indicators, and also 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. There are also limitations of the current work opening 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. (*11*) significant interrelationships were found when the analysis was performed at a tour-level. Therefore, questions still abound about the appropriate scale for studying the short-term choices and a temporal analysis using a multiday dataset will provide insights into the temporal scale appropriate for analyzing short-term vehicle choices. Second, there may be common unobserved attributes that affect the vehicle type choice and distance dimensions simultaneously. Exploration of complex error structures within the latent segmentation model framework is another interesting line of inquiry for future research. Lastly, vehicle choice may not be a person-level decision but a household-level decision. The exploration of vehicle choice as a household-level involving negotiation across different household members, their characteristics, and their activity-travel needs will be another interesting endeavor.

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Table 1 Summary Statistics for the Subsample

Variable Name	**New York**	**Los Angeles**	**Washington D.C.**	**Three Regions**
Number of survey respondents considered in the analysis	3071	3732	1623	8426
Percentage of males	48.3%	50.9%	49.2%	49.6%
Percentage with at least B.S. 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				
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*

Table 2 Model Estimation Summary

Model Description	LL	Number of Observations	Number of Parameters	AIC	BIC
1. Independent model where vehicle type choice affects distance	*-102461.8*	*8426*	*104*	205131.7	205863.8
2. Independent model where vehicle type choice affects distance with scale parameters to capture differences across regions	*-102467.7*	*8426*	*105*	205145.5	205884.6
3. Independent model where distance affects vehicle type choice	*-51170.1*	*8426*	*81*	102502.2	103072.3
4. Independent model where distance affects vehicle type choice with scale parameters to capture differences across regions	*-51171.0*	*8426*	*82*	102506.0	103083.2
5. Latent segmentation model	*-46509.1*	*8426*	*128*	93274.2	94175.2
6. Latent segmentation model with scale parameters to capture differences across regions	*-46467.4*	*8426*	*140*	93214.7	94200.2

Table 3 Model Estimation Results for the Latent Segmentation Component

Description	**Coeff**	**t-stat**
Constant	-1.6433	-13.9
Indicator for NY	-0.1511	-1.7
Male	0.4474	6.5
Age >=26 and Age <=39	0.3225	2.7
Age >=40 and Age <=54	0.5025	5.3
Age >=55 and Age <=64	0.3144	3.0
Flexible work schedule	0.1623	2.1
No fixed work place	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

Table 4 Model Estimation Results for the Latent Segment where Vehicle Type Choice Affects Distance (VTD)

Variable Description	**Auto**		**Van**		**SUV**		**Distance**	
	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
Socio-economic and Demographic Characteristics								
Male	-1.1993	-4.5	-1.6871	-4.2	-1.3320	-4.4		
Age >=18 and Age <=25	0.6620	2.8						
Age >=26 and Age <=39					-0.2785	-1.6		
Age >=40 and Age <=54			-0.3263	-1.6				
Age >=65							22.3999	2.9
At least a B.S. education	0.3968	2.2	0.4847	1.9	0.3997	2.0		
Self-employed	-0.2701	-1.7						
Part-time employment					0.3649	1.9		
Manufacturing, construction, maintenance, or farming occupation	-0.3512	-1.8						
Income >=50K and <75K			0.4891	1.7				
Income >=75K and <100K	0.5131	2.3	0.5549	1.7	0.5946	2.4		
Income >=100K							9.3141	2.1
Home in urban area					0.2866	1.9		
Number of people							-3.5046	-2.1
Number of workers	-0.1520	-2.2			-0.3480	-3.2		
Number of drivers					0.2397	2.5		
Travel day is a weekday							-19.6918	-3.7
Vehicle age <= 5 years			-0.4775	-2.3			19.8631	4.5
Activity-Travel Characteristics								
Presence of a work trip	0.4148	2.8						
Presence of a discretionary trip			0.4760	2.2				
Presence of a pick-up trip			0.4681	1.9				
Presence of a drop-off trip							7.4271	1.6
Average trip occupancy			0.4689	4.1	0.3261	3.6	13.7755	5.6
Interrelationship Variable								
Auto selected							-9.3568	-1.4
Van selected							-7.6593	-0.8
SUV selected							-5.9487	-0.8
Regional Characteristics								
Indicator for NY	-0.5893	-3.3					-13.7190	-1.9
Indicator for LA	-0.6828	-4.1					-23.6973	-3.7
Scale for LA	-0.4595	-2.0	-0.4595	-2.0	-0.4595	-2.0	-0.2495	-5.4
Scale for NY	-0.2859	-1.2	-0.2859	-1.2	-0.2859	-1.2	-0.1113	-2.3

Table 5a Model Estimation Results for the Latent Segment where Distance Affects Vehicle Type Choice (DVT): Socio-economic And Demographic Characteristics and Activity-Travel Characteristics

Variable Description	**Auto**		**Van**		**SUV**		**Distance**	
	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
Socio-economic and Demographic Characteristics								
Male	-2.2922	-11.7	-2.8389	-11.4	-2.3173	-11.5	1.5262	3.1
Age >=18 and Age <=25	0.7374	4.8	-0.9965	-3.7				
Age >=26 and Age <=39	-0.3660	-3.1					1.4105	1.9
Age >=40 and Age <=54	-0.3831	-4.0					1.0057	1.8
Age >=55 and Age <=64	-0.2205	-2.3						
At least a B.S. education	0.1168	1.7						
Self-employed	-0.2349	-2.1						
Flexible work schedule	0.2622	3.4						
Part-time employment	0.3512	2.0	0.6235	2.8	0.3106	1.6	-2.6895	-4.0
Sales and service occupation							1.4117	2.0
Clerical and admin support occupation					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					0.1366	1.6	2.9982	4.8
Income >=75K and <100K							1.0280	1.6
Income >=100K							2.2422	4.0
Home in urban area							-4.6087	-7.1
Number of people			0.1012	2.5			-1.1609	-4.8
Number of drivers							0.7975	2.2
Number of adults	0.0649	1.6						
Travel day is a weekday							1.2953	2.4
Vehicle age <= 5 Years					0.9237	5.3	2.8635	4.8
Vehicle age between 5 and 10 Years	-0.2854	-3.1			0.4475	2.5	1.2514	2.0
Vehicle age between 10 and 15 Years	0.2714	2.2			0.4366	2.1		
Activity-Travel Characteristics								
Presence of a Work Trip			-0.3910	-3.0			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					0.2669	3.6	5.3307	11.0
Presence of a Discretionary Trip	0.1634	2.3					8.1451	15.7
Presence of a Pick-Up Trip	0.4075	1.9	0.7051	2.8	0.6025	2.7	4.8175	6.0
Presence of a Drop-Off Trip							4.0237	7.4
Average trip occupancy	0.2699	2.9	0.7457	6.2	0.5487	5.1	2.0348	6.4

Table 5b Model Estimation Results for the Latent Segment where Distance Affects Vehicle Type Choice (DVT): Interrelationship and Regional Characteristics

Variable Description	**Auto**		**Van**		**SUV**		**Distance**	
	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
Interrelationship								
Distance traveled	0.0009	0.3	0.0006	0.1	-0.0004	-0.1		
Regional Characteristics								
Indicator for NY							-5.1807	-5.1
Indicator for LA	0.1719	2.1					-6.4402	-6.9
Scale for LA	0.1563	1.7	0.1563	1.7	0.1563	1.7	-0.1976	-5.3
Scale for NY	-0.1636	-1.7	-0.1636	-1.7	-0.1636	-1.7	-0.0432	-1.0
Male respondent in NY	-0.2733	-2.4						
Respondent living in LA and travel day is a weekday for	0.1505	1.8						
Respondent age >=18 and age <=25 in NY							2.2338	1.5
Respondent household income >=100K in DC							-2.9975	-2.4

Table 6 Predicted Choices using the Latent Segmentation Model

	All Regions	NY	LA	DC
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%