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An Exploration of Short-Term Vehicle Usage Decisions

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TABLE OF CONTENTS

ABSTRACT

Vehicle choice decisions are Important to consider because they have implications on fuel consumption and greenhouse gas emissions. Much research has been done in the past regarding the types of vehicles that people own and how much they use each vehicle on annual basis. However, these are all long-term vehicle choice decision, and very little research has been done to explore short-term decisions. Short-term decisions provide information about how much vehicles in the household are being used at a day-level. In addition to the capturing the role of socio-demographics and economic factors on the short-term vehicle choices, the fine scale temporal analysis allows for exploring the relationship between vehicle choices and daily activity-travel engagement decisions which shape the selection and use of different vehicles in the household fleet.

In the context of the short-term vehicle choices, there are two important choices to consider: the vehicle chosen from the household fleet to pursue the trip and the distance traveled. Further, there are important interrelationships between these two variables namely, vehicle choice may affect distance or distance may affect vehicle choice. Depending on the directionality of this relationship, there are different policy implications. It is important to understand these short-term decisions and their interrelationships so as to make informed decisions for creating efficient transportation systems, reducing fuel use, and decreasing greenhouse gas emissions.

To explore the relationship between distance and vehicle type, data from the 2009 National Household Travel Survey (NHTS) was used. The thesis is divided into two parts. In the first part, findings from the examination of distance and vehicle type choice dimensions are presented. This section also explores the potential interrelationships between the choice dimensions. Further, the section also discusses findings from a comparative analysis of differences in vehicle choice behaviors across three metropolitan areas namely New York, Los Angeles, and Washington. The second part of the thesis

explored the possibility that not one but both interdependencies could hold true but each for a different subgroup of the population to explain the short-term vehicle choice and usage behaviors. To this end, a latent segmentation approach was used to model both interdependencies and the corresponding interrelationships between vehicle type choice and distance within the same modeling framework. Both studies provide statistically significant and plausible results. Further, the results provide evidence in support of the importance of short-term vehicle choices and the importance of them in planning and policy analysis.

Chapter 1 - INTRODUCTION

A region's transportation system is the backbone of all its activity. It provides mobility, connectivity, accessibility, and reliability which in turn affect important aspects about individuals and businesses including economic activity and quality of life among other factors. The efficiency of the system influences how a region grows, develops, and changes. For this reason, it is important to assess the performance of the transportation system in order to maintain/improve the state of operations and also to plan for the future. A transportation model that simulates individual travel choices is often used for planning and policy analysis. A traditional approach to modeling the transportation systems has been the four-step model. Four-step model is based on aggregate principles wherein travel choices are studied at an aggregate by averaging them over different individuals. Due to the aggregate treatment of travel choices, four-step models are not applicable for conducting policy and planning analysis involving change in individual behaviors. In an effort to address this and other limitation of the four-step models, advanced models of the transportation system which focus on representing the individual decision maker and their travel decisions more accurately are being developed in a number of metropolitan regions across the United States. In the advanced models, activity engagement decisions are represented primarily and travel results from the need to engage in an activity at a different location. Given the focus of the activity engagement in deriving the travel patterns, these advanced model systems are also referred to as activity-based transportation models. Compared to the four-step models, these advanced models are comprised of a more accurate representation of the individual decision makers and their activity-travel engagement choices. Further they can also account for constrains and interactions that individuals and households experience in their decision-making process more accurately. Therefore, they are better suited for planning and policy analysis compared to traditional four-step models. (Federal Highway Administration 2014)

A key first step in the development of the advanced models is to characterize the activity-travel engagement choices of individuals and households. Everybody has different travel patterns based on their socio-economic and demographic characteristics, lifestyle preferences, and built environment features among many other factors. Some people may have a strict daily routine in which they always eat at the same place at the same time every day, while others may have dynamic schedules that vary greatly depending on the day of the week, time of the year, and daily preference. The study of the different attributes of travel behavior is an important to create accurate models of the transportation system that can be used to evaluate current conditions and forecast for the future. There is a tremendous body of literature in the transportation arena aimed at exploring trends in the choices and proposing techniques for modeling the how, when, where, why, and with whom of the activity-travel patterns pursued by individuals and households (Chorus et al 2006).

Among the different factors that characterize activity-travel patterns, an important factor to consider is mode choice. The mode that a person chooses to use has implications for energy consumption, greenhouse gas emissions, sustainability, and more. Depending on the availability, people can choose what mode of transportation to use to get around. They most commonly have the choices to drive, take transit, walk, or bike. For the driving mode, also the dominant transportation mode for personal mobility in most regions in the United States, the choice of the specific vehicle from the household vehicle fleet is of interest since it has specific implications for the energy that is consumed and the emissions that are generated. However, transportation models have typically considered all vehicles to be equal (apart from trucks in some cases; Schlappi et all 1993) and this may potentially lead to inaccurate assessment of the emissions and energy consumption (Cervero & Kockelman 1997, Zhao & Kockelman 2002a, 2002b). Therefore, the study of the specific vehicle that is chosen from the household fleet for trip engagement is important.

In the context of the choice of vehicle for driving mode, there are short-term and long-term choice dimensions at play each having implications on the activity-travel engagement patterns. Operating on a longer-term time scale is the study of the composition of the vehicle fleet in which the number of vehicles owned, the type of vehicles owned, the make and model of the vehicles are explored. A number of factors including a person's lifestyle can greatly influence what vehicle they buy. For example, a person concerned about the environment and fuel-efficiency may choose to buy a small sedan while someone concerned about safety may buy a large SUV. Female head of the households may buy minivans because they need to chauffer around their kids, and blue collared workers may buy pickup trucks to move equipment with ease. Many researchers have explored these long-term decisions and the rich body of literature on the topic is a testament to the fact. (Bhat & Sen 2006, Chorus et al 2006)

On the other hand, operating at a shorter-term time scale is the study of how much the different vehicles in the household are utilized for pursuing the trips at a day-level. In households where there is a single vehicle, the choice of the vehicle for trips by driving mode is an obvious one. However, when the household owns more than one vehicle, households may make a decision on what vehicle to use each day for the different trips based on a number of socio-economic and demographic factors. For example, age, gender, income, and occupation may influence which vehicle people choose to use for different activities (Bhat & Sen 2006, Collia et al 2003). Additionally, a person's everyday activities may have an impact on what vehicle they choose to use. A person might choose a different vehicle when they are going to work than when they are going shopping. Because there are so many factors, it is important to understand these choice behaviors to adequately understand the vehicle usage decisions and subsequently understand its implications on the transportation system and the environment. Some research has been done on short-term vehicle usage decisions; however, vehicle mileage is often explored at an aggregate level by considering the vehicle miles traveled throughout the year. The aggregation fails to recognize the differing constraints and interactions that may influence vehicle usage patterns and may lead to incorrect inferences. Therefore the study at a disaggregate level is an important one. Short-term decisions may be made at a day-level or at a tour-level, and there is limited research exploring the vehicle usage decisions at a disaggregate level (Paleti et al 2011, Giuliano & Dargay 2005). The focus of this research is to conduct a disaggregate exploration and contribute to the literature on the shorter-term vehicle usage decisions.

In the context of the shorter-term vehicle usage decisions, there are two important variables that need to be considered: the vehicle type chosen from the available vehicle fleet and the distance traveled to pursue daily activities. Socio-economic and demographic data as well as vehicle and trip characteristics all affect these two variables. Further, there are potential interrelationships between the two variables that are at play: vehicle type choice may affect the distance traveled or distance traveled may affect the vehicle type choice. Or perhaps, they are both true but hold for different portions of the population. It is very important to understand the interrelationships because the direction of the influence has different policy implications. For example, if distance traveled affects vehicle type choice, people first choose what distance they are going to travel to pursue their activities, and based on that, they choose a vehicle from their fleet. When implementing policies, it is important to consider both interrelationships so that the most effective policies can be implemented. This research provides information about the different interrelationships to better understand how the two short-term vehicle choice dimensions work together.

The focus of this study is aimed at adding to the literature on short-term vehicle usage decisions. To this end, there are three specific objectives of this research as described below,

1. To explore short-term vehicle usage decisions of vehicle choice and distance while considering the interdependency between the two dimensions using independent modeling frameworks

2. To explore the differences in the short-term vehicle usage behaviors (including vehicle type choice, distance, and interdependencies) across regions in the United States in an effort to understand the spatial transferability of the models and findings
3. To use an advanced modeling framework to study the two interdependencies within the same framework

To achieve these objectives, an empirical exploration was conducted using data from the 2009 National Household Travel Survey. Further, this research has been divided into two separate parts to address the objectives outlined above. The first study examined short-term vehicle usage decisions using simple independent models of vehicle type choice and distance using appropriate statistical formulations. Interdependencies were explored using one variable as an explanatory variable in the model of the other variable. Further, the spatial transferability of the interdependencies was explored to understand difference in short-term vehicle usage behaviors across three cities with different levels of automobile dependency. Building on the findings of the first exploratory study, the second study modeled short-term vehicle usage decisions employing advanced modeling frameworks which can accommodate the exploration of both interdependencies within the same model formulation.

The rest of the thesis is organized as follows. Chapter 2 describes the background information acquired from previous studies. Chapter 3 describes the first part of the thesis, the exploration of the spatial differences and the interdependencies between vehicle type choice and distance. This chapter includes subsections that give a brief introduction, a description of the data, the methodology, the model estimation results, and a discussion about the results. Chapter 4 describes the second part of the thesis, the exploration of the relationship between vehicle type choice and distance traveled using a latent segmentation approach. Subsections here include a brief introduction, data description, the methodology, the model estimation results, and a discussion. And finally, Chapter 5 gives a summary of the project and suggestions for future research.

Chapter 2 - BACKGROUND

There is a great amount of literature available regarding vehicle choice decisions. As discussed before, vehicle choice decisions can be divided into short and long-term. Long-term vehicle choice decisions often involve choices of number of vehicles and the types of vehicles owned. On the other hand, short-term vehicle decisions include choices regarding the utilization of the fleet of vehicles including the choice of vehicle for different individual activity and travel episodes and the distance traveled by the vehicle. Each of these long-term and short-term decisions is a function of a number of characteristics including demographics, location, land-use, and preference. This chapter provides a brief overview of the literature exploring the long-term and short-term vehicle ownership and utilization decisions.

A) Long-Term Vehicle Choices

There are a number of studies that have explored the long-term vehicle choices including the number of vehicles owned in a household (e.g. Cao and Cao 2013, Clark 2007), what types of vehicles are owned (e.g. Bhat and Sen 2006, Golob et al 1995, Cirillo and Liu 2013), and factors influencing these decisions. Different types of factors were explored in explaining the long-term vehicle choices. Some analyses used a series of socio-demographic and economic variables to understand trends in a certain country or region of the world. After noticing that large growth in vehicle ownership in Spain, (Matas and Raymond 2007) searched for the reasons that were causing this change. They found that the current increase in employment rates and income (before the Spanish financial crisis) caused urban sprawl and higher vehicle ownership rates. Likewise, Ireland had period of rapid economic growth from 1995 to 2001. An exploration of the causes found that household income and previous vehicle ownership were the strongest variables that explain household vehicle ownership; households that previously owned a vehicle were less likely to give it up regardless of their economic situation (Nolan 2010). The 'Baby Boomers' generation has always presented great changes in the United States, and there was concern about how vehicle ownership trends would change as the generation ages. A research study analyzed how age affects vehicle type ownership and discovered that older people worry less about vehicle performance and more about fuel-efficiency (Kavalec 1999). Several other studies explored the relationship between income, population, and vehicle ownership at a global scale. Results found that while developed countries are leveling off, vehicle ownership rates in developing countries are increasing rapidly. They conclude that if countries like China, India, and Brazil continue this trend, fuel demand and greenhouse gas emission will be a much greater concern than they already are. (Dargay 1997, Dargay 1998, Dargay et al 2007)

Multiple studies were interested in examining how different land-use variables affect vehicle ownership. After finding that increasing income in Spain was triggering urban sprawl, Matas et al (2009) examined how urban structure affects vehicle ownership. In particular, they saw that enhanced accessibility to public transportation decreases vehicle ownership. Another study modeled vehicle ownership, residential/work locations, commuting distance, and commute mode in San Francisco (Paleti et al 2012). The authors of the study concluded that residential/work locations and commuting distance affect how likely a person is to own a vehicle and vehicle ownership affects the mode used to commute to work. Since Transit-Oriented Developments (TODs) have recently been promoted as a way to reduce vehicle dependency, a study examined the Hiawatha Light Rail in Minneapolis-St. Paul (Cao & Cao 2013). By controlling self-selection, they found that transit alone does not affect vehicle ownership, but when combined with an adequate neighborhood design, vehicle ownership drops. In New York, there was debate over how residential parking availability affected vehicle ownership. An exploration revealed that off-street parking significantly impacts how many vehicles are owned, but on-street parking fluctuates a lot depending on other factors such as income and distance to subway (Guo 2013). Several additional studies explored how vehicle ownership differs in an urban setting versus a rural area. Two studies found that traditional neighborhoods are associated with passenger vehicles while suburban neighborhoods had a stronger relationship with larger vehicle (Cao et al 2006, Kim 2012). Another study related vehicle ownership in urban and rural settings to travel costs in the United Kingdom. They discovered that people living in rural areas were much less sensitive to changes in travel costs. Since people living in these areas often do not have other travel options, increasing travel cost may have some equity concerns that need to be addressed (Dargay 2001).

While many studies used income as one of the many variables in their analysis, others focused on the influence of income on vehicle ownership. An exploration in the United Kingdom analyzed the impact of income levels in different regions in the country (Clark 2007). Two other studies specifically looked at how changes in income affect vehicle ownership rates, one in the United Kingdom and the other in Taiwan (Dargay 2000, Jou et al 2012). They both discovered that an increase in income causes a much faster increase in vehicle ownership than a decrease in income causes a decrease in vehicle ownership. A study in the Netherlands focused on a different factor; they explored how the implementation of a kilometer-based tax versus the existing vehicle purchase tax would affect vehicle ownership (De Jong 2009). They learned that Dutch households react more to fixed costs than variable costs. The implementation of such a taxing system would lead to a 2.2% increase in vehicle ownership.

In addition, some studies have focused on opinion-based survey data to explore vehicle ownership. A San Francisco study examined how a person's opinions about the environment, travel, and land-use played a role (Choo & Mokhtarian 2004). They found relationships between a person's attitudes and the type of vehicle they owned. The probability of owning a compact car was higher for people that have stronger pro-density attitudes, and people that drive luxury vehicles commonly dislikes high density developments and had higher incomes. Another survey in Austin asked respondents about their attitudes towards vehicle costs under various scenarios (Musti & Kockelman 2005). Most people expressed that they would consider buying a hybrid vehicle if it costs $6,000 more than its gasoline-powered equivalent and support a feebate policy that would fee people that do not meet a certain vehicle efficiency level. Some studies have focused on abstract variables such as attitudes towards the environment (Choo & Mokhtarian 2004), opinions about cost and efficiency (Musti & Kockelman 2011), and psychological satisfaction (Wu et al 2007). And finally, a Japanese study analyzed factors that affect vehicle ownership in the early stages of motorization in a developing country (We et al 2007). They found that psychological satisfaction promotes vehicle ownership as it is not a necessity but seen as a status symbol. These papers provide insight on unobservable data that may influence fluctuations in model results.

In the literature, different definitions of vehicle type are used in the analyses of long-term. Studies that are solely concerned with environmental implications of vehicle use, such as fuel consumption and greenhouse gas emissions, differentiate vehicles by fuel efficiency. They often make the generalization that the larger a vehicle is, the less fuel efficient it is, thus dividing all vehicles into two groups: cars (autos and station wagons) and trucks (vans, SUVs, and pickup trucks)(Fang 2008). Some consider fuel type as a way to categorize vehicles (Flamm 2009), while others use body type to categorize vehicles. Within body type, some are very specific and consider up to nine different types (Choo and Mokhtarian 2004) while others group everything into four main groups: autos, vans, SUVs, and pickup trucks (Bhat and Sen 2006, Zhao and Kockelman 2002). One study in particular analyzed motorcycles and four-wheel vehicles separately due to the large number of motorcycles in the region (Jou et al 2012). A post 1979-recession study examined vehicle ownership by brand to determine how American vehicles compared to foreign ones and to examine brand loyalty (Mannering & Winston 1985). The majority of studies divide vehicle by body type, which is also the approach that was employed in this research to categorize vehicles. This is reasonable because even though the fuel efficiency standards for large body types have improved over the years, they are relatively still less fuel efficient than smaller body types. Given the strong negative correlation between body type and fuel efficiency standards (and subsequently the emissions and fuel consumption implications); vehicles were categorized by body types.

B) Short-Term Vehicle Choices

In addition to the long-term vehicle choice decisions of vehicle ownership and fleet composition, the exploration of the short-term decisions of vehicle utilization is also important to explore because it has direct implications for the fuel consumed and the emissions generated. Most studies have explored the short-term vehicle utilization at an aggregate level (household- or person-level) across long time periods using annual vehicle miles traveled (VMT, or vehicles kilometers traveled [VKT]). Many of these studies have simply explored these dimensions to better understand patterns in a given city. As Santiago de Chile rapidly motorizes, a study explored how the built environment affect vehicle ownership and usage (Zegras 2008). They found that income plays the biggest role in influencing how much people drive, but there was a clear relationship between neighborhood characteristics and vehicle usage. Specifically, shorter distance to the central business district and metro stations decreases annual VKT. Researchers in Maryland were curious to discover what factors influence vehicle usage (Cirillo & Liu 2013). Like the Chilean study, they found that higher income relates to higher VMT. In addition, they discovered that the combination of higher density and higher travel costs leads to a decrease in annual VMT.

Many other explorations have investigated the relationship between density and vehicle usage. Two studies specifically modeled household density, vehicle use, and fuel use. One used data from the state of California and found that households with a higher density of 1,000 housing units per square mile were associated with a decrease in in VMT of 1,200 miles and a decrease in fuel consumption of 65 gallons (Brownstone & Golob 2009). The other used United States national data and found that for the same higher density of 1,000 units per square mile, households drove 1,500 miles less and used 70 fewer gallons of fuel (Kim & Brownstone 2010). Although this suggests that an increase in density decreases annual VMT and fuel use, the authors conclude that the impacts are too small to use density as a policy tool to reduce VMT or greenhouse gas emissions. Similar studies have been done while considering two different vehicle types to assess fuel efficiency: small vehicles (autos and station wagons) and large vehicles (SUVs, vans, and trucks). In California, it was found that increasing residential density has a very small impact on vehicle type ownership and usage (Fang 2008). Other factors such as pedestrian-friendly urban designs and availability of transit must be incorporated to affect vehicle type ownership and usage. A similar study was also done using national data and the same results were obtained (Brownstone & Fang 2008). Although residential density slightly reduces large vehicle ownership and usage, the effects were concluded to be insignificant. A Swiss study classified vehicles by fuel type to study the impact of fuel price on vehicle type selection and usage (Jäggi et al 2012). As fuel price increased, the type of vehicle people chose was affected more than usage. People first changed from traditional gasoline to diesel, and as price increased even more, they changed to alternative fuel vehicles (natural gas, hybrid, and electric).

Some European explorations have focused on vehicle transactions and how vehicle usage plays a role on the types of vehicle people get. A Swedish study set up a model to explore how vehicle usage affects the acquisition of newer vehicles (Glerum et al 2013). With a recent focus on energy-efficient vehicles in Sweden, they want to determine types of vehicles people are purchasing in comparison to what they used to own. Likewise, a study was done in the Netherlands to model vehicle usage as a function of several socio-demographic variables and to determine what vehicle type people are more likely to obtain (De Jong 2006). They found that higher income and lower travel costs led to more vehicle usage, and people that drive longer distances tend to buy more fuel-efficient vehicles.

Other studies focused more on what type of vehicles people owned and used by classifying them by body type. A study in San Francisco used a multiple discrete-continuous extreme value model (MDCEV) to analyze vehicle type ownership and their usage (Bhat & Sen 2006). They found that many variables, including household demographics, residence location, and vehicle attributes, affect vehicle type ownership and usage. Among the results, they found that household with more children had higher preference for vans and SUVs, households with at least one worker are more likely to own minivans, males are more likely to own trucks, and increases in operating costs have a negative influence on the usage of all vehicle types except passenger cars. Likewise, a study in California used socio-economic and demographic data to explore nine different vehicle types and their usage (Golob et al 1995). Different ownership compositions yield various usage patterns. In general, younger people, men, workers, and persons with higher income drive more than their respective counterparts. In addition, another Californian study used surveys to determine how attitudes towards the environment affect vehicle usage (Flamm 2009). They found that knowledge about the environment did not impact driving but pro-environment attitudes decreased annual VMT.

It can be seen that short-term vehicle usage analyses in the literature have been dominated by an aggregate treatment of usage wherein the VMT is modeled independently for a long duration (e.g. yearly) or modeled together with long-term vehicle ownership decisions. This treatment of short-term vehicle usage decisions fails to accurately capture the interplay between vehicle type choice and activity-travel engagement decisions. For example, it does not capture whether larger vehicles were used for non-fixed activity purposes where the entire household is engaging in the destination activity or smaller vehicles were used for fixed activity purposes where the individuals are only engaging in the activity. Further, it also fails to capture any interdependency relationships between the vehicle type choice and usage decisions. Therefore, in order to analyze short-term vehicle choice decisions, a disaggregate analysis is needed where the choices can be studied more accurately.

There is very little literature that considers short-term vehicle choice decisions at a disaggregate level. Giuliano & Dargay 2005 is one such study that compares daily travel patterns, vehicle ownership, and urban form between the United States and Great Britain. They followed the definition that vehicle ownership is a long-term decision made based on residential location, and individual travel is a shorter-term decision based on the availability of vehicles and residential location. Among their results, they saw that higher density has a negative relationship with travel distance more significantly in the United States than in Great Britain. Also, the largest metropolitan areas in the United States were associated with more travel than London. The authors suggest that this is due to lower travel costs in the United States that allow people to travel long distances for common goods. Another study in the United States explored short-term vehicle usage in multi-vehicle households (Mannering 1983). The purpose was to determine how changes in fuel cost shift vehicle usage decisions. With a doubled fuel cost (from the current $1/gallon at the time the paper was written), the modeled showed a significant shift to more fuel-efficient vehicles. Vehicle usage patterns in multi-vehicle households are sensitive to changes in fuel cost. By switching to a more fuel-efficient vehicle, households maintain the same VMT but use less fuel and release less emissions. Similarly, another study decided to look at how reallocating vehicles efficiently among household members can reduce fuel consumption (Nam et al 2009). Based on daily travel patterns and fleet composition, the model assigned each vehicle to specific household members to reduce fuel usage. 59% of households in the United States can reduce their fuel consumption by 5.2% equating to 5 billion gallons of fuel. This means that the most fuel-efficient vehicles in households are not necessarily being used for longer daily trips. Two more recent studies have analyzed short-term vehicle choice decisions at a tour-level (Konduri et al 2011, Paleti et al 2011). They both built joint discrete-continuous models to explore the relationship between the choice of vehicle type and tour length. Both studies found that the case in which vehicle type choice affects distance yielded better results that the reverse scenario.

The primary focus of this study is therefore to contribute to this gap in the literature on the short-term vehicle utilization decisions at the disaggregate level while also accounting for the potential interplay between vehicle usage and activity-travel engagement decisions.

C) Modeling Short-term Vehicle Choices and Exploring the Interdependency between Choice Dimensions

In particular, the study focuses on two short-term vehicle decisions, vehicle type choice and distance traveled. There is a potential interrelationship between vehicle type choice and distance traveled, the choice of vehicle can affect the distance traveled or the distance traveled can affect the choice of the vehicle. The direction of the interdependence between these dimensions has implications for policy. Therefore, it is critical to consider the relationship between vehicle type choice and distance traveled when building models. In the first part of the thesis, independent models of the short-term vehicle usage decisions were built using data from the 2009 wave of the National Household Travel Survey (NHTS). The exploration also studied potential interdependencies between the vehicle type choice and distance dimensions by introducing them as explanatory variables in the model of the other variable. Further, the interrelationship between the choice dimensions was explored across different regions with varying levels of multimodal options in an effort to explore the spatial transferability of the short-term vehicle usage behaviors.

Joint modeling frameworks are often used to accurately model multiple choice dimensions and to tease out the interdependencies that exist between the choice dimensions. Given that the vehicle type choice is a discrete variable and the distance traveled is a continuous variable, joint discrete-continuous modeling frameworks are often used. In the literature, the joint discrete-continuous modeling frameworks can be categorized into simultaneous frameworks and sequential frameworks. In the simultaneous frameworks, the two choice dimensions are modeled simultaneously and the frameworks capture the potential error correlations that exist between the choice dimensions due to common unobserved variables (Mannering 1983). However, the simultaneous frameworks cannot be used to model the interdependencies as the choice dimensions cannot be entered as an explanatory variable. On the other hand in sequential frameworks, interdependency relationships can be explored by introducing one choice dimension as an explanatory variable in the model of the other choice dimension (Giuliano & Dargay 2005, Konduri et al 2011, Paleti et al 2011). However, a limitation of the sequential frameworks is that an interdependency relationship has to be established upfront. This approach assumes that there is a single interdependency relationship that explains the behaviors of the entire population even though it is possible that different subpopulation may exhibit different interdependency relationships. Therefore, there is a need for modeling frameworks that can overcome the limitations of sequential and simultaneous modeling frameworks for exploring the short-term vehicle choice decisions. In the second part of the thesis, a latent segmentation based modeling framework was used which overcomes the limitations of sequential and simultaneous frameworks in the literature. The latent segmentation framework can explore alternate dependency relationships in a single model formulation to explain the short-term vehicle usage behaviors of different population groups. Data from the 2009 National Household Travel Survey (NHTS) was also utilized in this exploration.

Chapter 3 - Exploration of Spatial Differences and Interdependencies between Vehicle Type Choice and Distance

A) Introduction

This section of the thesis presents simple models to analyze the interdependencies between vehicle type and distance as well as the spatial differences in the models. Vehicle type choice is a discrete variable since it can only take a value among the predetermined vehicle types and needs to be modeled as such. Distance, on the other hand, is a continuous variable since it can theoretically be any value. Therefore, vehicle type choice is modeled using a multinomial logit model and to model the distance variable a linear regression model formulation was used. This set of models was estimated for each of the interdependencies, in which the other was used as an explanatory variable (i.e. when distance affects vehicle type choice, distance was an explanatory variable in the multinomial logit model and vice-versa). The results that were obtained from the models determine the importance of considering the directionality of the interrelationship between distance and vehicle type choice. If the results are the same, it means that the direction of the causality is not significant. However, if the results are different, it means that either one of the two interdependencies is correct or they both hold true but for different portions of the population. Further to explore the spatial transferability of the data, three metropolitan regions were considered, and a set of models built for each region. How similar or different the results are was used to determine the potential for spatial transferability of the model and findings. If the results are different, caution needs to be exercised when using data from different regions.

The remainder of this chapter is organized as follows. Section B provides a description of the data and Part C describes the methodology. Part D describes the model estimation results, and Part E gives a brief discussion about the results.

B) Data Description

All of the models estimated for this study were done using data from the Nation Household Travel Survey (NHTS). NHTS is a periodical survey in the United States carried out to help transportation planners and policy makers make adequate decisions. It is a 24-hour travel diary that includes all trips pursued by everyone in a household with specific information about each trip. (NHTS 2014)

The data is divided into four different files: a household file, person file, vehicle file, and a trip file. The household file provides socio-economic and demographic data including household income, location type (rural, suburban, urban, census track, etc.), number of people in household, and more. The person file includes person-specific data such as age, gender, worker status, occupation type, driver status, and more. The vehicle file provides information about each vehicle in every household including age, make, model, vehicle type, mileage, and type of fuel. Finally, the trip file describes every trip performed by every person in the survey. Each trip has information about mode, distance, purpose, and duration. If a person used a vehicle, the vehicle identification number provides a link to the vehicle file to obtain specific information about the vehicle used. (NHTS 2014)

Like with most statistical explorations, the data used influences greatly the results that obtained. Since different people in different areas behave differently, a certain region may yield different results than other areas. The NHTS data can be divided by Metropolitan Statistical Area (MSA) for location specific analyses. In order to purse the first part of this exploration, three metropolitan regions were used: New York, NY, Los Angeles, CA, and Washington, DC. These three regions provide an adequate number of samples in the NHTS data to be able to undergo this exploration. In addition, these three regions were chosen due to their differences in automobile dependency and structure. The New York City metropolitan area is the most populous and densest in the United States, and it is not a very automobile dependent city. Los Angeles is the second most populous but has a very automobile-oriented transportation system. Washington, DC is a much smaller city, but is the metropolitan area with the second highest transit ridership in the United States. In addition, for the possibility of exploring the temporal differences among these three regions, the sample sizes for data from previous years were taken into account. In the 1995 NHTS dataset, these were the only metropolitan areas that provided a high number of samples. (NHTS 2014, Data.gov 2014)

The vehicle file includes information regarding vehicle type. The data provides nine different vehicle types: automobile/car/station wagon, van (mini, cargo, and passenger), sports utility vehicle, pickup truck, other truck, RV (recreational vehicle), motorcycle, golf cart, and other. For the purposes of this study, the vehicle types were consolidated into four types namely, automobile/car/station wagon (referred to as auto from now on), van (mini, cargo, passenger, simply referred to as van), sports utility vehicle (referred to as SUV), and the aggregate of pickup truck and other truck (simple referred to as truck).

The interest of this research was to obtain information about people's preference to a specific vehicle type within a short-term time scale. In order to capture a preference of a specific vehicle type as opposed to others, people must be able to make a choice of what vehicle to use for trips throughout the day. There are two possible time scales that need to be considered: within a day or at a day-level. In order to observe this at a within a day-level, people need to be switching vehicle throughout the day. NHTS data was explored to understand the number of persons that change vehicles throughout the day surveyed. It was found that only 5.01% of all persons switch vehicles in the middle of the day. This is most likely due to the inconvenience to driving home to switch vehicles and pursue additional trips. Since this represents a very small portion of the population, it shows that vehicle choice may not be happening at a within a day-level. Therefore, the most appropriate way to undergo this analysis is to conduct a day-level exploration of vehicle type choice and distance traveled.

By analyzing the data at a day-level, conclusions can be drawn from the type of vehicle used throughout the day and characteristics pertaining to the corresponding trips. In households where there is a single vehicle, the choice of the vehicle for trips by driving mode is an obvious one so this is not of interest in the study. However, when the household owns more than one vehicle, households may make a decision on what vehicle to use each day for the different trips. In order to understand the tradeoffs and adjustments in the choice of vehicle type on any given day, the data must be restricted to the persons of interest. To capture a person's preference to a specific vehicle type, they must have the option to use at least two different vehicle type, but only used one throughout the day of analysis. Therefore, restrictions have been established to only consider persons that own two or more vehicle type and drove the same vehicle throughout the entire day. In addition, restrictions have been put in place to only consider adults and drivers to avoid irregular patterns of the counterparts. And finally, since survey questions often provide respondents with the choice to skip a question, a restriction has been incorporated to only consider persons with all valid trips. TABLE 1 shows the total samples that meet each restriction and all five restrictions.

TABLE 1 Sample Data Restrictions

City / Region	Total Persons	Multiple Vehicles Available	Same Vehicle All Day	Adults Only	Drivers Only	All Trips Valid	All Five Restrictions	Percentage Restricted Sample
New York	14,607	6,743	6,601	12,244	11,096	5,221	2,601	17.8%
Los Angeles	14,435	8,233	7,554	12,045	11,127	5,643	3,095	21.4%
Washington	5,562	3,662	2,753	4,531	4,409	2,155	1,320	23.7%
National	308,901	189,557	168,713	263,572	249,882	132,010	76,233	24.7%

Vehicle Characteristics

Once the data has been narrowed down to the sample of interest, it is important to familiarize oneself with the information and characteristics of the data to be able to draw conclusions from the results that were obtained from the models. Households that have at least one person that meets the restricted criteria were identified to be explored in detail. All of these households own at least two vehicles and use at least one, but it is also of interest to identify how many households use all of the vehicles they own and how many use less.

TABLE 2 shows these weighted values and percentages. Interestingly, most households in New York used the full fleet while most households in Los Angeles and Washington used less (more so in Los Angeles). The national data shows slightly more households that use the full fleet of vehicles. Households that used less of than the full fleet of vehicles type available made a choice of what vehicle to use from their fleet. Likewise, they chose not to use other types. That is not to say that households that used the entire fleet didn't make a decision, but this decision may be linked to other factors.

TABLE 2 Vehicle Fleet Usage by Households in NY, LA, DC, and Entire U.S.

City / Region	Less than Full Fleet		Full Fleet	
	Value	Percentage	Value	Percentage
New York	734,846	46.1%	*858,011*	*53.9%*
Los Angeles	948,891	55.4%	*764,830*	*44.6%*
Washington	533,103	52.2%	*487,678*	*47.8%*
National	15,002,881	49.0%	*15,607,135*	*51.0%*

To explore this data at a more disaggregate scale, a comparison can be made between the number of vehicle types a household owns and the number of vehicle types they used. TABLE 3 shows the number of vehicle types owned and used per household, and TABLE 4 shows the corresponding cell percentages with respect to the total value of each region. The italic cells (diagonal) in these tables represent households that used all of the vehicles types they own. The blue cells (below the diagonal) represent households that used less vehicles types than what they have available.

Across all regions, the highest percentage of vehicle types owned is two. Likewise, the highest percentage of vehicles used is two in New York, Los Angeles, and Washington but in the entire United States the highest percentage of people use one (though close to two). Out of the households that own two vehicle types in New York and Washington, more than half used both type. However, in Los Angeles and the national dataset, the majority only used one.

TABLE 3 Vehicle Ownership Vs Usage by Number of Vehicles in NY, LA, DC, & Entire U.S (Total Vehicles)

City	Vehicles Owned	Vehicles Used				Total
		1	2	3	4	
New York	2	614,581	*828,845*	—	—	**1,443,426**
	3	38,364	79,797	*29,166*	—	**147,327**
	4	205	1,851	48	—	**2,104**
	Total	**653,150**	**910,493**	**29,214**	**—**	**1,592,857**
Los Angeles	2	730,913	*709,101*	—	—	**1,440,014**
	3	82,883	122,708	*55,729*	—	**261,320**
	4	1,293	4,708	6,386	—	**12,387**
	Total	**815,089**	**836,517**	**62,115**	**—**	**1,713,721**
Washington	2	429,659	*444,008*	—	—	**873,667**
	3	35,095	65,187	*37,571*	—	**137,853**
	4	623	2,491	48	*6,099*	**9,261**
	Total	**465,377**	**511,686**	**37,619**	**6,099**	**1,020,781**
National Data	2	17,343,917	*15,921,637*	—	—	**33,265,554**
	3	1,896,558	3,142,338	*1,013,139*	—	**6,052,035**
	4	64,470	75,011	48,367	*21,414*	**209,262**
	Total	**19,304,945**	**19,138,986**	**1,061,506**	**21,414**	**39,526,851**

TABLE 4 Vehicle Ownership Vs Usage by Number of Vehicles in NY, LA, DC, & Entire U.S (Percentages)

City	Vehicles Owned	Vehicles Used				Total
		1	2	3	4	
New York	2	38.6%	*52.0%*	—	—	**90.6%**
	3	2.4%	5.0%	*1.8%*	—	**9.2%**
	4	0.0%	0.1%	0.0%	—	**0.1%**
	Total	**41.0%**	**57.2%**	**1.8%**	**—**	**100.0%**
Los Angeles	2	42.7%	*41.4%*	—	—	**84.0%**
	3	4.8%	7.2%	*3.3%*	—	**15.2%**
	4	0.1%	0.3%	0.4%	—	**0.7%**
	Total	**47.6%**	**48.8%**	**3.6%**	**—**	**100.0%**
Washington	2	42.1%	*43.5%*	—	—	**85.6%**
	3	3.4%	6.4%	*3.7%*	—	**13.5%**
	4	0.1%	0.2%	0.0%	*0.6%*	**0.9%**
	Total	**45.6%**	**50.1%**	**3.7%**	**0.6%**	**100.0%**
National Data	2	43.9%	*40.3%*	—	—	**84.2%**
	3	4.8%	7.9%	*2.6%*	—	**15.3%**
	4	0.2%	0.2%	0.1%	*0.1%*	**0.5%**
	Total	**48.8%**	**48.4%**	**2.7%**	**0.1%**	**100.0%**

While these tables provide useful information, they can be disaggregated even further by specifically identifying what combinations of vehicle types are owned and used. TABLE 5 shows a weighted comparison between the vehicles owned and used in each region. A four-digit code is used to indicate the vehicle type composition. Each digit represents a binary value for the availability/use of each vehicle type. A "1" represents that the vehicle type is available/used and a "0" indicates that it is not available/used. The first digit (on the left) represents autos, the second vans, the third SUV, and the fourth (on the right) trucks.

TABLE 6 shows the corresponding cell percentages. The highest cell percentage everywhere is the ownership and usage of auto and SUV in the same household (NY 25.6%, LA 16.5%, and DC 18.4%). The aggregate ownership category was also auto and SUV for all three regions, but the aggregate usage changes. While New York stayed the same, Los Angeles has the highest percentage in households that only used an auto. This means that out of all combinations, only using an auto was the most common. In Washington, only using an auto was the most common, but auto and SUV was a close second (21.4% and 20.0% respectively).

TABLE 7 shows the same information but for the entire national data (the tables were separated due to their large size), and TABLE 8 shows the cell percentages. The highest percentage cell is still auto and SUV. Likewise, the highest owned category is the same, and the highest usage category is auto only. From the italic (full fleet usage) cells, it can be noted that the highest three cells all include auto and the lowest five are households that own three or more vehicle types

TABLE 5 Vehicle Ownership Vs Usage by Fleet Composition in NY, LA, & DC (Total Households)

City	Vehicles Owned	Vehicles Used															Total
		0001	0010	0011	0100	0101	0110	0111	1000	1001	1010	1011	1100	1101	1110	1111	
New York	0011	9,906	26,984	*38,963*	—	—	—	—	—	—	—	—	—	—	—	—	75,853
	0101	754	—	—	5,343	*7,501*	—	—	—	—	—	—	—	—	—	—	13,598
	0110	—	57,462	—	19,791	—	*51,220*	—	—	—	—	—	—	—	—	—	128,473
	0111	143	1,620	313	5,896	33	—	*3,484*	—	—	—	—	—	—	—	—	11,489
	1001	10,931	—	—	—	—	—	—	48,455	*143,708*	—	—	—	—	—	—	203,094
	1010	—	226,692	—	—	—	—	—	110,402	—	*407,578*	—	—	—	—	—	744,672
	1011	2,416	3,866	5,630	—	—	—	—	6,036	13,398	15,950	*10,976*	—	—	—	—	58,272
	1100	—	—	—	56,792	—	—	—	41,070	—	—	—	*179,875*	—	—	—	277,737
	1101	70	—	—	5,163	109	—	—	4,267	9,034	—	—	4,125	*564*	—	—	23,332
	1110	—	1,873	—	3,038	—	14,587	—	3,976	—	12,843	—	3,773	—	*14,141*	—	54,231
	1111	—	60	—	—	1,309	—	—	146	—	384	—	157	—	48	—	2,104
	Total	**24,220**	**318,557**	**44,906**	**96,023**	**8,952**	**65,807**	**3,484**	**214,352**	**166,140**	**436,755**	**10,976**	**187,930**	**564**	**14,189**	**—**	**1,592,855**
Los Angeles	0011	33,786	62,744	*74,753*	—	—	—	—	—	—	—	—	—	—	—	—	171,283
	0101	5,875	—	—	16,224	*33,393*	—	—	—	—	—	—	—	—	—	—	55,492
	0110	—	7,183	—	12,821	—	*22,249*	—	—	—	—	—	—	—	—	—	42,253
	0111	172	2,432	470	751	—	2,333	*2,269*	—	—	—	—	—	—	—	—	8,427
	1001	63,219	—	—	—	—	—	—	135,728	*170,736*	—	—	—	—	—	—	369,683
	1010	—	123,019	—	—	—	—	—	151,817	—	*281,952*	—	—	—	—	—	556,788
	1011	10,013	26,598	31,474	—	—	—	—	14,478	19,917	24,660	*29,196*	—	—	—	—	156,336
	1100	—	—	—	43,850	—	—	—	74,648	—	—	—	*126,017*	—	—	—	244,515
	1101	1,174	—	—	5,886	4,014	—	—	9,123	5,600	—	—	11,757	*15,280*	—	—	52,834
	1110	—	6,840	—	2,219	—	4,713	—	3,197	—	10,344	—	7,425	—	*8,984*	—	43,722
	1111	—	825	1,480	468	—	1,054	—	—	389	—	1,450	1,785	958	3,978	—	12,387
	Total	**114,239**	**229,641**	**108,177**	**82,219**	**37,407**	**30,349**	**2,269**	**388,991**	**196,642**	**316,956**	**30,646**	**146,984**	**16,238**	**12,962**	**—**	**1,713,720**
Washington	0011	24,875	18,756	*31,862*	—	—	—	—	—	—	—	—	—	—	—	—	75,493
	0101	455	—	—	3,972	*10,240*	—	—	—	—	—	—	—	—	—	—	14,667
	0110	—	1,457	—	6,507	—	*13,551*	—	—	—	—	—	—	—	—	—	21,515
	0111	—	741	2,123	85	903	5,991	*85*	—	—	—	—	—	—	—	—	9,928
	1001	47,332	—	—	—	—	—	—	84,714	*96,512*	—	—	—	—	—	—	228,558
	1010	—	98,381	—	—	—	—	—	60,525	—	*187,348*	—	—	—	—	—	346,254
	1011	3,602	8,043	9,481	—	—	—	—	3,426	22,457	3,865	*16,757*	—	—	—	—	67,631
	1100	—	—	—	23,409	—	—	—	59,276	—	—	—	*104,495*	—	—	—	187,180
	1101	520	—	—	—	1,014	—	—	7,934	217	—	—	2,118	*1,111*	—	—	12,914
	1110	—	1,437	—	6,590	—	426	—	2,717	—	12,607	—	3,985	—	*19,618*	—	47,380
	1111	—	127	37	496	—	—	—	—	69	—	—	2,385	—	48	*6,099*	9,261
	Total	**76,784**	**128,942**	**43,503**	**41,059**	**12,157**	**19,968**	**85**	**218,592**	**119,255**	**203,820**	**16,757**	**112,983**	**1,111**	**19,666**	**6,099**	**1,020,781**

TABLE 6 Vehicle Ownership Vs Usage by Fleet Composition in NY, LA, & DC (Percentages)

City	Vehicles Owned	Vehicles Used															Total
		0001	0010	0011	0100	0101	0110	0111	1000	1001	1010	1011	1100	1101	1110	1111	
New York	0011	0.6%	1.7%	*2.4%*	—	—	—	—	—	—	—	—	—	—	—	—	**4.8%**
	0101	0.0%	—	—	0.3%	*0.5%*	—	—	—	—	—	—	—	—	—	—	**0.9%**
	0110	—	3.6%	—	1.2%	—	*3.2%*	—	—	—	—	—	—	—	—	—	**8.1%**
	0111	0.0%	0.1%	0.0%	0.4%	0.0%	—	*0.2%*	—	—	—	—	—	—	—	—	**0.7%**
	1001	0.7%	—	—	—	—	—	—	3.0%	*9.0%*	—	—	—	—	—	—	**12.8%**
	1010	—	14.2%	—	—	—	—	—	6.9%	—	*25.6%*	—	—	—	—	—	**46.8%**
	1011	0.2%	0.2%	0.4%	—	—	—	—	0.4%	0.8%	1.0%	*0.7%*	—	—	—	—	**3.7%**
	1100	—	—	—	3.6%	—	—	—	2.6%	—	—	—	*11.3%*	—	—	—	**17.4%**
	1101	0.0%	—	—	0.3%	0.0%	—	—	0.3%	0.6%	—	—	0.3%	*0.0%*	—	—	**1.5%**
	1110	—	0.1%	—	0.2%	—	0.9%	—	0.2%	—	0.8%	—	0.2%	—	*0.9%*	—	**3.4%**
	1111	—	0.0%	—	—	0.1%	—	—	0.0%	—	0.0%	—	0.0%	—	0.0%	—	**0.1%**
	Total	**1.5%**	**20.0%**	**2.8%**	**6.0%**	**0.6%**	**4.1%**	**0.2%**	**13.5%**	**10.4%**	**27.4%**	**0.7%**	**11.8%**	**0.0%**	**0.9%**	**—**	**100.0%**
Los Angeles	0011	2.0%	3.7%	*4.4%*	—	—	—	—	—	—	—	—	—	—	—	—	**10.0%**
	0101	0.3%	—	—	0.9%	*1.9%*	—	—	—	—	—	—	—	—	—	—	**3.2%**
	0110	—	0.4%	—	0.7%	—	*1.3%*	—	—	—	—	—	—	—	—	—	**2.5%**
	0111	0.0%	0.1%	0.0%	0.0%	—	0.1%	*0.1%*	—	—	—	—	—	—	—	—	**0.5%**
	1001	3.7%	—	—	—	—	—	—	7.9%	*10.0%*	—	—	—	—	—	—	**21.6%**
	1010	—	7.2%	—	—	—	—	—	8.9%	—	*16.5%*	—	—	—	—	—	**32.5%**
	1011	0.6%	1.6%	1.8%	—	—	—	—	0.8%	1.2%	1.4%	*1.7%*	—	—	—	—	**9.1%**
	1100	—	—	—	2.6%	—	—	—	4.4%	—	—	—	*7.4%*	—	—	—	**14.3%**
	1101	0.1%	—	—	0.3%	0.2%	—	—	0.5%	0.3%	—	—	0.7%	*0.9%*	—	—	**3.1%**
	1110	—	0.4%	—	0.1%	—	0.3%	—	0.2%	—	0.6%	—	0.4%	—	*0.5%*	—	**2.6%**
	1111	—	0.0%	0.1%	0.0%	—	0.1%	—	—	0.0%	—	0.1%	0.1%	0.1%	0.2%	—	**0.7%**
	Total	**6.7%**	**13.4%**	**6.3%**	**4.8%**	**2.2%**	**1.8%**	**0.1%**	**22.7%**	**11.5%**	**18.5%**	**1.8%**	**8.6%**	**0.9%**	**0.8%**	**—**	**100.0%**
Washington	0011	2.4%	1.8%	*3.1%*	—	—	—	—	—	—	—	—	—	—	—	—	**7.4%**
	0101	0.0%	—	—	0.4%	*1.0%*	—	—	—	—	—	—	—	—	—	—	**1.4%**
	0110	—	0.1%	—	0.6%	—	*1.3%*	—	—	—	—	—	—	—	—	—	**2.1%**
	0111	—	0.1%	0.2%	0.0%	0.1%	0.6%	*0.0%*	—	—	—	—	—	—	—	—	**1.0%**
	1001	4.6%	—	—	—	—	—	—	8.3%	*9.5%*	—	—	—	—	—	—	**22.4%**
	1010	—	9.6%	—	—	—	—	—	5.9%	—	*18.4%*	—	—	—	—	—	**33.9%**
	1011	0.4%	0.8%	0.9%	—	—	—	—	0.3%	2.2%	0.4%	*1.6%*	—	—	—	—	**6.6%**
	1100	—	—	—	2.3%	—	—	—	5.8%	—	—	—	*10.2%*	—	—	—	**18.3%**
	1101	0.1%	—	—	—	0.1%	—	—	0.8%	0.0%	—	—	0.2%	*0.1%*	—	—	**1.3%**
	1110	—	0.1%	—	0.6%	—	0.0%	—	0.3%	—	1.2%	—	0.4%	—	*1.9%*	—	**4.6%**
	1111	—	0.0%	0.0%	0.0%	—	—	—	—	0.0%	—	—	0.2%	—	0.0%	*0.6%*	**0.9%**
	Total	**7.5%**	**12.6%**	**4.3%**	**4.0%**	**1.2%**	**2.0%**	**0.0%**	**21.4%**	**11.7%**	**20.0%**	**1.6%**	**11.1%**	**0.1%**	**1.9%**	**0.6%**	**100.0%**

TABLE 7 Vehicle Ownership Vs Usage by Fleet Composition with National Data (Total Households)

City	Vehicles Owned	Vehicles Used															Total
		0001	**0010**	**0011**	**0100**	**0101**	**0110**	**0111**	**1000**	**1001**	**1010**	**1011**	**1100**	**1101**	**1110**	**1111**	
Total	**0011**	820,981	1,659,435	*2,376,647*	—	—	—	—	—	—	—	—	—	—	—	—	**4,857,063**
	0101	252,025	—	—	541,048	*680,816*	—	—	—	—	—	—	—	—	—	—	**1,473,889**
	0110	—	362,212	—	284,426	—	*634,576*	—	—	—	—	—	—	—	—	—	**1,281,214**
	0111	24,671	77,053	31,405	54,554	40,079	66,305	*28,126*	—	—	—	—	—	—	—	—	**322,193**
	1001	1,805,757	—	—	—	—	—	—	4,473,086	*4,190,461*	—	—	—	—	—	—	**10,469,304**
	1010	—	2,650,389	—	—	—	—	—	2,469,307	—	*5,375,691*	—	—	—	—	—	**10,495,387**
	1011	240,150	460,188	531,615	—	—	—	—	413,405	436,459	920,490	*560,444*	—	—	—	—	**3,562,751**
	1100	—	—	—	945,012	—	—	—	1,080,241	—	—	—	*2,663,444*	—	—	—	**4,688,697**
	1101	69,944	—	—	182,703	203,315	—	—	179,123	202,251	—	—	314,263	*202,594*	—	—	**1,354,193**
	1110	—	79,266	—	58,549	—	75,605	—	56,952	—	181,544	—	139,005	—	*221,974*	—	**812,895**
	1111	2,710	18,332	5,516	13,994	8,642	17,559	13,149	29,436	7,674	6,300	15,876	29,320	8,113	11,229	*21,414*	**209,264**
	Total	**3,216,238**	**5,306,875**	**2,945,183**	**2,080,286**	**932,852**	**794,045**	**41,275**	**8,701,550**	**4,836,845**	**6,484,025**	**576,320**	**3,146,032**	**210,707**	**233,203**	**21,414**	**39,526,850**

TABLE 8 Vehicle Ownership Vs Usage by Fleet Composition with National Data (Percentages)

City	Vehicles Owned	Vehicles Used															Total
		0001	**0010**	**0011**	**0100**	**0101**	**0110**	**0111**	**1000**	**1001**	**1010**	**1011**	**1100**	**1101**	**1110**	**1111**	
Total	**0011**	2.1%	4.2%	*6.0%*	—	—	—	—	—	—	—	—	—	—	—	—	**12.3%**
	0101	0.6%	—	—	1.4%	*1.7%*	—	—	—	—	—	—	—	—	—	—	**3.7%**
	0110	—	0.9%	—	0.7%	—	*1.6%*	—	—	—	—	—	—	—	—	—	**3.2%**
	0111	0.1%	0.2%	0.1%	0.1%	0.1%	0.2%	*0.1%*	—	—	—	—	—	—	—	—	**0.8%**
	1001	4.6%	—	—	—	—	—	—	11.3%	*10.6%*	—	—	—	—	—	—	**26.5%**
	1010	—	6.7%	—	—	—	—	—	6.2%	—	*13.6%*	—	—	—	—	—	**26.6%**
	1011	0.6%	1.2%	1.3%	—	—	—	—	1.0%	1.1%	2.3%	*1.4%*	—	—	—	—	**9.0%**
	1100	—	—	—	2.4%	—	—	—	2.7%	—	—	—	*6.7%*	—	—	—	**11.9%**
	1101	0.2%	—	—	0.5%	0.5%	—	—	0.5%	0.5%	—	—	0.8%	*0.5%*	—	—	**3.4%**
	1110	—	0.2%	—	0.1%	—	0.2%	—	0.1%	—	0.5%	—	0.4%	—	*0.6%*	—	**2.1%**
	1111	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	*0.1%*	**0.5%**
	Total	**8.1%**	**13.4%**	**7.5%**	**5.3%**	**2.4%**	**2.0%**	**0.1%**	**22.0%**	**12.2%**	**16.4%**	**1.5%**	**8.0%**	**0.5%**	**0.6%**	**0.1%**	**100.0%**

In addition to the choice of vehicle type, it is also important to explore the utilization of different vehicles on any given day. TABLE 9 shows the total trips by each vehicle type in each region and TABLE 10 shows the corresponding percentages. In all three regions, the greatest ownership corresponds to autos and the second, SUVs. New York has more vans than trucks, but Los Angeles and Washington have more trucks than Vans. TABLE 11 shows the trips rates per vehicle type. New York has the lowest auto trips rates and the highest SUV and Van trip rates. On the other hand, Los Angeles has the highest auto and truck rates but is tied with Washington for the lowest Van and SUV rates.

TABLE 12 shows the total day distance by vehicle type in each region. The average day and trip distances were calculated; TABLE 13 and TABLE 14 show the results respectively. Washington had the highest average auto and truck day distance, but the lowest van day distance. New York had the highest SUV day distance and Los Angeles had the highest van trip distance.

TABLE 9 Total Trips by Vehicle Type in NY, LA, & DC

City	Auto	Van	SUV	Truck	Total
New York	1,878,261	4,722,575	1,072,189	13,085,081	100.0%
Los Angeles	1,797,517	3,960,819	2,175,432	14,758,911	100.0%
Washington	889,624	2,020,263	985,495	6,849,182	100.0%

TABLE 10 Trip Distribution by Vehicle Type in NY, LA, & DC (Percentage)

City	Auto	Van	SUV	Truck	Total
New York	41.4%	14.4%	36.1%	8.2%	100.0%
Los Angeles	46.2%	12.2%	26.8%	14.7%	100.0%
Washington	43.1%	13.0%	29.5%	14.4%	100.0%

TABLE 11 Trip Rate by Vehicle Type in NY, LA, & DC (Trips/Person)

City	Auto	Van	SUV	Truck	Total
New York	1.7	0.6	1.5	0.3	4.1
Los Angeles	1.9	0.5	1.1	0.6	4.0
Washington	1.6	0.5	1.1	0.5	3.7

Trip Rate = Total Trips/Population

TABLE 12 Total Day Distance by Vehicle Type in NY, LA, & DC

City	Auto	Van	SUV	Truck	Total
New York	55,784,132	16,214,066	46,894,620	14,638,525	133,531,343
Los Angeles	64,796,615	17,119,881	37,883,489	26,430,231	146,230,217
Washington	53,425,450	8,039,579	21,514,483	15,734,798	98,714,310

TABLE 13 Average Day Distance by Vehicle Type in NY, LA, & DC (Miles)

City	Auto	Van	SUV	Truck	Total
New York	17.3	5.0	14.6	4.5	41.5
Los Angeles	17.7	4.7	10.4	7.2	40.0
Washington	29.0	4.4	11.7	8.5	53.5

Average Day Distance = Total Day Distance / Population

TABLE 14 Average Trip Distance by Vehicle Type (Miles)

City	Auto	Van	SUV	Truck	Total
New York	10.3	8.6	9.9	13.7	10.2
Los Angeles	9.5	9.5	9.6	12.1	9.9
Washington	18.1	9.0	10.6	16.0	14.4

Average Trip Distance = Total Day Distance / Total Trips

Household Characteristics

The differences in household characteristics between the three regions can provide insight that may explain different results obtain across the different regions. TABLE 15 summarizes five different characteristics. Household size is different between the three regions; Los Angeles has the largest households and Washington the smallest households. Los Angeles has the largest number of drivers and New York has least. New York has the most workers per household and Los Angeles has the least, although very close to Washington. Finally, the number of children and elderly were compared. These are important because they represent persons that are dependent. The number of children is very similar in all three regions, but New York has slightly less. Los Angeles has the largest number of elderly and Washington the least. Adding the two variables together, New York has the least number of dependent members per household and Los Angeles has the most.

Another important household characteristic to consider is income. Much of the literature has compared vehicle usage to household income (Cirillo & Liu 2013, Golob et al 1995, De Jong 2006) thus it is important to do so in this exploration. NHTS data provides income data by intervals of \$10,000 a year. In order to capture the income distribution among the population, quartiles have been used. The range, in which each quartile lands, is demonstrated in TABLE 16. The third quartile (75th Percentile, P75) is the same for all three regions with a value of over \$100,000. The median (50th Percentile, P50) is the same for New York and Washington, but Los Angeles is lower. And finally the first quartile (25th Percentile) is the lowest in Los Angeles and the highest in New York. Overall, this shows that New York City has the highest overall household income, and Los Angeles has the lowest.

TABLE 15 Household Characteristics in NY, LA, & DC (Average Persons)

Vehicle Fleet Usage			Household Characteristics				
City	Less Than Full Fleet	Full Fleet	HHSIZE	Drivers	Workers	Children	Elderly
New York	46.1%	53.9%	3.31	2.31	1.65	0.6	0.24
Los Angeles	55.4%	44.6%	3.49	2.43	1.58	0.64	0.27
Washington	52.2%	47.8%	3.22	2.36	1.59	0.64	0.22

TABLE 16 Household Income in NY, LA, & DC (\$1,000)

Vehicle Fleet Usage			Income (\$1,000's)		
City	Less Than Full Fleet	Full Fleet	P25	P50	P75
New York	46.1%	53.9%	55 - 60	80 - 100	Over 100
Los Angeles	55.4%	44.6%	35 - 40	65 - 70	Over 100
Washington	52.2%	47.8%	45 - 50	80 - 100	Over 100

Person Characteristics

Person attributes should also be examined to get a good sense for the data. TABLE 17 shows what percentage of the sample are male, educated, and workers. It also shows the age mean, the age median, and the age distribution into five different age groups. There are more males than females across all regions, the most educated region is Los Angeles, and New York has the most workers. The age mean and median are similar across all regions but New York has the eldest average population. From the distribution, it can be seen that Los Angles has the most people that are 18-25 years old, Washington the most 26-39 year-olds, Los Angeles the most 40-54 year-olds, New York the most 55-64 year-olds, and Washington the most people that are over 65 years-old.

TABLE 18 shows the employment characteristics out of people that are workers. There is information about occupation type, part-time positions, flexibility with work schedule and location, and people that have multiple jobs. Los Angeles has the most people in sales or service position. Washington has the most in clerical, and admin support positions. Los Angeles has the most manufacturing, construction, maintenance, and farming positions. And has the most professional, managerial, and technical positions. In addition Los Angeles has the most part-time jobs. Washington the most persons employed with flexible work schedules and Los Angeles the most without a fixed work location. And finally, the percentage of persons with multiple jobs was even across the regions.

TABLE 17 Person Characteristics in NY, LA, DC, and All Regions

City	Males	Educated	Workers	Age Mean	Age Median	18-25	26-39	40-54	55-64	Over 65
New York	51.3%	46.4%	79.6%	43.9	43.0	13.3%	24.6%	36.0%	19.1%	6.9%
Los Angeles	54.4%	30.7%	75.8%	41.8	42.0	19.4%	23.6%	36.9%	12.9%	7.2%
Washington	51.6%	43.0%	74.7%	43.0	41.0	15.8%	28.5%	33.5%	12.4%	9.8%
National	52.7%	39.1%	76.9%	42.8	42.0	16.4%	25.0%	35.9%	15.1%	7.7%

TABLE 18 Person Employment Characteristics in NY, LA, DC, and All Regions

City	Sales, Service	Clerical, Admin Support	Manufacturing, Construction, Maintenance, Farming	Professional, Managerial, Technical	Part-time	Flexible Work Schedule	No Fixed Work Place	Multiple Jobs
New York	31.5%	9.3%	12.7%	45.7%	18.8%	34.0%	2.4%	9.3%
Los Angeles	31.7%	11.9%	18.3%	36.4%	23.1%	33.4%	2.5%	9.4%
Washington	20.1%	14.3%	14.3%	51.0%	18.7%	52.3%	1.3%	9.4%
National	29.3%	11.4%	15.3%	43.0%	20.5%	37.6%	2.2%	9.4%

Trip Characteristics

Next, trip characteristics relating to the purpose of a trip were analyzed. Eight different trip purposes were considered.

- Home: Any trip whose destination was home
- Work: Trips whose purpose was work-related including work meeting and trips.
- School: Any trip related to school or religious activity.
- Maintenance: This includes personal obligations, personal services, pet care, shopping, errands, buying goods and services, and meals.
- Discretionary: Any optional activity including any social and recreational event.
- Pick-Up: Picking someone up.
- Drop-off: Dropping someone off.
- Other: Any trip that did not fall in any of the previous categories.

TABLE 19 shows the total number of trips by purpose, and TABLE 20 shows the corresponding distribution. The distribution makes logical sense. Home has the highest percentage since everyone that travels goes home at least once a day. Maintenance is second because it includes meals, one of the most common activities, and trips whose destination is work are third. Within each category, New York has the most maintenance and discretionary trips, Los Angeles has the most home trips, and Washington had the most work and school trips. The aggregate of pick-up and drop-off trips is consistent with the number of dependent members in a household. Los Angeles has the largest number of dependents and the largest number of pick-up/drop-off trips. Likewise, New York has the least of both.

TABLE 21 expresses the average trip rate by purpose in each region obtained by dividing the total number of trips by the weighted population of the region. Los Angeles had the highest home trip rates followed by New York. New York had the lowest work trip but the highest maintenance and discretionary trip rates which is consistent with the distribution percentages. The highest total trip rates were seen in New York and the lowest in Washington.

TABLE 22 shows the total day distance by purpose. To better evaluate the data, TABLE 23 and TABLE 24 show the average day distance per person and the average trip distance, respectively. In both, the region with greatest total distance is Washington. People in New York drive the longest day distance for discretionary activities, but Washington still holds the longest discretionary trip distance. This suggests that people in New York have more discretionary trips, which is exactly what was observed in the trip distribution and trip rate. A similar observation can be made between New York and Los Angeles's maintenance trips. People in New York travel a longer day distance but a shorter trip distance suggesting more trips which is consistent with the trips distribution and trip rates. All of these observations regarding vehicle fleet composition and usage present evidence to the importance of the short-term vehicle choices. Further, the exploratory analysis provides evidence to differences in the vehicle choices across regions. The exploratory analysis also provides evidence of the relationship between vehicle choices and a variety of attributes including household- and person-demographics, and daily activity-travel engagement patterns.

TABLE 19 Total Trips by Purpose in NY, LA, & DC

City	Home	Work	School	Maintenance	Discretionary	Pick-up	Drop-off	Other	Total
New York	4,380,430	1,758,697	294,322	3,380,446	1,402,200	493,634	624,541	750,810	13,085,081
Los Angeles	5,303,051	2,220,699	527,892	3,299,764	1,274,826	644,012	788,766	699,901	14,758,911
Washington	2,386,632	1,127,999	270,489	1,577,890	533,829	221,839	336,949	393,554	6,849,182

TABLE 20 Trip Distribution by Purpose in NY, LA, & DC (Percentage)

City	Home	Work	School	Maintenance	Discretionary	Pick-up	Drop-off	Other	Total
New York	33.5%	13.4%	2.2%	25.8%	10.7%	3.8%	4.8%	5.7%	100.0%
Los Angeles	35.9%	15.0%	3.6%	22.4%	8.6%	4.4%	5.3%	4.7%	100.0%
Washington	34.8%	16.5%	3.9%	23.0%	7.8%	3.2%	4.9%	5.7%	100.0%

TABLE 21 Trip Rate by Purpose in NY, LA, & DC (Trips/Person)

City	Home	Work	School	Maintenance	Discretionary	Pick-up	Drop-off	Other	Total
New York	1.4	0.5	0.1	1.1	0.4	0.2	0.2	0.2	4.1
Los Angeles	1.5	0.6	0.1	0.9	0.3	0.2	0.2	0.2	4.0
Washington	1.3	0.6	0.1	0.9	0.3	0.1	0.2	0.2	3.7

Trip Rate = Total Trips/Population

TABLE 22 Total Day Distance by Purpose in NY, LA, & DC (Miles)

City	Home	Work	School	Maintenance	Discretionary	Pick-up	Drop-off	Other	Total
New York	42,862,734	23,575,327	2,618,451	18,235,834	22,590,055	2,732,150	8,954,244	11,962,547	133,531,343
Los Angeles	52,198,034	29,548,477	5,541,303	18,465,363	16,834,755	3,961,761	5,258,705	14,421,819	146,230,217
Washington	31,624,929	18,758,552	3,554,317	12,091,866	10,239,515	2,037,026	2,172,359	18,235,746	98,714,310

TABLE 23 Average Day Distance by Purpose in NY, LA, & DC (Miles)

City	Home	Work	School	Maintenance	Discretionary	Pick-up	Drop-off	Other	Total
New York	13.3	7.3	0.8	5.7	7.0	0.8	2.8	3.7	41.5
Los Angeles	14.3	8.1	1.5	5.1	4.6	1.1	1.4	3.9	40.0
Washington	17.1	10.2	1.9	6.6	5.5	1.1	1.2	9.9	53.5

Average Day Distance = Total Day Distance / Population

TABLE 24 Average Trip Distance by Purpose in NY, LA, & DC (Miles)

City	Home	Work	School	Maintenance	Discretionary	Pick-up	Drop-off	Other	Total
New York	9.8	13.4	8.9	5.4	16.1	5.5	14.3	15.9	10.2
Los Angeles	9.8	13.3	10.5	5.6	13.2	6.2	6.7	20.6	9.9
Washington	13.3	16.6	13.1	7.7	19.2	9.2	6.4	46.3	14.4

Average Trip Distance = Total Day Distance / Total Trips

C) Methodology

In understanding the short-term vehicle choices, there are two dimensions of interest that were modeled: distance and vehicle type choice. Distance is a continuous variable and was modeled using a linear regression modeling framework. Vehicle type choice is a discrete variable and was modeled following a multinomial logit model. A brief overview of the two model formulations for distance and vehicle type choices are presented below:

Linear Regression Model

Let x_1, x_2, …, x_k,… x_K be a set of K explanatory (independent) variables that were used to explain the dependent variable y. The linear regression model takes the form,

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots \beta_k x_k + \cdots + \beta_K x_K + \varepsilon \quad (1)$$

where,

ε is a random error term and

β_k is the coefficient associated with x_k; there are a total of K such coefficients corresponding to each of the K independent variables (k = 1, 2, …, k, …, K)

β_0 is a constant

The coefficients (β) are estimated by minimizing the sum of squared errors (SSE). The distance models employing the linear regression model formulation were estimated using SPSS package (SPSS 2014). In these models, y represents the distance in miles.

Multinomial Logit Model

Let q be the index for the individual and t denote the index for the discrete alternatives (t = 1, 2, … T). The utility associated with selecting alternative t (U_t) can be expressed as,

$$U_t = V_t + \varepsilon_t \quad (2)$$

where,

ε_t is a random error term

V_t represents the systematic component of the utility

Further, the systematic utility is assumed to be linear in parameters as,

$$V_t = \beta_{t0} + \beta_{t1}x_{t1} + \beta_{t2}\beta_{t2} + \cdots \beta_{tk}x_{tk} \ldots + \beta_{tK}x_{tK} \quad (3)$$

Where,

x_{tk} represents the explanatory variables used to explain the utility for alternative t

β_{tk} is the coefficient associated with explanatory variable x_{tk}

β_{t0} is the constant associated with the alternative t

Assuming that the ε_t are Gumbel distributed, the probability that alternative t is selected is given as,

$$P_t = \frac{e^{V_t}}{\sum_{i=0}^{T} e^{V_i}} \quad (3)$$

The coefficients (β) are estimated by maximizing the log-likelihood approach. The vehicle type choice models employing the multinomial logit modeling framework were estimated using Biogeme software (Biogeme 2013).

D) Model Estimation Results

Models of vehicle type choice and distance were estimated to explore the short-term vehicle choices. In an effort to explore the interdependencies between the two vehicle choice dimensions, two sets of models were estimated. In the first set of models, distance was modeled first, and vehicle type choice was modeled after with the distance variable as an explanatory variable. In the second set of models, vehicle type choice was modeled first, and distance modeled next with vehicle type choice as an explanatory variable. Lastly, the above two sets of models were estimated to explore the differences in the short-term vehicle usage decisions across the three regions including New York, Los Angeles, Washington DC, using data for the three regions. Also, a set of models were estimated using a pooled sample. In the pooled sample, records from the three regions were combined to estimate a single model while also teasing out the differing effects across the three regions.

Distance Affecting Vehicle Type Choice: Distance Model

TABLE 25 and TABLE 26 show the linear regression results for the interdependency in which distance affects vehicle type choice. Each row represents a different variable with the given variable name, description, and results. One model was done for each region: New York, Los Angeles, Washington, and a pooled dataset of all three regions together. All four models are showed in these tables and for each model the coefficient value, standard error, and t-value are displayed. What is most important to note in these models is the common trends and differences that can be observed in the coefficient values.

Five variables were consistent throughout the four models. The gender variable shows a positive relationship with distance across all regions indicating that males drive more than females, a trend that has been observed previously in the literature (Golob et al 1995). The youngest age group (AGE01), 18-25, showed a negative relationship with distance across all regions contradicting what has been observed in previous studies (Golob et al 1995). The urban indicator variable (URBAN), which specifies that a person lives in an urban area, showed a negative relationship with distance across all modes as well. A household is indicated to be in an urban area in NHTS if it is located in a census block that is defined as urban according to the census. The census has two definitions for urban areas: urbanized areas and urban clusters. Urbanized areas are defined as a continuous built-up area with a population of 50,000 or more, and urban clusters are designated as areas of 2,500 people but less than 50,000 (US Census Bereau). This can be related to much literature that has explored land-use characteristics and the corresponding impact on vehicle usage. Many projects have indicated that higher density reduces VMT (Brownstone & Golob 2009, Kim & Brownstone 2010), while others have concluded that density alone does not reduce mileage but when combined with other parameters such as higher travel costs, increased transit availability, or more pedestrian-friendly urban form, VMT decreases (Cirillo & Liu 2013, Fang 2008, Brownstone & Fang 2010). Since these factors can be represented by the urban variable, the trends noted are consistent with previous observations. Also, the number of drivers in a household (DRVRCNT) showed a negative relationship with distance throughout the four models, and the presence of a school trip (SCHOOL_IND) showed a positive relationship with distance in all regions.

Other age group variables showed different relationships across regions. The 26-39 age group (AGE02) showed a positive relationship with distance in New York and Los Angeles but a negative one in Washington and the pooled dataset. The 40-54 age group (AGE03) showed a positive relationship with Los Angeles and the pooled dataset while showing a negative relationship with Washington. The 55-64 age group (AGE04) only showed a positive relationship with New York. And lastly, persons over 65 years of age (AGE05) showed a negative relationship with distance across the three cities. This is in accordance with a study which previously noted that retired persons drive less (Golob 1995).

The different income level analyzed showed different relationships across the regions. The lowest level (INC01), less than $50,000 showed a negative relationship with distance in the three cities. Likewise, the second income level (INC02), $50,000-$75,000, showed a negative relationship in Los Angeles, Washington, and the pooled dataset. The third level (INC03), $75,000-$100,000, showed a negative relationship in New York and Los Angeles, but a positive one in Washington and the pooled dataset. The highest income level (INC04), more than $100,000, did not show a significant relationship with distance in the models. The change in sign in Washington and the pooled dataset with the higher income may suggest that higher income is associated with more driving. This would be consistent with much literature that analyzed income and vehicle usage (Golob et al 1995, Cirillo & Liu 2013, De Jong 2006).

Other household characteristics were significant across the regions and showed differences in their relationship with distance. The household size (HHSIZE) showed a negative relationship in New York and Los Angeles suggesting that persons that live in bigger households travel less distance. The number of workers in a household (WRKCOUNT) had a negative relationship in Washington, but a positive one in New York and Los Angeles.

A variable indicating whether a person is a worker (WORKER) showed a positive relationship with distance in Los Angeles. More specific employment variables showed significant differences across regions. Persons that are self-employed (SELF-EMP) showed a positive relationship in New York, Los Angeles, and the pooled dataset but a negative one in Washington. Persons with flexible work schedules (FLEXTIME) had a positive relationship with distance in Los Angeles and Washington while persons without a fixed work location (NOFXDWK) showed a positive relationship in Los Angeles but a negative one in New York, Washington and the pooled dataset. In Los Angeles and Washington, people with multiple jobs (MULTJOBS) had a positive relationship with distance, but those with part-time jobs (PARTTIME) had a negative relationship along with the pooled dataset while New York's part-time workers had a positive relationship. In terms of occupation, people in positions relating to sales or service, clerical or administrative support, manufacturing, construction, maintenance, and farming had a negative relationship with distance in Washington but a positive one in New York and Los Angeles. The pooled dataset had different values for different occupations.

The presence of other purpose-specific trips also showed different relationship across the regions. The presence of a home trip (HOME) had a negative relationship in New York and Los Angeles while the presence of a work trip (WORK) was negative in Los Angeles and Washington but positive in the pooled dataset. The presence of maintenance trips (MAINT) was positive in New York and negative in Washington and the pooled dataset while discretionary trips (DISC) had a positive relationship in all three. Pickup trips (PICKUP) were positive in Los Angeles and negative in New York, Washington, and the pooled dataset, but drop-off trips (DROPOFF) were positive in the three cities.

In addition, weekday trips (WEEKDAY) had a negative relationship with distance in New York. Higher educated persons (DEGREE), with at least a Bachelor's Degree, had a negative relationship with distance in Los Angeles. And finally the age of the vehicle was considered. Newer vehicle (VEHAGE01), 0-5 years-old, had a positive relationship in New York and the pooled dataset but negative in Washington. Some literature has found newer vehicles to be driven more (Golob et al 1995). Vehicle 5-10 years-old (VEHAGE02) were positive in New York and the pooled dataset but negative in Los Angeles, and vehicle 10-15 years-old were negative in New York, Los Angeles, and the pooled dataset.

The pooled dataset included three more variables to account for each of the cities. Both, the New York indicator variable (NY_IND) and the Los Angeles indicator variable (LA_IND), showed a negative relationship with distance. Given that both variables were significant, the Washington indicator variable (DC_IND) was not included to serve as a base variable.

In addition to the four models described, a fifth model was estimated using the pooled dataset. The results are shown in TABLE 27. In contrast to the previous pooled dataset model, this one does not include the city indicator variable, but instead cross-variables were tested to see how these variables compare across regions within the same model. For example, the MALE_NY variable refers to males in New York. Since the regular MALE variable has a coefficient value of 23.88 and the MALE_NY variable has a value of -19.43, an observation can be made that males have a positive relationship with distance in New York, but it is less than the average of the three regions.

In accordance with the variables that encompass all three regions, New York had six cross-variables, Los Angles had five, and Washington had four. These were all consistent with the signage of the relationship that was observed in the average of all three cities (like gender in New York). Some cross-variables were significant even though the general variable was not; each region had three of these. And finally some cross-variables had opposite relationships when compared to the general variable.

There were five variables that had opposite relationships. In New York, persons employed in clerical or administrative support positions show a negative relationship with distance while the average shows a positive relationship. In Los Angeles, the 26-39 age group and persons without a fixed work location show a positive relationship while the average is positive. And in Washington, the 26-39 age group and the presence of a maintenance trip had a positive relationship while the average was negative. These variables are the ones that undoubtedly show that there are differences across the regions in the distance model.

TABLE 25 Linear Regression Model - Distance Affects Vehicle Type 1

Variable	Description	New York			Los Angeles			Washington			Pooled Dataset		
		β	Std. Err.	t	β	Std. Err.	t	β	Std. Err.	t	β	Std. Err.	t
(Constant)		78.59	0.24	327.28	85.99	0.21	417.68	89.08	0.28	321.62	53.24	0.12	448.26
GENDER	Male	10.28	0.07	156.86	4.84	0.05	90.20	16.16	0.10	166.37	9.79	0.04	249.87
AGE	Continuous Variable	—	—	—	—	—	—	—	—	—	—	—	—
AGE01	18 -25	-7.53	0.11	-66.80	-3.57	0.10	-36.99	-17.86	0.19	-92.09	-9.58	0.07	-142.44
AGE02	26-39	8.49	0.08	103.89	2.65	0.09	29.58	-19.73	0.15	-127.32	-0.84	0.05	-15.62
AGE03	40-54	—	—	—	4.58	0.08	55.83	-10.45	0.15	-69.51	0.71	0.05	14.46
AGE04	55-64	5.57	0.09	59.89	—	—	—	—	—	—	—	—	—
AGE05	Over 65	-3.13	0.13	-23.66	-2.65	0.12	-22.52	-8.11	0.20	-40.24	—	—	—
WORKER	Person is a Worker	—	—	—	5.13	0.10	53.61	—	—	—	—	—	—
INC01	<= $50k	-6.43	0.09	-70.51	-3.51	0.07	-52.68	-8.51	0.13	-66.59	—	—	—
INC02	$50k < and <= $75k	—	—	—	-4.28	0.07	-57.08	-19.93	0.15	-135.77	-7.02	0.05	-136.30
INC03	$75k < and <= $100K	-8.16	0.08	-99.38	-4.95	0.07	-67.02	15.98	0.13	126.04	1.38	0.05	27.92
INC04	Over $100k	—	—	—	—	—	—	—	—	—	—	—	—
URBAN	Urban Area	-17.53	0.09	-184.69	-14.26	0.12	-123.81	-11.25	0.11	-103.47	-11.04	0.06	-185.01
HHSIZE	No. of People in HH	-3.24	0.03	-104.15	-0.28	0.02	-12.58	—	—	—	—	—	—
WRKCOUNT	No. of Workers in HH	3.80	0.05	80.89	3.69	0.04	96.66	-4.39	0.07	-58.62	—	—	—
DRVRCNT	No. of Drivers in HH	-1.27	0.06	-22.71	-1.64	0.04	-40.83	-7.87	0.07	-113.24	-2.74	0.02	-119.65
NUMADLT	No. of Adults in HH	—	—	—	—	—	—	—	—	—	—	—	—
SELF_EMP	Person is Self-Employed	10.90	0.11	101.52	4.24	0.09	49.68	-2.74	0.18	-15.03	4.09	0.06	63.34
HOME_IND	Presence of a Home Trip	-29.66	0.12	-247.42	-37.77	0.13	-284.11	—	—	—	—	—	—
WORK_IND	Presence of a Work Trip	—	—	—	-0.25	0.06	-4.29	-4.25	0.12	-36.64	7.33	0.04	176.07
SCHOOL_IND	Presence of a School Trip	9.68	0.12	83.12	0.77	0.08	9.90	5.84	0.15	39.10	5.18	0.06	84.44
MAINT_IND	Presence of a Maintenance Trip	1.50	0.06	23.96	—	—	—	-3.38	0.09	-35.91	-0.16	0.04	-4.14
DISC_IND	Presence of a Discretionary Trip	11.72	0.07	166.71	—	—	—	7.12	0.11	63.87	16.67	0.04	397.14
PICKUP_IND	Presence of a Pick-Up Trip	-12.12	0.11	-110.13	5.54	0.08	65.79	-6.58	0.16	-42.37	-0.55	0.05	-10.15
DROPOFF_IND	Presence of a Drop-Off Trip	24.65	0.10	246.36	2.78	0.08	35.14	9.01	0.13	69.99	—	—	—

TABLE 26 Linear Regression Model - Distance Affects Vehicle Type 2

Variable	Description	New York			Los Angeles			Washington			Pooled Dataset		
		β	Std. Err.	t	β	Std. Err.	t	β	Std. Err.	t	β	Std. Err.	t
WEEKDAY	Travel Day is a Weekday	-20.34	0.07	-286.40	—	—	—	—	—	—	—	—	—
TOTAL_TRIPS	Total No. of Trips During Day	—	—	—	—	—	—	—	—	—	—	—	—
DEGREE	Person has at least a Bachelor's Degree	—	—	—	-2.63	0.06	-43.50	—	—	—	—	—	—
FLEXTIME	Flexible Work Schedule	—	—	—	4.10	0.06	66.99	10.27	0.11	93.87	—	—	—
NOFXDWK	No Fixed Work Place	-38.84	0.24	-160.59	15.80	0.18	87.77	-6.92	0.46	-15.04	-0.98	0.14	-6.90
MULTJOBS	Person has Multiple Jobs	—	—	—	7.19	0.10	73.92	3.14	0.18	17.30	—	—	—
PARTTIME	Part Time Job	5.21	0.09	55.12	-2.09	0.08	-27.66	-6.00	0.14	-42.22	2.61	0.05	47.54
OCCUP01	Sales / Service	-6.14	0.08	-77.57	-6.82	0.07	-92.39	4.72	0.14	34.09	-4.54	0.05	-92.51
OCCUP02	Clerical / Admin Support	-17.15	0.12	-141.04	-3.72	0.10	-37.69	17.62	0.16	111.66	1.29	0.07	18.80
OCCUP03	Manuf/Construct/Maintenance/Farming	-6.76	0.11	-59.85	-7.02	0.09	-80.06	8.57	0.18	46.94	-4.03	0.06	-64.23
OCCUP04	Professional/Managerial/Technical	—	—	—	—	—	—	—	—	—	—	—	—
NUMONTRP	Average No. of People on Trips	—	—	—	—	—	—	—	—	—	—	—	—
VEHAGE01	Vehicle Age <= 5 Years	20.99	0.13	164.88	—	—	—	-1.93	0.12	-16.20	7.43	0.07	111.05
VEHAGE02	Vehicle Between Age 5 < and <= 10 Years	20.68	0.13	163.38	-3.08	0.05	-56.05	3.48	0.12	28.29	7.02	0.07	102.40
VEHAGE03	Vehicle Age Between 10 < and <= 15 Years	-2.75	0.14	-19.03	-6.23	0.07	-85.02	—	—	—	-2.50	0.08	-32.74
NY_IND	New York Indicator										-11.84	0.05	-235.21
LA_IND	Los Angeles Indicator										-10.79	0.05	-216.47
DC_IND	Washington Indicator										—	—	—

TABLE 27 Linear Regression Model - Distance Affects Vehicle Type - Pooled Dataset Model with Cross-Variables

Variable	β	Std. Err.	t
(Constant)	43.20	0.12	351.38
MALE	23.88	0.08	305.01
AGE01	-7.20	0.14	-52.26
AGE02	-0.41	0.08	-5.31
AGE03	2.22	0.05	42.80
INC02	-2.81	0.08	-34.54
INC03	0.99	0.05	18.61
URBAN	-13.81	0.06	-215.85
DRVRCNT	-2.57	0.02	-112.04
SELF_EMP	2.82	0.16	17.95
WORK_IND	5.78	0.04	130.85
SCHOL_IND	3.44	0.07	48.73
MAINT_IND	-3.60	0.05	-78.47
DISC_IND	11.25	0.09	120.95
PICKUP_IND	-1.48	0.06	-23.49
NOFXDWK	-24.84	0.20	-121.99
PARTTIME	0.40	0.07	5.81
OCCUP01	-7.75	0.05	-141.36
OCCUP02	7.85	0.08	94.54
OCCUP03	-5.21	0.06	-80.57
VEHAGE01	8.06	0.07	110.26
VEHAGE02	6.91	0.07	100.04
VEHAGE03	-2.17	0.08	-28.15
MALE_NY	-19.43	0.10	-202.52
AGE01_NY	-5.73	0.16	-36.03
WORKER_NY	8.74	0.08	108.84
INC02_NY	-7.08	0.11	-62.27
SELF_EMP_NY	0.89	0.19	4.71
DISC_IND_NY	8.10	0.11	72.13
TOTAL_TRIPS_NY	1.21	0.01	83.44
FLEXTIME_NY	-1.98	0.07	-26.49
PARTTIME_NY	3.55	0.11	31.14
OCCUP02_NY	-22.98	0.14	-161.06
VEHAGE01_NY	-4.69	0.08	-61.97
MALE_LA	-16.27	0.09	-173.06
AGE01_LA	2.88	0.15	19.02
AGE02_LA	2.56	0.10	26.10
INC01_LA	-1.24	0.07	-17.92
URBAN_LA	2.91	0.10	30.56
SELF_EMP_LA	3.57	0.18	19.67
DISC_IND_LA	3.36	0.11	30.27
DEGREE_LA	-1.67	0.07	-25.45
FLEXTIME_LA	3.77	0.07	56.24
NOFXDWK_LA	44.79	0.29	155.37
AGE02_DC	6.18	0.12	53.13
AGE04_DC	16.57	0.13	125.71
INC02_DC	-10.42	0.15	-69.86
INC04_DC	2.93	0.09	34.17
SCHOOL_IND_DC	4.77	0.14	34.28
MAINT_IND_DC	8.59	0.09	99.69
PICKUP_IND_DC	-0.69	0.15	-4.60
WEEKDAY_DC	-7.32	0.09	-84.88
OCCUP01_DC	7.08	0.12	57.04

Distance Affecting Vehicle Type Choice: Vehicle Type Choice Model

Like for the continuous distance modes, four discrete vehicle type choice models were estimated: New York, Los Angeles, Washington, and a fourth using the pooled dataset. TABLE 28 shows the coefficient values for all four models. TABLE 29, TABLE 30, TABLE 31, and TABLE 32 show each individual models for only the significant variables and the corresponding coefficient, p, and t values for each. For each model, individual variables for auto, van, and SUV were used; trucks were not included to be used as base variables. This indicates that all coefficient values reflect a choice's utility with respect to trucks (a person's preference with respect to truck). Across all models, only one variable was significant and consistent throughout all models, gender. The male indicator showed a negative relationship with each vehicle type in every model suggesting that males prefer trucks to the other modes. This is consistent with literature that has found the same trend (Bhat & Sen 2006). The observed distance variable was included in all the models to account for the interdependency at study. However, it was only significant for the auto variable in the Washington model (p-value=0.04, t-value=2.05) and the utility was very small (0.00287, rounded to 0.00 in the tables).

Additional significant variables indicate vehicle type preference in each model. In the New York model, the 18-25 age group showed a preference of autos and SUVs to trucks. The 26-39 age group prefers trucks to autos, but persons over 65 years of age prefer autos to trucks. Literature has found that older persons worry less about vehicle performance and more about fuel efficiency suggesting that they prefer autos over other modes (Kavalec 1999). People whose day included a work trip prefer autos to trucks and trucks to SUVs and vans while people that engage in a school trip prefer autos, vans, and SUVs to trucks. In addition, those that engage in a pickup trip prefer trucks to vans and SUVs. Regarding employment, persons with part-time positions prefer vans over trucks and persons in clerical or administrative support positions prefer trucks to autos and SUVs. Persons that used a new vehicle prefer SUVs to trucks and those who used vehicles between 5 and 10 years old prefer vans and SUVs to trucks.

In Los Angeles, the youngest age group prefers autos to trucks and trucks to vans and persons over 65 years of age prefer autos to trucks like in New York. People that live in an urban setting prefer autos and SUVs over trucks. Regarding purpose-specific trips throughout the day, people that engage in a home trip prefer autos and SUVs to trucks and work trips prefer trucks to any other mode. Previous literature has found that workers prefer vans the least (Bhat & Sen 2006). People that engage in maintenance activities prefer autos to trucks and those that engage in discretionary activities prefer SUVs to trucks. Higher educated persons prefer autos over trucks which may reflect what previous studies have determined about environmental awareness. They have found trends that people that are informed about the aware about environmental issues drive more fuel efficient vehicles (Flamm 2009). Part-time employees prefer any type over truck and persons with manufacturing, construction, maintenance, and farming positions prefer trucks to autos. People that use new vehicles in Los Angeles prefer SUVs to trucks, those that use 5-10 year old vehicles prefer SUVs to trucks and trucks to autos, and those that use 10-15 year old vehicles prefer autos and SUVs to trucks.

In Washington, the youngest age group prefers truck to vans like in Los Angeles. People that earn between $50,000 and $75,000 prefer vans to trucks. Likewise, higher households prefer vans to trucks. People that engage in a work trip prefer autos to trucks and trucks to vans. Similarly, school trips prefer autos to trucks, but people that engage in a pickup trip prefer SUV to truck. Weekday trips prefer trucks to autos and vans. Persons that engage in a high number of trips (TOTAL_TRIPS) prefer to use trucks to the other three types. Higher educated persons prefer autos and SUVs to trucks. In terms of occupation, people in clerical and administrative positions prefer autos and SUVs to trucks while those in manufacturing, construction, maintenance, and farming positions prefer trucks to autos like in Los

Angeles. People that drive newer vehicle prefer SUVs to trucks and those that drive 5-10 year old vehicles prefer trucks to autos.

In the model that was estimated with the pooled dataset, similar observations can be derived. The youngest age group prefers autos to trucks like in New York and Los Angeles and trucks to vans like in Los Angeles and Washington. People in urban settings prefer SUVs to trucks like in Los Angeles and higher household prefer vans to trucks like they do in Washington. People engaging in work trips prefer trucks to vans and SUVs. People in clerical and administrative support positions prefer SUVs to trucks and those in manufacturing, construction, maintenance, and farming positions prefer autos to trucks like in Los Angeles and Washington and SUVs to trucks like in Washington. People that drive new vehicles prefer SUVs to trucks like in all three individual models and those that drive 5-10 year old vehicles prefer trucks to autos like in Los Angeles and Washington. Several other variables yielded similar results. Persons that engage in a school, maintenance, or pickup trip along with higher educated persons and those that are employed in part-time positions all prefer autos, vans, and SUVs to trucks.

Because of the way that multinomial logit models are built, comparisons across models cannot be made with certainty. In order to make comparable observations more analysis is needed. Elasticities/marginal effects can be calculated to determine the sensitivity of each variable in the models, or the pooled dataset can be used to create cross-variables that show comparable coefficient values within the same model. In this research, the pooled data approach has been selected to make these comparisons. The model results are showed in TABLE 33.

There were a several variables that show similar preferences across the regions, but other variables showed a different order of preference in different regions. People that drive vehicles that are 5 to 10 years-old in New York prefer vans to autos to trucks while the general variable with all of the pooled data, shows a preference of SUV to truck to auto. In Washington, persons that engaged in a work trip prefer to use an auto to an SUV to a truck, but in the aggregate pooled that, those persons prefer trucks to SUVs to autos. People that have part-time positions prefer trucks to SUVs to autos to vans in Washington, but the pooled data suggested that they prefer vans to SUVs to autos to trucks. Between the regions some similarities can be observed. Males in New York and Washington both prefer trucks to autos and people over 65 years of age prefer autos to trucks in both New York and Los Angeles. However, there is a notable difference. People that engage in a discretionary activity in Los Angeles prefer SUVs to trucks while those in Washington prefer trucks to SUVs. These differences that can be observed within the same model indicate that there are significant differences between the regions in the multinomial logit model when distance affects vehicle type choice.

TABLE 28 Multinomial Logit Model - Distance Affects Vehicle Type

Variable	Description	New York			Los Angeles			Washington			Pooled Dataset		
		Auto	Van	SUV	Auto	Van	SUV	Auto	Van	SUV	Auto	Van	SUV
ASC	Alternative Specific Constant	2.25	2.59	1.98	0.64	2.06	0.37	0.80	0.91	0.86	1.52	1.51	0.98
GENDER	Male	-2.87	-3.35	-2.80	-1.92	-2.45	-2.04	-1.83	-2.94	-2.18	-2.06	-2.70	-2.13
AGE	Continuous Variable	—	—	—	—	—	—	—	—	—	—	—	—
AGE01	18 -25	2.00	—	0.99	0.93	-1.01	—	—	-1.57	—	0.95	-0.99	—
AGE02	26-39	—	—	—	—	—	—	—	—	—	—	—	—
AGE03	40-54	-0.17	—	—	—	—	—	—	—	—	—	—	—
AGE04	55-64	—	—	—	—	—	—	—	—	—	—	—	—
AGE05	Over 65	0.24	—	—	0.27	—	—	—	—	—	—	—	—
WORKER	Person is a Worker	—	—	—	—	—	—	—	—	—	—	—	—
INC01	<= $50k	—	—	—	—	—	—	—	—	—	—	—	—
INC02	$50k < and <= $75k	—	—	—	—	—	—	—	0.69	—	—	—	—
INC03	$75k < and <= $100K	—	—	—	—	—	—	—	—	—	—	—	—
INC04	Over $100k	—	—	—	—	—	—	—	—	—	—	—	—
URBAN	Urban Area	—	—	—	0.42	—	0.44	—	—	—	—	—	0.16
HHSIZE	No. of People in HH	—	—	—	—	—	—	—	0.17	—	—	0.14	—
WRKCOUNT	No. of Workers in HH	—	—	—	—	—	—	—	—	—	—	—	—
DRVRCNT	No. of Drivers in HH	—	—	—	—	—	—	—	—	—	—	—	—
NUMADLT	No. of Adults in HH	—	—	—	—	—	—	—	—	—	—	—	—
SELF_EMP	Person is Self-Employed	—	—	—	—	—	—	—	—	—	—	—	—
HOME_IND	Presence of a Home Trip	—	—	—	0.53	—	0.52	—	—	—	—	—	—
WORK_IND	Presence of a Work Trip	—	-0.97	-4.14	-0.22	-0.86	-0.75	0.30	-0.89	—	—	-0.85	-0.42
SCHOOL_IND	Presence of a School Trip	1.19	0.82	0.98	—	—	—	0.52	—	—	0.52	0.38	0.44
MAINT_IND	Presence of a Maintenance Trip	—	—	—	0.25	—	—	—	—	—	0.07	0.18	0.26
DISC_IND	Presence of a Discretionary Trip	—	—	—	—	—	0.15	—	—	—	—	—	—
PICKUP_IND	Presence of a Pick-Up Trip	—	0.58	0.24	—	—	—	—	—	0.43	0.38	0.77	0.57
DROPOFF_IND	Presence of a Drop-Off Trip	—	—	—	—	—	—	—	—	—	—	—	—
WEEKDAY	Travel Day is a Weekday	—	—	—	—	—	—	0.40	0.53	—	—	—	—
TOTAL_TRIPS	Total No. of Trips During Day	—	—	—	—	—	—	0.07	0.14	0.11	—	—	—
DEGREE	Person has at least a Bachelor's Degree	—	—	—	0.15	—	—	0.26	—	0.45	0.27	0.27	0.23
FLEXTIME	Flexible Work Schedule	—	—	—	—	—	—	—	—	—	—	—	—
NOFXDWK	No Fixed Work Place	—	—	—	—	—	—	—	—	—	—	—	—
PARTTIME	Part Time Job	—	0.34	—	0.42	0.69	0.33	—	—	—	0.24	0.47	0.29
OCCUP01	Sales / Service	—	—	—	—	—	—	—	—	—	—	—	—
OCCUP02	Clerical / Admin Support	-0.59	—	-0.42	—	—	—	0.91	—	1.19	—	—	0.25
OCCUP03	Manuf/Construct/Maintenance/Farming	—	—	—	-0.42	—	—	-0.56	—	—	-0.62	—	-0.30
OCCUP04	Professional/Managerial/Technical	—	—	—	—	—	—	—	—	—	—	—	—
NUMONTRP	Average No. of People on Trips	—	—	—	—	—	—	—	—	—	—	—	—
VEHAGE01	Vehicle Age <= 5 Years	—	—	0.81	—	—	0.60	—	—	0.50	—	—	0.77
VEHAGE02	Vehicle Between Age 5 < and <= 10 Years	—	0.48	0.43	-2.01	—	0.55	-0.30	—	—	-0.23	—	—
VEHAGE03	Vehicle Age Between 10 < and <= 15 Years	—	—	—	0.32	—	0.38	—	—	—	—	—	—
DIST	Total Distance Traveled During the Day	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NY_IND	New York Indicator										—	—	0.12
LA_IND	Los Angeles Indicator										—	—	—
DC_IND	Washington Indicator										—	—	—

TABLE 29 Multinomial Logit Model - Distance Affects Vehicle Type - New York

Variable	Description	Auto			Van			SUV		
		β	p	t	β	p	t	β	p	t
ASC	Alternative Specific Constant	2.25	0.00	10.92	2.59	0.00	10.43	1.98	0.00	8.04
GENDER	Male	-2.87	0.00	-13.02	-3.35	0.00	-13.04	-2.80	0.00	-12.19
AGE01	18 -25	2.00	0.00	10.43	—	—	—	0.99	0.00	2.98
AGE03	40-54	-0.17	0.07	-1.83	—	—	—	—	—	—
AGE05	Over 65	0.24	0.06	1.90	—	—	—	—	—	—
WORK_IND	Presence of a Work Trip	—	—	—	-0.97	0.00	-6.16	-4.14	0.00	-4.14
SCHOOL_IND	Presence of a School Trip	1.19	0.02	2.38	0.82	0.14	1.46	0.98	0.06	1.88
PICKUP_IND	Presence of a Pick-Up Trip	—	—	—	0.58	0.01	2.67	0.24	0.12	1.57
PARTTIME	Part Time Job	—	—	—	0.34	0.10	1.66	—	—	—
OCCUP02	Clerical / Admin Support	-0.59	0.00	-2.96	—	—	—	-0.42	0.06	-1.88
VEHAGE01	Vehicle Age <= 5 Years	—	—	—	—	—	—	0.81	0.00	5.63
VEHAGE02	Vehicle Between Age 5 < and <= 10 Years	—	—	—	0.48	0.00	3.15	0.43	0.01	2.78
DIST	Total Distance Traveled During the Day	0.00	0.86	0.17	0.00	0.91	0.11	0.00	0.90	0.13

TABLE 30 Multinomial Logit Model - Distance Affects Vehicle Type - Los Angeles

Variable	Description	Auto			Van			SUV		
		β	p	t	β	p	t	β	p	t
ASC	Alternative Specific Constant	0.64	0.06	1.85	2.06	0.00	11.30	0.37	0.36	0.91
GENDER	Male	-1.92	0.00	-14.65	-2.45	0.00	-13.34	-2.04	0.14	-14.34
AGE01	18 -25	0.93	0.00	6.17	-1.01	0.00	-3.07	—	—	—
AGE05	Over 65	0.27	0.01	2.58	—	—	—	—	—	—
URBAN	Urban Area	0.42	0.05	1.98	—	—	—	0.44	0.06	1.91
HOME_IND	Presence of a Home Trip	0.53	0.04	2.06	—	—	—	0.52	0.07	1.81
WORK_IND	Presence of a Work Trip	-0.22	0.08	-1.75	-0.86	0.00	-4.78	-0.75	0.00	-5.39
MAINT_IND	Presence of a Maintenance Trip	0.25	0.01	2.65	—	—	—	—	—	—
DISC_IND	Presence of a Discretionary Trip	—	—	—	—	—	—	0.15	0.15	1.43
DEGREE	Person has at least a Bachelor's Degree	0.15	0.07	1.83	—	—	—	—	—	—
PARTTIME	Part Time Job	0.42	0.03	2.21	0.69	0.01	2.52	0.33	0.12	1.55
OCCUP03	Manuf/Construct/Maintenance/Farming	-0.42	0.00	-2.98	—	—	—	—	—	—
VEHAGE01	Vehicle Age <= 5 Years	—	—	—	—	—	—	0.60	0.00	3.44
VEHAGE02	Vehicle Between Age 5 < and <= 10 Years	-2.01	0.07	-1.82	—	—	—	0.55	0.01	2.76
VEHAGE03	Vehicle Age Between 10 < and <= 15 Years	0.32	0.03	2.21	—	—	—	0.38	0.12	1.56
DIST	Total Distance Traveled During the Day	0.00	0.56	0.59	0.00	0.80	0.25	0.00	0.58	0.56

TABLE 31 Multinomial Logit Model - Distance Affects Vehicle Type - Washington

Variable	Description	Auto			Van			SUV		
		β	p	t	β	p	t	β	p	t
ASC	Alternative Specific Constant	0.80	0.00	3.07	0.91	0.03	2.19	0.86	0.00	3.51
GENDER	Male	-1.83	0.00	-9.29	-2.94	0.00	-10.91	-2.18	0.00	-9.92
AGE01	18 -25	—	—	—	-1.57	0.00	-3.28	—	—	—
INC02	\$50k < and <= \$75k	—	—	—	0.69	0.03	2.23	—	—	—
HHSIZE	No. of People in HH	—	—	—	0.17	0.01	2.61	—	—	—
WORK_IND	Presence of a Work Trip	0.30	0.03	2.16	-0.89	0.00	-3.45	—	—	—
SCHOOL_IND	Presence of a School Trip	0.52	0.01	2.47	—	—	—	—	—	—
PICKUP_IND	Presence of a Pick-Up Trip	—	—	—	—	—	—	0.43	0.10	1.66
WEEKDAY	Travel Day is a Weekday	0.40	0.01	2.59	0.53	0.05	1.97	—	—	—
TOTAL_TRIPS	Total No. of Trips During Day	0.07	0.10	1.66	0.14	0.01	2.47	0.11	0.04	2.06
DEGREE	Person has at least a Bachelor's Degree	0.26	0.11	1.60	—	—	—	0.45	0.02	2.35
OCCUP02	Clerical / Admin Support	0.91	0.02	2.36	—	—	—	1.19	0.00	2.95
OCCUP03	Manuf/Construct/Maintenance/Farming	-0.56	0.04	-2.09	—	—	—	—	—	—
VEHAGE01	Vehicle Age <= 5 Years	—	—	—	—	—	—	0.50	0.00	3.10
VEHAGE02	Vehicle Between Age 5 < and <= 10 Years	-0.30	0.03	-2.23	—	—	—	—	—	—
DIST	Total Distance Traveled During the Day	0.00	0.04	2.05	0.00	0.79	0.27	0.00	0.28	-1.08

TABLE 32 Multinomial Logit Model - Distance Affects Vehicle Type - Pooled Dataset

Variable	Description	Auto			Van			SUV		
		β	p	t	β	p	t	β	p	t
ASC	Alternative Specific Constant	1.52	0.00	13.66	1.51	0.00	8.01	0.98	0.00	5.28
GENDER	Male	-2.06	0.00	-21.38	-2.70	0.00	-21.35	-2.13	0.00	-20.15
AGE01	18 -25	0.95	0.00	8.97	-0.99	0.00	-4.24	—	—	—
URBAN	Urban Area	—	—	—	—	—	—	0.16	0.04	2.09
HHSIZE	No. of People in HH	—	—	—	0.14	0.00	4.56	—	—	—
WORK_IND	Presence of a Work Trip	—	—	—	-0.85	0.00	-8.33	-0.42	0.00	-6.46
SCHOOL_IND	Presence of a School Trip	0.52	0.00	2.95	0.38	0.09	1.70	0.44	0.02	2.26
MAINT_IND	Presence of a Maintenance Trip	0.07	0.13	1.53	0.18	0.15	1.44	0.26	0.01	2.66
PICKUP_IND	Presence of a Pick-Up Trip	0.38	0.02	2.36	0.77	0.00	4.05	0.57	0.00	3.36
DEGREE	Person has at least a Bachelor's Degree	0.27	0.01	2.79	0.27	0.03	2.11	0.23	0.03	2.14
PARTTIME	Part Time Job	0.24	0.10	1.66	0.47	0.01	2.52	0.29	0.07	1.84
OCCUP02	Clerical / Admin Support	—	—	—	—	—	—	0.25	0.03	2.17
OCCUP03	Manuf/Construct/Maintenance/Farming	-0.62	0.00	-5.48	—	—	—	-0.30	0.03	-2.24
VEHAGE01	Vehicle Age <= 5 Years	—	—	—	—	—	—	0.77	0.00	5.94
VEHAGE02	Vehicle Between Age 5 < and <= 10 Years	-0.23	0.00	-3.17	—	—	—	—	—	—
DIST	Total Distance Traveled During the Day	0.00	0.07	1.78	0.00	0.40	0.84	0.00	0.36	0.91
NY_IND	New York Indicator	—	—	—	—	—	—	0.12	0.04	2.01
LA_IND	Los Angeles Indicator	—	—	—	—	—	—	—	—	—
DC_IND	Washington Indicator	—	—	—	—	—	—	—	—	—

TABLE 33 Multinomial Logit Model - Distance Affects Vehicle Type - Pooled Dataset Model with Cross-Variables

Variable	Description	Auto			Van			SUV		
		β	p	t	β	p	t	β	p	t
ASC	Alternative Specific Constant	1.57	0.00	14.79	1.55	0.00	0.03	1.22	0.00	6.62
GENDER	Male	-1.98	0.00	-19.55	-2.74	0.00	-21.42	-2.13	0.00	-19.25
AGE01	18 -25	0.84	0.00	6.60	-1.00	0.00	-4.24	—	—	—
URBAN	Urban Area	—	—	—	—	—	—	0.17	0.03	2.18
HHSIZE	No. of People in HH	—	—	—	0.13	0.00	4.30	—	—	—
WORK_IND	Presence of a Work Trip	—	—	—	-0.87	0.00	-8.53	-0.42	0.00	-5.69
SCHOOL_IND	Presence of a School Trip	0.50	0.00	2.83	0.34	0.13	1.53	0.43	0.03	2.19
MAINT_IND	Presence of a Maintenance Trip	—	—	—	—	—	—	0.15	0.02	2.34
PICKUP_IND	Presence of a Pick-Up Trip	0.40	0.01	2.46	0.76	0.00	3.98	0.58	0.00	3.45
DEGREE	Person has at least a Bachelor's Degree	0.30	0.00	3.04	0.25	0.05	1.95	0.23	0.03	2.21
PARTTIME	Part Time Job	0.48	0.00	2.94	0.71	0.00	3.35	0.49	0.01	2.73
OCCUP02	Clerical / Admin Support	—	—	—	—	—	—	0.19	0.13	1.50
OCCUP03	Manuf/Construct/Maintenance/Farming	-0.57	0.00	-4.98	—	—	—	-0.28	0.04	-2.09
VEHAGE01	Vehicle Age <= 5 Years	—	—	—	—	—	—	0.72	0.00	5.50
VEHAGE02	Vehicle Between Age 5 < and <= 10 Years	-0.25	0.00	-2.99	—	—	—	0.47	0.00	3.19
VEHAGE03	Vehicle Age Between 10 < and <= 15 Years	0.20	0.05	1.99	—	—	—	0.29	0.09	1.69
DIST	Total Distance Traveled During the Day	0.00	0.11	1.62	0.00	0.51	0.66	0.00	0.52	0.65
GENDER_NY	Cross Variable for NY Region	-0.32	0.00	-3.39	—	—	—	—	—	—
AGE01_NY	Cross Variable for NY Region	0.39	0.06	1.91	—	—	—	—	—	—
AGE05_NY	Cross Variable for NY Region	0.30	0.01	2.69	—	—	—	—	—	—
VEHAGE02_NY	Cross Variable for NY Region	0.34	0.00	3.03	0.56	0.00	3.61	—	—	—
AGE05_LA	Cross Variable for LA Region	0.23	0.02	2.26	—	—	—	—	—	—
SELF_EMP_LA	Cross Variable for LA Region	-0.32	0.04	-2.08	—	—	—	-0.33	0.06	-1.86
DISC_IND_LA	Cross Variable for LA Region	—	—	—	—	—	—	0.14	0.13	1.50
WEEKDAY_LA	Cross Variable for LA Region	-0.16	0.06	-1.86	—	—	—	-0.37	0.00	-3.87
GENDER_DC	Cross Variable for DC Region	—	—	—	—	—	—	-0.32	0.05	-1.93
INC01_DC	Cross Variable for DC Region	—	—	—	—	—	—	-0.34	0.12	-1.57
SELF_EMP_DC	Cross Variable for DC Region	-0.66	0.00	-2.82	—	—	—	—	—	—
WORK_IND_DC	Cross Variable for DC Region	0.33	0.02	2.38	—	—	—	0.32	0.08	1.73
DISC_IND_DC	Cross Variable for DC Region	—	—	—	—	—	—	-0.32	0.05	-1.93
TOTAL_TRIPS_DC	Cross Variable for DC Region	—	—	—	0.06	0.02	2.36	—	—	—
PARTTIME_DC	Cross Variable for DC Region	-0.81	0.01	-2.43	-0.98	0.03	-2.20	-0.61	0.11	-1.62
OCCUP02_DC	Cross Variable for DC Region	0.62	0.10	1.65	—	—	—	0.60	0.15	1.45

Vehicle Type Choice Affecting Distance: Vehicle Type Choice Model

Similar models were developed for the opposite interdependency, vehicle type choice affecting distance. These models did not include the distance variable since the interdependency indicates that it is not a factor when modeling vehicle type choice. The four models developed are shown in TABLE 34 and individually in TABLE 35, TABLE 36, TABLE 37, and TABLE 38 for New York, Los Angeles, Washington, and the pooled dataset, respectively.

These results were similar to the observations made in the opposite causalities with a few exceptions. First, many variables that were previously significant are not significant in this causality. Likewise, many variables that were not significant earlier and now significant under this causalities. In New York, during weekdays people prefer autos to trucks and persons employed in manufacturing, construction, maintenance, and farming positions prefer trucks to autos. In Los Angeles, higher households prefer vans to trucks. In Washington, persons that are self-employed prefer trucks to autos. In the pooled dataset, the eldest age group prefers autos to trucks, persons that engage in a discretionary activity prefer any type over truck, and persons that drive new vehicle prefer trucks to SUVs. One variable that was significant under both interdependencies changed its relationship to trucks. The youngest age group in Los Angeles preferred vans to trucks in the first interdependency, but when vehicle type choice affects distance, they prefer trucks to vans.

To make comparison across regions within the same model, the pooled dataset was used to add cross-variables with respect to each city. The results from this model are shown in TABLE 39. Out of the variables that were significant in both a specific region and the general pooled dataset, five showed consistent results, but one did not. People that used vehicles between 5 and 10 years-old, preferred SUVs to trucks in Los Angeles but trucks to SUVs with respect to the pooled data.

When comparing this model to the pooled dataset model in the opposite interdependency, some differences can be seen. Educated persons prefer autos to vans to SUVs to truck while in the previous interdependency, they preferred SUVs to autos to vans to trucks. People that drive vehicles that are 5 to 10 years-old prefer SUVs to trucks to autos, but they previously preferred trucks to SUVs to Autos. And finally, those who drive 10 to 15 year-old vehicles, now prefer SUVs to autos to trucks but previously preferred trucks to SUVs.

With these models, the differences and similarities between the two interdependencies can be observed and acknowledged. Though several variables are similar between the two, several are not.

TABLE 34 Multinomial Logit Model - Vehicle Type Affects Distance -

Variable	Description	New York			Los Angeles			Washington			Pooled Dataset		
		Auto	Van	SUV	Auto	Van	SUV	Auto	Van	SUV	Auto	Van	SUV
ASC	Alternative Specific Constant	2.30	3.12	2.78	1.04	1.54	0.77	0.78	1.72	1.11	1.80	1.72	1.85
GENDER	Male	-2.90	-3.41	-2.90	-1.90	-2.43	-2.03	-1.86	-2.97	-2.25	-2.10	-2.73	0.17
AGE	Continuous Variable	—	—	—	—	—	—	—	—	—	—	—	—
AGE01	18 -25	2.12	—	1.00	0.92	-1.10	—	—	-1.17	0.97	0.97	-1.02	—
AGE02	26-39	—	—	—	—	—	—	—	—	—	—	—	—
AGE03	40-54	-0.15	—	—	—	—	—	—	—	—	—	—	—
AGE04	55-64	—	—	—	—	—	—	—	—	—	—	—	—
AGE05	Over 65	0.26	—	—	0.22	—	—	—	—	—	0.25	—	—
WORKER	Person is a Worker	—	—	—	—	—	—	—	—	—	—	—	—
INC01	<= $50k	—	—	—	—	—	—	—	—	—	—	—	—
INC02	$50k < and <= $75k	—	—	—	—	—	—	—	0.59	—	—	—	—
INC03	$75k < and <= $100K	—	—	—	—	—	—	—	—	—	—	—	—
INC04	Over $100k	—	—	—	—	—	—	—	—	—	—	—	—
URBAN	Urban Area	—	—	—	—	—	—	—	—	—	—	—	—
HHSIZE	No. of People in HH	—	—	—	—	0.14	—	—	—	—	—	0.12	—
WRKCOUNT	No. of Workers in HH	—	—	—	—	—	—	—	—	—	—	—	—
DRVRCNT	No. of Drivers in HH	—	—	—	—	—	—	—	—	—	—	—	—
NUMADLT	No. of Adults in HH	—	—	—	—	—	—	—	—	—	—	—	—
SELF_EMP	Person is Self-Employed	—	—	—	—	—	—	-0.77	—	—	—	—	—
HOME_IND	Presence of a Home Trip	—	—	—	0.55	—	0.52	—	—	—	—	—	—
WORK_IND	Presence of a Work Trip	-0.32	-1.19	-0.64	-0.22	-0.90	-0.74	0.41	-0.60	—	—	-0.87	-0.47
SCHOOL_IND	Presence of a School Trip	—	—	—	—	—	—	0.49	—	—	0.52	0.38	0.42
MAINT_IND	Presence of a Maintenance Trip	—	—	—	0.25	—	—	—	—	—	—	—	0.15
DISC_IND	Presence of a Discretionary Trip	—	—	—	—	—	0.16	—	—	—	0.21	0.25	0.17
PICKUP_IND	Presence of a Pick-Up Trip	—	0.49	—	—	—	—	—	—	0.40	0.43	0.81	0.60
DROPOFF_IND	Presence of a Drop-Off Trip	—	—	—	0.32	0.76	0.44	—	—	—	—	—	—
WEEKDAY	Travel Day is a Weekday	0.21	—	—	—	—	—	0.29	—	—	—	—	—
TOTAL_TRIPS	Total No. of Trips During Day	—	—	—	—	—	—	0.10	0.17	0.10	—	—	—
DEGREE	Person has at least a Bachelor's Degree	—	—	—	0.15	—	—	0.28	—	0.48	0.31	0.24	0.26
FLEXTIME	Flexible Work Schedule	—	—	—	—	—	—	—	—	—	—	—	—
NOFXDWK	No Fixed Work Place	—	—	—	—	—	—	—	—	—	—	—	—
PARTTIME	Part Time Job	—	0.31	—	0.43	0.70	0.35	—	—	—	—	0.25	—
OCCUP01	Sales / Service	—	—	—	—	—	—	—	—	—	—	—	—
OCCUP02	Clerical / Admin Support	—	—	—	—	—	—	1.20	—	1.51	0.23	—	0.43
OCCUP03	Manuf/Construct/Maintenance/Farming	-0.55	—	-0.44	-0.42	—	—	—	—	—	-0.58	—	-0.30
OCCUP04	Professional/Managerial/Technical	—	—	—	—	—	—	—	—	—	—	—	—
NUMONTRP	Average No. of People on Trips	—	—	—	—	—	—	—	—	—	—	—	—
VEHAGE01	Vehicle Age <= 5 Years	—	-0.32	—	—	—	—	—	—	—	-0.32	—	—
VEHAGE02	Vehicle Between Age 5 < and <= 10 Years	—	—	—	-0.20	0.33	0.56	—	—	—	-0.48	—	-0.25
VEHAGE03	Vehicle Age Between 10 < and <= 15 Years	—	—	—	—	—	0.39	—	—	—	—	—	-0.28
NY_IND	New York Indicator										—	—	0.123
LA_IND	Los Angeles Indicator										—	—	—
DC_IND	Washington Indicator										—	—	—

TABLE 35 Multinomial Logit Model - Vehicle Type Affects Distance - New York

Variable	Description	Auto			Van			SUV		
		β	p	t	β	p	t	β	p	t
ASC	Alternative Specific Constant	2.30	0.00	10.35	3.12	0.00	12.56	2.78	0.00	13.04
GENDER	Male	-2.90	0.00	-13.16	-3.41	0.00	-13.30	-2.90	0.00	-12.66
AGE01	18 -25	2.12	0.00	7.04	—	—	—	1.00	0.00	3.05
AGE03	40-54	-0.15	0.11	-1.59	—	—	—	—	—	—
AGE05	Over 65	0.26	0.04	2.09	—	—	—	—	—	—
WORK_IND	Presence of a Work Trip	-0.32	0.10	-1.66	-1.19	0.00	-5.18	-0.64	0.00	-1.66
PICKUP_IND	Presence of a Pick-Up Trip	—	—	—	0.49	0.02	2.32	—	—	—
WEEKDAY	Travel Day is a Weekday	0.21	0.04	2.08	—	—	—	—	—	—
PARTTIME	Part Time Job	—	—	—	0.31	0.13	1.53	—	—	—
OCCUP03	Manuf/Construct/Maintenance/Farming	-0.55	0.01	-2.72	—	—	—	-0.44	0.05	-1.98
VEHAGE01	Vehicle Age <= 5 Years	—	—	—	-0.32	0.02	-2.35	—	—	—

TABLE 36 Multinomial Logit Model - Vehicle Type Affects Distance - Los Angeles

Variable	Description	Auto			Van			SUV		
		β	p	t	β	p	t	β	p	t
ASC	Alternative Specific Constant	1.04	0.00	3.80	1.54	0.00	-3.28	0.77	0.02	2.28
GENDER	Male	-1.90	0.00	-14.58	-2.43	0.00	-13.18	-2.03	0.00	-14.28
AGE01	18 -25	0.92	0.00	6.08	-1.10	0.00	-3.28	—	—	—
AGE05	Over 65	0.22	0.04	2.05	—	—	—	—	—	—
HHSIZE	No. of People in HH	—	—	—	0.14	0.01	2.75	—	—	—
HOME_IND	Presence of a Home Trip	0.55	0.03	2.15	—	—	—	0.52	0.06	1.85
WORK_IND	Presence of a Work Trip	-0.22	0.07	-1.81	-0.90	0.00	-4.97	-0.74	0.00	-5.37
MAINT_IND	Presence of a Maintenance Trip	0.25	0.01	2.61	—	—	—	—	—	—
DISC_IND	Presence of a Discretionary Trip	—	—	—	—	—	—	0.16	0.13	1.50
DROPOFF_IND	Presence of a Drop-Off Trip	0.32	0.11	1.59	0.76	0.00	3.01	0.44	0.04	2.09
DEGREE	Person has at least a Bachelor's Degree	0.15	0.08	1.77	—	—	—	—	—	—
PARTTIME	Part Time Job	0.43	0.02	2.26	0.70	0.01	2.52	0.35	0.11	1.60
OCCUP03	Manuf/Construct/Maintenance/Farming	-0.42	0.00	-2.94	—	—	—	—	—	—
VEHAGE02	Vehicle Between Age 5 < and <= 10 Years	-0.20	0.08	-1.77	0.33	0.02	2.29	0.56	0.00	2.82
VEHAGE03	Vehicle Age Between 10 < and <= 15 Years	—	—	—	—	—	—	0.39	0.11	1.60

TABLE 37 Multinomial Logit Model - Vehicle Type Affects Distance - Washington

Variable	Description	Auto			Van			SUV		
		β	p	t	β	p	t	β	p	t
ASC	Alternative Specific Constant	0.78	0.00	3.13	1.72	0.00	5.28	1.11	0.00	4.31
GENDER	Male	-1.86	0.00	-9.55	-2.97	0.00	-10.98	-2.25	0.00	-10.30
AGE01	18 -25	—	—	—	-1.17	0.01	-2.54	0.97	—	—
INC02	$50k < and <= $75k	—	—	—	0.59	0.05	1.92	—	—	—
SELF_EMP	Person is Self-Employed	-0.77	0.00	-3.43	—	—	—	—	—	—
WORK_IND	Presence of a Work Trip	0.41	0.00	2.98	-0.60	0.01	0.23	—	—	—
SCHOOL_IND	Presence of a School Trip	0.49	0.02	2.33	—	—	—	—	—	—
PICKUP_IND	Presence of a Pick-Up Trip	—	—	—	—	—	—	0.40	0.11	1.58
WEEKDAY	Travel Day is a Weekday	0.29	0.04	2.01	—	—	—	—	—	—
TOTAL_TRIPS	Total No. of Trips During Day	0.10	0.02	2.35	0.17	0.00	3.02	0.10	0.05	1.99
DEGREE	Person has at least a Bachelor's Degree	0.28	0.07	1.80	—	—	—	0.48	0.01	2.54
OCCUP02	Clerical / Admin Support	1.20	0.04	2.08	—	—	—	1.51	0.01	2.56

TABLE 38 Multinomial Logit Model - Vehicle Type Affects Distance - Pooled Dataset

Variable	Description	Auto			Van			SUV		
		β	p	t	β	p	t	β	p	t
ASC	Alternative Specific Constant	1.80	0.00	16.24	1.72	0.00	10.24	1.85	0.00	15.33
GENDER	Male	-2.10	0.00	-21.49	-2.73	0.00	-21.59	0.17	0.11	1.59
AGE01	18 -25	0.97	0.00	9.29	-1.02	0.00	-4.35	—	—	—
AGE05	Over 65	0.25	0.00	3.55	—	—	—	—	—	—
HHSIZE	No. of People in HH	—	—	—	0.12	0.00	3.87	—	—	—
WORK_IND	Presence of a Work Trip	—	—	—	-0.87	0.00	-8.57	-0.47	0.00	-6.92
SCHOOL_IND	Presence of a School Trip	0.52	0.00	2.93	0.38	0.09	1.71	0.42	0.03	2.16
MAINT_IND	Presence of a Maintenance Trip	—	—	—	—	—	—	0.15	0.02	2.32
DISC_IND	Presence of a Discretionary Trip	0.21	0.03	2.17	0.25	0.06	1.89	0.17	0.11	1.59
PICKUP_IND	Presence of a Pick-Up Trip	0.43	0.01	2.63	0.81	0.00	4.22	0.60	0.00	3.58
DEGREE	Person has at least a Bachelor's Degree	0.31	0.00	3.19	0.24	0.06	1.86	0.26	0.01	2.48
PARTTIME	Part Time Job	—	—	—	0.25	0.06	1.86	—	—	—
OCCUP02	Clerical / Admin Support	0.23	0.10	1.63	—	—	—	0.43	0.01	2.74
OCCUP03	Manuf/Construct/Maintenance/Farming	-0.58	0.00	-5.01	—	—	—	-0.30	0.03	-2.24
VEHAGE01	Vehicle Age <= 5 Years	-0.32	0.00	-4.13	—	—	—	—	—	—
VEHAGE02	Vehicle Between Age 5 < and <= 10 Years	-0.48	0.00	-5.56	—	—	—	-0.25	0.00	-2.98
VEHAGE03	Vehicle Age Between 10 < and <= 15 Years	—	—	—	—	—	—	-0.28	0.02	-2.41
NY_IND	New York Indicator	—	—	—	—	—	—	0.123	0.04	2.03
LA_IND	Los Angeles Indicator	—	—	—	—	—	—	—	—	—
DC_IND	Washington Indicator	—	—	—	—	—	—	—	—	—

TABLE 39 Multinomial Logit Model - Vehicle Type Affects Distance - Pooled Dataset Model with Cross Variables

Variable	Description	All Regions								
		Auto			Van			SUV		
		β	p	t	β	p	t	β	p	t
ASC	Alternative Specific Constant	1.81	0.00	16.08	1.71	0.00	9.93	1.89	0.00	15.40
GENDER	Male	-2.00	0.00	-19.73	-2.75	0.00	-21.67	-2.20	0.00	-20.67
AGE01	18 -25	0.87	0.00	6.98	-1.01	0.00	-4.30	—	—	—
AGE05	Over 65	0.25	0.00	3.48	—	—	—	—	—	—
HHSIZE	No. of People in HH	—	—	—	0.12	0.00	3.85	—	—	—
WORK_IND	Presence of a Work Trip	—	—	—	-0.88	0.00	-8.62	0.47	0.00	-6.92
SCHOOL_IND	Presence of a School Trip	0.43	0.02	2.37	0.44	0.05	1.98	0.47	0.02	2.42
MAINT_IND	Presence of a Maintenance Trip	—	—	—	—	—	—	0.16	0.01	2.47
DISC_IND	Presence of a Discretionary Trip	0.21	0.03	2.14	0.24	0.07	1.81	0.18	0.09	1.67
PICKUP_IND	Presence of a Pick-Up Trip	0.42	0.01	2.59	0.80	0.00	4.17	0.59	3.48	0.17
DEGREE	Person has at least a Bachelor's Degree	0.25	0.01	2.44	0.21	0.10	1.62	1.86	0.10	1.66
PARTTIME	Part Time Job	—	—	—	0.21	0.12	1.54	—	—	—
OCCUP02	Clerical / Admin Support	0.20	0.15	1.44	—	—	—	0.60	0.00	3.28
OCCUP03	Manuf/Construct/Maintenance/Farming	-0.56	0.00	-4.86	—	—	—	-0.29	0.03	-2.18
VEHAGE01	Vehicle Age <= 5 Years	-0.30	0.00	-3.85	—	—	—	—	—	—
VEHAGE02	Vehicle Between Age 5 < and <= 10 Years	-0.47	0.00	-4.86	—	—	—	-0.28	0.02	-2.34
VEHAGE03	Vehicle Age Between 10 < and <= 15 Years	—	—	—	—	—	—	-0.28	0.01	-2.45
GENDER_NY	Cross Variable for NY Region	-0.32	0.00	-3.61	—	—	—	—	—	—
AGE01_NY	Cross Variable for NY Region	0.36	0.08	1.77	—	—	—	—	—	—
AGE04_NY	Cross Variable for NY Region	0.16	0.10	1.64	—	—	—	—	—	—
URBAN_NY	Cross Variable for NY Region	—	—	—	—	—	—	0.18	0.02	2.29
SCHOOL_IND_NY	Cross Variable for NY Region	0.34	0.08	1.76	—	—	—	—	—	—
VEHAGE02_NY	Cross Variable for NY Region	0.21	0.11	1.58	0.39	0.02	2.34	—	—	—
SELF_EMP_LA	Cross Variable for LA Region	-0.31	0.04	-2.05	—	—	—	-0.31	0.07	-1.81
OCCUP02_LA	Cross Variable for LA Region	—	—	—	—	—	—	-0.47	0.03	-2.16
VEHAGE02_LA	Cross Variable for LA Region	—	—	—	—	—	—	0.27	0.05	1.92
INC01_DC	Cross Variable for DC Region	—	—	—	-0.47	0.10	-1.67	-0.46	0.03	-2.21
INC04_DC	Cross Variable for DC Region	-0.34	0.02	-2.32	—	—	—	-0.41	0.02	-2.35
SELF_EMP_DC	Cross Variable for DC Region	-0.71	0.00	-3.16	—	—	—	—	—	—
DEGREE_DC	Cross Variable for DC Region	0.32	0.05	2.00	—	—	—	0.36	0.06	1.90

Vehicle Type Choice Affecting Distance: Distance Model

Like with the alternate interdependency, linear regression models were estimated. TABLE 40 and TABLE 41 show the results for the interdependency in which vehicle type choice affects distance. The models were built by first incorporating the explanatory variables for the usage of each vehicle type (except truck to serve as the base variable). The indicator variable for auto (AUTO_USED) showed a positive relationship with distance in Washington and a negative relationship in New York, Los Angeles, and the pooled dataset. The van and SUV variables (VAN_USED and SUV_USED respectively) showed a negative relationship with distance in all four models. This suggests that people drive longer distances with trucks in New York, Los Angeles, and the pooled dataset.

In comparison to the alternate dependency, many variables that were significant previously are not significant now and vice-versa. People in the 40-54 age group in New York and the eldest group in the pooled dataset showed a negative relationship with distance. People that earn between $50,000 and $75,000 in New York and over $100,000 in Washington both showed a negative relationship with distance. The presence of a work trip in New York showed a positive relationship while the number of workers was positive in Washington and negative in the pooled dataset. Persons that belong to households with high number of adults in Washington had a negative relationship with distance. In New York, persons with flexible work schedules or multiple jobs showed a positive relationship with distance. And finally people that used new vehicles in Los Angeles showed a positive relationship with distance.

Apart from differences in variables' significance, there were also some differences between variables that were significant under both interdependencies. In Washington, people that do not have fixed work locations previously had a negative relationship with distance but now have a positive relationship. People that have multiple jobs or are employed in sales, service, manufacturing, construction, maintenance, or farming positions switched from a positive relationship with distance to a negative one.

In the pooled dataset, people that engage in a school trip or work in manufacturing, construction, maintenance, or farming positions had positive relationship and now have a negative relationship. And finally people that are 26-39 years-old, do not have a fixed work location, are employed in part-time jobs, or used a new vehicle switched from a negative to a positive relationship with distance.

Like with the previous sets of models, the pooled dataset model was used to examine the differences across regions and between the two interdependencies. Across regions within the same model, 12 cross-variables were consistent with the variables that encompass the entire pooled data and 10 were missing significant pooled variables. The remaining cross-variables were inconsistent with the pooled variables.

Persons 26-39 years-old, persons that engaged in a work trip, and those who do not have a fixed work location in New York showed a negative relationship with distance while the pooled dataset showed a positive relationship. In Los Angeles, people that engaged in a maintenance trip and those employed in manufacturing, construction, maintenance, farming, or part-time positions also showed a negative relationship while the pooled data showed a positive relationship.

Apart from the differences in the pooled datasets that were previously described, two more notable differences can be noted between the causalities. First, workers with flexible work schedules in New York showed a negative relationship with distance under the previous interdependency but a positive one when vehicle type affects distance. And second, persons that do not have a fixed work location in Los Angeles showed a positive relationship with distance in this model but had shown a negative relationship with distance in the pooled dataset when distance affects vehicle type.

TABLE 40 Linear Regression Model - Vehicle Type Affects Distance 1

Variable	Description	New York			Los Angeles			Washington			Pooled Dataset		
		β	Std. Err.	t	β	Std. Err.	t	β	Std. Err.	t	β	Std. Err.	t
(Constant)		64.29	0.19	341.75	81.12	0.22	362.41	64.07	0.29	224.11	57.88	0.10	567.03
AUTO_USED	Indicator that an Auto was used	-7.15	0.12	-61.52	-1.26	0.07	-16.94	7.00	0.15	26.36	-1.56	0.06	-25.74
VAN_USED	Indicator that a Van was used	-3.74	0.14	-27.19	-1.94	0.10	-19.58	-22.96	0.20	-115.72	-6.35	0.08	-83.05
SUV_USED	Indicator that an SUV was used	-2.05	0.12	-17.09	-3.73	0.08	-46.35	-14.04	0.16	-88.96	-6.80	0.06	-106.08
GENDER	Male	12.20	0.07	181.28	5.06	0.05	92.00	9.83	0.10	99.54	8.55	0.04	212.36
AGE	Continuous Variable	—	—	—	—	—	—	—	—	—	—	—	—
AGE01	18 -25	—	—	—	-4.49	0.10	-45.85	-16.70	0.19	-87.00	—	—	—
AGE02	26-39	2.19	0.08	26.95	2.01	0.09	22.40	-20.56	0.16	-129.25	3.18	0.05	62.83
AGE03	40-54	-5.21	0.07	-71.22	4.46	0.08	54.44	-10.02	0.15	-65.31	4.48	0.05	96.74
AGE04	55-64	—	—	—	—	—	—	—	—	—	—	—	—
AGE05	Over 65	—	—	—	-2.76	0.12	-23.46	-1.27	0.20	-6.29	-3.28	0.08	-41.97
WORKER	Person is a Worker	—	—	—	6.87	0.09	73.98	44.11	0.18	244.03	—	—	—
INC01	<= $50k	-16.61	0.09	-175.86	-2.95	0.07	-43.70	—	—	—	—	—	—
INC02	$50k < and <= $75k	-13.94	0.09	-150.27	-4.36	0.07	-58.19	—	—	—	-7.28	0.05	-139.72
INC03	$75k < and <= $100K	-11.52	0.09	-133.89	-4.81	0.07	-65.20	—	—	—	2.24	0.05	45.03
INC04	Over $100k	—	—	—	—	—	—	-0.82	0.10	-8.45	—	—	—
URBAN	Urban Area	-16.29	0.10	-169.90	-13.68	0.12	-118.72	-10.64	0.11	-98.04	-10.73	0.06	-177.35
HHSIZE	No. of People in HH	—	—	—	-0.25	0.02	-11.07	5.24	0.05	110.34	—	—	—
WRKCOUNT	No. of Workers in HH	-4.68	0.04	-119.57	3.40	0.04	89.03	-9.95	0.08	-126.48	-1.05	0.02	-47.27
DRVRCNT	No. of Drivers in HH	—	—	—	-1.42	0.04	-35.30	-0.85	0.14	-6.04	—	—	—
NUMADLT	No. of Adults in HH	—	—	—	—	—	—	-3.36	0.14	-24.58	—	—	—
SELF_EMP	Person is Self-Employed	6.78	0.11	60.74	4.63	0.08	54.61	—	—	—	5.66	0.06	87.36
HOME_IND	Presence of a Home Trip	—	—	—	-37.00	0.13	-275.61	—	—	—	—	—	—
WORK_IND	Presence of a Work Trip	18.94	0.07	253.00	-0.71	0.06	-11.73	-18.44	0.11	-160.66	0.28	0.04	6.85
SCHOOL_IND	Presence of a School Trip	7.45	0.12	63.86	0.97	0.08	12.43	—	—	—	-1.09	0.06	-18.00
MAINT_IND	Presence of a Maintenance Trip	4.25	0.06	66.12	-2.31	0.05	-44.74	-3.74	0.09	-40.83	0.28	0.04	7.26
DISC_IND	Presence of a Discretionary Trip	17.64	0.07	255.90	—	—	—	4.33	0.11	39.65	—	—	—
PICKUP_IND	Presence of a Pick-Up Trip	-14.88	0.11	-135.18	5.77	0.08	68.54	-3.85	0.15	-25.12	-0.19	0.06	-3.34
DROPOFF_IND	Presence of a Drop-Off Trip	26.17	0.10	264.13	2.85	0.08	36.00	6.89	0.13	54.08	—	—	—

TABLE 41 Linear Regression Model - Vehicle Type Affects Distance 2

Variable	Description	New York			Los Angeles			Washington			Pooled Dataset		
		β	Std. Err.	t	β	Std. Err.	t	β	Std. Err.	t	β	Std. Err.	t
WEEKDAY	Travel Day is a Weekday	-25.57	0.07	-354.87	—	—	—	—	—	—	—	—	—
TOTAL_TRIPS	Total No. of Trips During Day	—	—	—	—	—	—	—	—	—	—	—	—
DEGREE	Person has at least a Bachelor's Degree	—	—	—	-2.24	0.06	-37.01	—	—	—	—	—	—
FLEXTIME	Flexible Work Schedule	0.45	0.07	6.06	—	—	—	0.44	0.11	3.86	—	—	—
NOFXDWK	No Fixed Work Place	-29.08	0.24	-118.88	14.21	0.18	79.25	8.01	0.45	17.75	3.21	0.14	22.33
MULTJOBS	Person has Multiple Jobs	20.15	0.12	171.85	7.01	0.10	72.25	-2.95	0.18	-16.56	12.02	0.07	166.69
PARTTIME	Part Time Job	10.61	0.09	113.04	-1.58	0.08	-20.79	-14.02	0.14	-98.59	0.67	0.05	12.47
OCCUP01	Sales / Service	-5.92	0.08	-75.36	-6.88	0.07	-93.15	-8.62	0.14	-62.20	—	—	—
OCCUP02	Clerical / Admin Support	—	—	—	-3.98	0.10	-40.31	9.81	0.16	61.36	1.04	0.07	15.43
OCCUP03	Manuf/Construct/Maintenance/Farming	-1.24	0.11	-10.78	-7.30	0.09	-82.94	-7.19	0.19	-37.71	-3.82	0.06	-61.32
OCCUP04	Professional/Managerial/Technical	—	—	—	—	—	—	—	—	—	—	—	—
NUMONTRP	Average No. of People on Trips	—	—	—	—	—	—	—	—	—	—	—	—
VEHAGE01	Vehicle Age <= 5 Years	4.93	0.07	74.60	8.21	0.08	101.62	-4.34	0.10	-43.87	5.15	0.04	136.01
VEHAGE02	Vehicle Between Age 5 < and <= 10 Years	—	—	—	3.09	0.08	37.60	—	—	—	—	—	—
VEHAGE03	Vehicle Age Between 10 < and <= 15 Years	—	—	—	-0.31	0.09	-3.31	-7.03	0.13	-55.78	—	—	—
NY_IND	New York Indicator										-10.85	0.05	-213.60
LA_IND	Los Angeles Indicator										-11.91	0.05	-237.59
DC_IND	Washington Indicator										—	—	—

TABLE 42 Linear Regression Model - Vehicle Type Affects Distance - Pooled Dataset Model with Cross-Variables

Variable	β	Std. Err.	t
(Constant)	50.43	0.10	483.63
AUTO_USED	-1.80	0.06	-29.34
VAN_USED	-6.96	0.08	-90.16
SUV_USED	-6.93	0.06	-106.91
MALE	10.91	0.05	219.95
AGE02	5.79	0.06	93.10
AGE03	1.79	0.06	29.95
AGE05	-1.52	0.10	-15.81
INC02	-6.78	0.12	-55.56
INC03	4.09	0.05	76.52
URBAN	-13.00	0.06	-215.04
WRKCOUNT	-1.84	0.03	-64.85
SELF_EMP	6.35	0.16	40.86
WORK_IND	1.74	0.05	32.82
SCHOL_IND	-0.15	0.06	-2.35
MAINT_IND	4.95	0.05	101.48
PICKUP_IND	-2.51	0.06	-41.73
NOFXDWK	12.99	0.41	31.89
MULTJOBS	15.57	0.09	163.92
PARTTIME	4.35	0.07	59.47
OCCUP02	1.15	0.09	12.89
OCCUP03	-6.44	0.08	-76.60
VEHAGE01	3.50	0.05	70.28
MALE_NY	-6.13	0.07	-81.88
AGE02_NY	-5.88	0.09	-65.15
AGE05_NY	-2.88	0.15	-19.00
INC02_NY	-1.95	0.15	-13.41
INC04_NY	7.73	0.07	114.65
SELF_EMP_NY	1.24	0.19	6.68
WORK_IND_NY	-2.41	0.08	-30.17
FLEXTIME_NY	1.72	0.07	23.32
NOFXDWK_NY	-28.55	0.47	-60.59
OCCUP03_NY	4.88	0.14	35.87
AGE03_LA	4.42	0.08	53.29
WORKER_LA	-1.37	0.10	-14.20
INC02_LA	3.55	0.14	25.05
WRKCOUNT_LA	1.45	0.04	37.22
SELF_EMP_LA	-0.46	0.18	-2.48
MAINT_IND_LA	-10.91	0.07	-153.23
DROPOFF_IND_LA	4.89	0.08	59.74
DEGREE_LA	-1.94	0.07	-29.50
FLEXTIME_LA	3.81	0.07	53.81
NOFXDWK_LA	3.19	0.46	6.99
MULTJOBS_LA	-8.85	0.15	-60.02
PARTTIME_LA	-5.04	0.11	-45.70
OCCUP01_LA	-6.95	0.08	-84.20
OCCUP02_LA	-2.38	0.14	-16.84
VEHAGE01_LA	1.58	0.08	19.66
VEHAGE02_LA	-0.82	0.07	-11.54
AGE01_DC	-3.79	0.12	-32.70
INC01_DC	-0.26	0.10	-2.65

Comparison of Model-Fit Statistics

In order to compare the different models, different model-fit statistics have been analyzed. To test the statistical significance of the models, the F-test value for the linear regression models is used and the log-likelihood ratio is used for the multinomial logit models. To analyze the goodness of fit of the models, R^2 values were used for the linear regression models and a pseudo-R^2 value (Rho^2) for the multinomial logit models. These are shown in TABLE 43 and TABLE 44, and they are described in detail below.

Testing Statistical Significance of the Models

For the linear regression models, an F-test has been used to test the significance of the models. The null hypothesis of the F-test assigns a value of zero to all of the coefficients leaving only the constants in the model of the dependent variable. The alternative hypothesis states that at least one coefficient is not zero. By observing the F-test values in TABLE 43, it is clear that the large numbers reject the null hypothesis. Therefore, the models estimated using only constants are not true, and the models estimated are statistically significant.

For the multinomial logit models, a log-likelihood ratio has been used. The null hypothesis, which is represented by the null log-likelihood, assigns a value of zero to all coefficient values assuming that the probability of each alternative is equal. The final log-likelihood pertains to the model estimated using all the coefficients. The difference between these, multiplied by 2, gives the log-likelihood ratio which is used to test the significance of the model. The values in TABLE 44 show very large values that reject the null hypothesis meaning that the probability across the alternatives is not equal.

Goodness of Fit Statistics

To measure the goodness of the models and compare between the two interdependencies, R^2 and pseudo-R^2 have been used for the linear regression, and multinomial logit models, respectively. Within each interdependency, the goodness of fit values cannot be compared across regions because each region has a different dataset. However, the same region can be compared between the two interdependencies to see which one provides the best fit of the data.

Differences can clearly be seen across the models. The linear regions models, shown in TABLE 43, do not favor one interdependency. New York and the pooled models show a higher R^2 value for the case in which distance affects vehicle type, while the Los Angeles and Washington models show greater values when vehicle type choice is affecting distance. In addition, the pooled dataset models with the cross-variables always yielded a better R^2 that the simple pooled dataset models.

Unlike R^2 which measures the variability, the pseudo-R^2 values for the multinomial logit models can only be used to compare the goodness of fit across the models. These can be seen in TABLE 44. New York, Washington, and the pooled dataset models all show a better fit for the interdependency in which distance affects vehicle type. Los Angeles yields very similar values but slightly greater for the case in which vehicle type affects distance.

TABLE 43 Model-Fit Statistics for the Linear Regression Models

Distance Affecting Vehicle Type

City/Statistics	F	R Squared
New York	20,171.423	0.145
Los Angeles	80,72.975	0.060
Washington	6,787.021	0.090
Pooled Dataset	20,689.193	0.052
Pooled Dataset with Cross-Variables	12,118.451	0.670

Vehicle Type Affecting Distance

City/Statistics	F	R Squared
New York	19,331.754	0.135
Los Angeles	7,395.176	0.063
Washington	9,414.352	0.129
Pooled Dataset	12,101.175	0.032
Pooled Dataset with Cross-Variables	6,478.836	0.036

TABLE 44 Model Fit Statistics for the Multinomial Logit Models

Distance Affecting Vehicle Type

City/Statistics	Null log-likelihood	Final log-likelihood	Likelihood Ratio Test	Rho-Squared
New York	-2293.888	-1993.308	601.159	0.131
Los Angeles	-2870.479	-2508.984	722.99	0.126
Washington	-1261.88	-1069.302	385.157	0.153
Pooled Dataset	-6426.247	-5631.373	1589.748	0.124
Pooled Dataset with Cross-Variables	-6426.247	-5583.426	1685.641	0.131

Vehicle Type Affecting Distance

City/Statistics	Null log-likelihood	Final log-likelihood	Likelihood Ratio Test	Rho-Squared
New York	-2293.888	-2001.431	584.914	0.127
Los Angeles	-2870.479	-2505.383	730.192	0.127
Washington	-1261.88	-1082.666	358.428	0.142
Pooled Dataset	-6426.247	-5640.013	1572.467	0.122
Pooled Dataset with Cross-Variables	-6426.247	-5604.535	1643.423	0.128

E) Discussion

The model estimation results show different values for each interdependency. This implies that the models are different and that the direction of the interrelationship does matter when modeling vehicle type choice and distance. Therefore, the models cannot be used interchangeably suggesting that either one of the two models is correct or they both hold but for different portions of the population. In order to explore which is true, a modeling framework that considers both interdependencies is required.

The framework that was used in the second part of this study is a latent segmentation model. This framework models the variables sequentially, but it allows for alternative causalities to be modeled within the same framework. In other words, it models both possible interdependencies between vehicle type choice and distance traveled by using the one that best fits the data for each individual. This disaggregate approach can help understand what portion of the population follow each interdependency.

Chapter 4 – EXPLORING THE RELATIONSHIP BETWEEN VEHICLE TYPE CHOICE AND DISTANCE TRAVELED: A LATENT SEGMENTATION APPROACH

A) Introduction

From the first section of the thesis (Chapter 3) it can clearly be observed that there are differences everywhere. Within each interdependency, there are many differences across the regions. While the pooled dataset provides an average value of the entire data, observations can be made that suggest that it does not favor every region. The relationship with distance and vehicle types shows different directions in the different regions. This means that there are clear behavioral spatial differences that need to be considered when building a model for a specific area.

Between the two interdependencies, differences can also be observed. These differences suggest two possible conclusions, either only one of the two interdependencies is correct, or they both hold true but for different portions of the population. In order to explore this, a modeling framework that encompasses both interdependencies is necessary. Vehicle type choice is a discrete variable since it can only take a value among the predetermined vehicle types and needs to be modeled as such. Distance, on the other hand, is a continuous variable since it can theoretically be any value. Because these variables are modeled differently, a discrete-continuous modeling framework is necessary to examine the interrelationship between them. Several discrete-continuous frameworks have been proposed to explore this (Bhat & Sen 2006, Jäggi et al 2012, Glerum et al 2013). Based on the formulation of the discrete and continuous choices, the modeling methodologies can be categorized into simultaneous frameworks and sequential frameworks. In the simultaneous frameworks, both choice variables are examined at the same time. The problem with this approach is that it assumes that both decisions are made simultaneously which may behaviorally be inaccurate because individuals most likely do not hold the cognitive capacity to make simultaneous choices, and there may be a very small gap between the choices. Second, the approach prevents incorporating causal relationships in the modeling framework where one variable affects the other. In sequential frameworks, the choices are assumed to be made sequentially, which does allow for accommodating conditionality where one decision can influence the other. However, in this approach, one has to assume an interrelationship to apply to the entire population which may not be accurate. In reality, it may be the case that different population subgroups may exhibit different interdependencies. Therefore, there is a need for a methodology which can allow for modeling the discrete and continuous choice dimensions while also accommodating the alternative interdependencies under a single framework.

In this research, an alternative discrete-continuous modeling approach utilizing the concept of latent class segmentation (Bhat 1997 Greene and Hensher 2003, Bhat et al 2004) is used to model vehicle choice and usage decisions. The latent segmentation approach is proposed to accommodate alternative interdependencies within the same modeling framework. The model probabilistically allocates individuals to each interdependency based on several explanatory variables. The rest of the chapter is organized as follows. Section B describes the data and Section C presents the methodology. The models estimation results are described in Section D and discussed in Section E.

B) Data Composition

Like in the first part, 2009 NHTS data was used. In order to accurately explore the interdependencies and avoid any influence from the previous exploration, data from the Dallas-Fort Worth metropolitan area was used. This metropolitan area was chosen because it provided the third highest sample size in the 2009 NHTS dataset (after New York, Los Angeles, and San Diego). Further, it is a city with a high level of automobile dependency and thus made it ideal for the exploration of short-term vehicle usage decisions. The number of individuals that are switch vehicles throughout the day is again very small (approximately 5%). The study sample was limited to the same restrictions as before, individuals with multiple vehicle types available in the household fleet, who used the same vehicle throughout the entire study day, are adults and drivers, and who only had valid trips throughout the day.

The vehicle ownership characteristics were examined like before. TABLE 45 shows the percentage of households that used the full household fleet and those that used less. It can be noted that only a few more than half the households used less than the entire household fleet. TABLE 46 shows the number of vehicles owned versus the number of vehicles used and TABLE 47 shows the corresponding cell percentages with respect to the total. The great majority of households own two vehicles types and out of those, most used both vehicle types.

TABLE 48 shows the disaggregate vehicle ownership and usage combinations using the previous 4-dgit binary code for the availability/use of each vehicle type, and TABLE 499 shows the corresponding cell percentages. A “1” represents that the vehicle type is available/used and a “0” indicates that it is not available/used. The first digit (on the left) represents autos, the second vans, the third SUV, and the fourth (on the right) trucks. The highest cell percentage corresponds to households that own an auto and an SUV and used both, but the highest usage category is households that only used auto.

TABLE 45 Vehicle Fleet Usage by Households in Dallas

Less than Full Fleet		Full Fleet	
Value	Percentage	Value	Percentage
1,925	50.8%	*1,865*	*49.2%*

TABLE 46 Vehicle Ownership Vs Usage by Number of Vehicles in Dallas (Total Vehicles)

Vehicles Owned	Vehicles Used				Total
	1	2	3	4	
2	1,551	*1,771*	—	—	**3,322**
3	128	234	*89*	—	**451**
4	5	4	3	*5*	**17**
Total	**1,684**	**2,009**	**92**	**5**	**3,790**

TABLE 47 Vehicle Ownership Vs Usage by Number of Vehicles in Dallas (Percentages)

Vehicles Owned	Vehicles Used				Total
	1	2	3	4	
2	40.9%	*46.7%*	—	—	**87.7%**
3	3.4%	6.2%	*2.3%*	—	**11.9%**
4	0.1%	0.1%	0.1%	*0.1%*	**0.4%**
Total	**44.4%**	**53.0%**	**2.4%**	**0.1%**	**100.0%**

TABLE 48 Vehicle Ownership Vs Usage by Fleet Composition in Dallas (Total Households)

Vehicles Owned	Vehicles Used															Total
	0001	0010	0011	0100	0101	0110	0111	1000	1001	1010	1100	1011	1101	1110	1111	
0011	82	164	*302*	0	0	0	0	0	0	0	0	0	0	0	0	**548**
0101	21	0	0	62	*55*	0	0	0	0	0	0	0	0	0	0	**138**
0110	0	18	0	20	0	*35*	0	0	0	0	0	0	0	0	0	**73**
0111	0	5	5	4	2	2	*7*	0	0	0	0	0	0	0	0	**25**
1001	169	0	0	0	0	0	0	381	*493*	0	0	0	0	0	0	**1,043**
1010	0	255	0	0	0	0	0	216	0	*669*	0	0	0	0	0	**1,140**
1100	0	0	0	73	0	0	0	90	0	0	*217*		0	0	0	**380**
1011	19	36	51	0	0	0	0	27	18	68		*40*	0	0	0	**259**
1101	5	0	0	8	16	0	0	5	20	0	16		*24*	0	0	**94**
1110	0	6	0	3	0	8	0	10	0	11	17		0	*18*	0	**73**
1111	1	0	0	2	1	3	0	2	0	0	0	0	3	0	*5*	**17**
Total	**297**	**484**	**358**	**172**	**74**	**48**	**7**	**731**	**531**	**748**	**250**	**40**	**27**	**18**	**5**	**3,790**

TABLE 49 Vehicle Ownership Vs Usage by Fleet Composition in Dallas (Percentages)

Vehicles Owned	Vehicles Used															Total
	0001	0010	0011	0100	0101	0110	0111	1000	1001	1010	1100	1011	1101	1110	1111	
0011	2.2%	4.3%	*8.0%*	—	—	—	—	—	—	—	—	—	—	—	—	**14.5%**
0101	0.6%	—	—	1.6%	*1.5%*	—	—	—	—	—	—	—	—	—	—	**3.6%**
0110	—	0.5%	—	0.5%	—	*0.9%*	—	—	—	—	—	—	—	—	—	**1.9%**
0111	—	0.1%	0.1%	0.1%	0.1%	0.1%	*0.2%*	—	—	—	—	—	—	—	—	**0.7%**
1001	4.5%	—	—	—	—	—	—	10.1%	*13.0%*	—	—	—	—	—	—	**27.5%**
1010	—	6.7%	—	—	—	—	—	5.7%	—	*17.7%*	—	—	—	—	—	**30.1%**
1100	—	—	—	1.9%	—	—	—	2.4%	—	—	*5.7%*	—	—	—	—	**10.0%**
1011	0.5%	0.9%	1.3%	—	—	—	—	0.7%	0.5%	1.8%	—	*1.1%*	—	—	—	**6.8%**
1101	0.1%	—	—	0.2%	0.4%	—	—	0.1%	0.5%	—	0.4%	—	*0.6%*	—	—	**2.5%**
1110	—	0.2%	—	0.1%	—	0.2%	—	0.3%	—	0.3%	0.4%	—	—	*0.5%*	—	**1.9%**
1111	0.0%	—	—	0.1%	0.0%	0.1%	—	0.1%	—	—	—	—	0.1%	—	*0.1%*	**0.4%**
Total	**7.8%**	**12.8%**	**9.4%**	**4.5%**	**2.0%**	**1.3%**	**0.2%**	**19.3%**	**14.0%**	**19.7%**	**6.6%**	**1.1%**	**0.7%**	**0.5%**	**0.1%**	**100.0%**

TABLE 50 presents all the descriptive statistics for the subsample. The average household size is nearly three persons per household with mean vehicle ownership value of 2.65 vehicles. Nearly 19 percent of the households have an income of less than $45,000 and about 28 percent of the households have an income between $45,000 and $100,000. Average trip rate is close to 4.19 trips per person with 1.43 trips bound for home, 0.60 trips destined to fixed activity locations including work and school, nearly 1.82 trips for out-of-home non-fixed activities and about 0.31 trips for serving household and non-household members. Average travel distance logged by individuals per day is nearly 49.54 miles with an average trip occupancy of 1.68 persons out of which nearly 0.52 individuals are household members along with the driver and the other small share is with non-household members. The subsample is comprised of nearly equal percentage of males and females. 33 percent of the subsample is comprised of non-workers with about 44 percent of the individuals holding a bachelors, graduate or professional degree. Almost about 28 percent of the people can alter or adjust their work schedules. The subsample is dominated by Caucasians (with about 85 percent of the subsample) followed by a small share of Black (about 5 percent) and Hispanic (about 3 percent) individuals.

TABLE 51 presents an overview of activity-travel characteristics by vehicle type chosen. This helps identify the potential relationship between the choice of vehicle type and the activity-travel agenda for the day. Van is associated with average trip occupancy followed by SUV, auto, and truck. The presence of household members on the trip also follows the same order. Trucks are associated with longer daily travel distance followed by SUV, van and auto. This hints at an inverse relationship between body types and distance when the vehicle types and distance traveled are compared without accounting for the composition of the household fleet of vehicle types. However, this is not necessarily true and the potential relationship between vehicle type choice and distance is highlighted when the activity-travel characteristics by vehicle type selected are explored while controlling for the household fleet composition. Auto is associated with longer travel distance when the household fleet is comprised of auto, van and truck vehicle types. Similarly, auto is associated with longer travel distances when the household fleet is comprised of an auto, van, and SUV. SUV appears to be the preferred body type whenever there are two vehicle types in the household fleet. However, it is not the case when there are three or more vehicle types in the household fleet. These observations from Table 3 point to the potential role of vehicle fleet composition and availability in the selection and utilization of vehicle types. Therefore, it is important to represent this constraint in any modeling framework of vehicle type choice so that the model estimation results are appropriate.

TABLE 50 Descriptive Characteristics of the Dallas Dataset

Variable Description	Mean	Standard Deviation
Person Attributes		
Percentage of females	51.0%	0.5
Percentage of non-workers	33.0%	0.47
Percentage of individuals with a Bachelors, Graduate or Professional Degree	44.0%	0.5
Percentage of individuals who can set or change start time of work day	28.0%	0.45
Percentage of individuals with age greater than equals 65	19.0%	0.39
Percentage of individuals who are White	85.0%	0.36
Percentage of individuals who are Black	5.0%	0.22
Percentage of individuals who are Hispanic	3.0%	0.17
Percentage of individuals whose occupation is sales / service	17.0%	0.38
Percentage of individuals whose occupation is Clerical / Administrative	8.0%	0.27
Household Attributes		
Average household size	3.03	1.26
Availability of vehicles (vehicle count / household size)	0.99	0.47
Ration of number of children to number of adults	0.21	0.4
Percentage of households with income <= 44,999	19.0%	0.4
Percentage of households with income > 44,999 and <= 99,999	28.0%	0.45
Percentage of households with address in an urban area	71.0%	0.45
Percentage of households with address not in an urban area	23.0%	0.42
Trip Attributes		
Total number of trips during the day	4.19	2.41
Number of home trip during the day	1.43	0.83
Number of work trip during the day	0.58	0.91
Sum of school trip during the day	0.02	0.18
Number of maintenance trip during the day	1.35	1.5
Number of discretionary trip during the day	0.47	0.77
Number of other trip during the day	0.03	0.17
Number of pick-up/drop-off trip during the day	0.31	0.79
Total travel distance across all trips during the day	49.54	80.36
Average number of household occupants on all trips during the day	0.52	0.74
Average occupancy across all trips during the day	1.68	0.93
Vehicle Attributes		
Percentage of vehicles less than 5 years old	49.0%	0.5
Percentage of vehicles between 5 and 10 years old	34.0%	0.47

TABLE 51 Daily Activity-travel Characteristics by Vehicle Type Chosen

Household Fleet Composition	Vehicle Type Selected	Frequency	Percentages	Mean Daily Travel Distance (miles)	Average Daily Trip Frequency	Number of Persons	Number of Household Members
	Auto	1518	40%	46.9	4.1	1.6	0.4
	Van	390	10%	48.4	5	2.2	0.9
	SUV	1095	29%	49.9	4.4	1.8	0.6
	Truck	787	21%	54.8	3.8	1.5	0.4
SUV, Truck	SUV	319	58%	47.1	4.4	1.9	0.6
SUV, Truck	Truck	229	42%	62.3	4	1.5	0.3
Van, Truck	Van	94	68%	45.6	5.2	2.5	1
Van, Truck	Truck	44	32%	36.5	4	1.6	0.5
Van, SUV	Van	36	49%	42.1	4	2.3	1
Van, SUV	SUV	37	51%	55.7	3.7	1.7	0.5
Auto, Truck	Auto	636	61%	46.7	4	1.6	0.5
Auto, Truck	Truck	407	39%	50.1	3.7	1.5	0.4
Auto, SUV	Auto	548	48%	43.1	4.1	1.5	0.4
Auto, SUV	SUV	592	52%	49.1	4.3	1.8	0.7
Auto, Van	Auto	193	51%	37.6	4.3	1.6	0.5
Auto, Van	Van	187	49%	54.3	5.1	2	0.8
Van, SUV, Truck	Van	10	40%	38.3	6.1	2.6	0.7
Van, SUV, Truck	SUV	9	36%	79.8	4.3	1.2	0.1
Van, SUV, Truck	Truck	6	24%	39	2.2	1.1	0
Auto, SUV, Truck	Auto	79	31%	63.2	3.9	1.4	0.3
Auto, SUV, Truck	SUV	115	44%	56.8	4.6	1.7	0.6
Auto, SUV, Truck	Truck	65	25%	75.5	3.8	1.6	0.5
Auto, Van, Truck	Auto	26	28%	44	3.9	1.3	0.2
Auto, Van, Truck	Van	36	38%	43.6	4.8	2.3	0.9
Auto, Van, Truck	Truck	32	34%	48.9	4.4	1.6	0.5
Auto, Van, SUV	Auto	32	44%	136.2	3.6	1.3	0.3
Auto, Van, SUV	Van	20	27%	32.5	3.8	2.3	1.2
Auto, Van, SUV	SUV	21	29%	51	4.6	1.9	0.8
Auto, Van, SUV, Truck	Auto	4	24%	27	4.8	1.6	0.6
Auto, Van, SUV, Truck	Van	7	41%	44.2	5.3	1.8	0.8
Auto, Van, SUV, Truck	SUV	2	12%	64	3.5	2.4	0.9
Auto, Van, SUV, Truck	Truck	4	24%	31.4	3.3	1	0

C) Methodology

The latent segmentation based discrete-continuous modeling approach is presented in this section. The modeling approach consists of three components: (1) a latent segmentation component, (2) a vehicle type choice component for each segment and (3) distance component for each segment. The first component represents a binary logit model with the alternatives consisting of the two causal structures relating vehicle type choice and distance variables. The vehicle type component takes the form of a multinomial logit model with the choice of vehicle types as the alternatives. The distance component is a continuous variable represented as a linear regression model.

Let q be the index for individuals (q = 1, 2, ..., Q) and i denote the index for the latent segments (i = 1 or 2), v denote the index for the vehicle type alternatives (v = 1, 2…V), and d denote the index for distance. With this notation, the mathematical notation for three components takes the following form:

$$u_{qi}^{*} = \alpha x_{qi} + \varepsilon_{qi} \tag{5}$$

$$u_{qiv}^{*} = \beta_i x_{qiv} + \varepsilon_{qiv} \tag{6}$$

$$u_{qid}^{*} = \gamma_i x_{qid} + \varepsilon_{qid} \tag{7}$$

where u_{qi}^{*}represents the utility derived by the q^{th} individual in selecting the i^{th} latent segment, u_{qiv}^{*} represents the utility derived by choosing vehicle type alternative v in the i^{th} latent segment, and u_{qid}^{*} represents distance travelled in the i^{th} latent segment. x_{qi},x_{qim}, and x_{qis} represent exogenous variables affecting the three choice dimensions of interest noted above. ε_{qi} and ε_{qiv} are assumed to follow Type 1 Gumbel distribution and ε_{qid} is assumed to be normally distributed with a variance of σ^2 . $\alpha, \beta_i, \gamma_i$ represent the corresponding coefficient vectors to be estimated.

The probability expression for the choice of the latent segment and the vehicle type choice takes the standard multinomial logit form as expressed in Equations 8 and 9 respectively.

$$P_{qi} = \frac{\exp(\alpha_i x_{qi})}{\sum_{j=1}^{I} \exp(\alpha_i x_{qj})} \tag{8}$$

$$P_{qiv} = \frac{\exp(\beta_i x_{qiv})}{\sum_{v=1}^{V} \exp(\beta_i x_{qiv})} \tag{9}$$

For the distance logged variable, the probability expression is provided as follows

$$P_{qid} = \frac{1}{\sigma} \varphi \left[\frac{(u_{qid}^{*} - u_{qd})}{\sigma} \right] \tag{10}$$

where u_{qd} represents the observed vehicle mileage travelled by individual q and ϕ represents the standard normal probability density function.

With these preliminaries, the latent segmentation based probability for joint choice of vehicle type *v* and distance u_{qd} with two segments can be formulated as follows:

$$P_{qvd} = P_{q1} \prod_{j=1}^{V} (P_{q1j})^{\delta_j} (P_{q1d}|v) + P_{q2} P_{q2d} \prod_{j=1}^{V} (P_{q2j}|d)^{\delta_j} \quad (11)$$

where δ_j represents an indicator variable for vehicle type selection and assumes a value 1 if the vehicle type is selected and 0 otherwise. The first term in Equation (11) reflects the first latent segment representing the causal sequence where vehicle type selection is made first and this in turn affects the distance traveled. The second term on the other hand reflects the second causal sequence where the distance variable affects the choice of vehicle type selection. The log-likelihood at the individual q is defined as:

$$L_q = \ln(P_{qvd}) \quad (12)$$

$$L = \sum_q Lq \quad (13)$$

The log-likelihood function is constructed based on the above probability expression, and maximum likelihood estimation is employed to estimate the $\alpha_i, \beta_i, \gamma_i, \sigma$ parameters. The model is programmed using GAUSS matrix programming language.

D) Model Estimation Results

Before the latent segmentation model was estimated, individual (also referred to as independent) models were created for each interdependency. Since this chapter of the thesis analyzes a different metropolitan area than the previous section, it is important to build these models and see how the variables interact. The independent models also provide the starting values for the estimation of the latent segmentation based model.

Distance Affecting Vehicle Type Choice: Distance Model

First, the linear regression model was built for the case in which distance affects vehicle type choice. The model estimation results are found in TABLE 52. Like with the independent models in the previous chapter, the coefficient value indicates the directionality of the relationship with distance. The variables that had a positive relationship with distance were the average number of occupants on trips, the total number of trips, the presence of a discretionary trip, the availability of vehicles, and if the household was not in an urban area. The variables that had a negative relationship with distance were: presence of a maintenance trip, female respondent, persons over 65 years of age, and persons that were unemployed.

TABLE 52 Linear Regression Model – Distance Affecting Vehicle Type Choice - Dallas

Variable	Description	β	t
(Constant)		2.8369	52.55
trphhacc_mean	Average Number of Occupants on Trips	0.0846	3.59
numtrips	Total Number of Trips During Day	0.1255	16.24
disctr_i	Presence of a Discretionary Trip	0.1962	5.48
maintr_i	Presence of Maintenance Trip	-0.2455	-6.31
veh_ava	Availability of vehicles (vehicle count / household size)	0.1370	3.85
highinc	Less Than $44,999		
rural	Not Urban Area	0.3445	9.15
female	Female	-0.1751	-5.37
elder	Age Greater Than 65	-0.1301	-2.86
nworker	Non-Worker	-0.2271	-5.82

Distance Affecting Vehicle Type Choice: Vehicle Type Choice Model

The multinomial logit models were built in the same way as before. The alternative vehicle types were auto, van, SUV, and truck was used as the base variable. This means that are coefficient values are with respect to truck as shown in Table 53. An increase in total distance traveled throughout the day showed a negative relationship in all vehicle type with respect to truck meaning that those persons prefer any type to truck. Persons with a higher number of occupants on trips throughout the day showed prefer trucks to autos and SUVs to trucks. People that engage in a discretionary trip prefer vans to trucks and those that engage in a maintenance trip prefer SUVs to trucks. People with more vehicles available prefer trucks to vans. Persons that live in households with less than $50,000 income prefer vans to trucks and those that are not in urban areas prefer trucks to autos. Educated persons (with at least a Bachelor's Degree) prefer an auto to a truck, persons older than 65 years of age prefer vans to trucks, and unemployed persons prefer autos to trucks. People that are employed in clerical and administrative support positions prefer any mode to truck and those employed in manufacturing, construction, maintenance, or farming positions prefer truck to any other type. Additionally, persons with flexible work schedules prefer truck to vans and SUVs.

Table 53 Multinomial Logit Model – Distance Affecting Vehicle Type Choice - Dallas

Variable	Description	Auto		Van		SUV	
		β	t	β	t	β	t
(Constant)	Constant	0.4770	5.40	0.7638	3.72	0.3588	3.46
trpmiles_sum	Total Distance Traveled During the Day	-0.0008	-1.23	-0.0010	-1.03	-0.0013	-1.77
trphhacc_mean	Average Number of Occupants on Trips	-0.1300	-1.96			0.3857	4.99
disctr_i	Presence of a Discretionary Trip			0.3704	2.42		
maintr_i	Presence of Maintenance Trip					0.1546	1.65
veh_ava	Availability of vehicles (vehicle count / household size)			-0.6057	-3.11		
highinc	Less Than $44,999			0.5775	3.42		
rural	Not Urban Area	-0.1985	-2.19				
degrecv	Person has at least a Bachelor's Degree	0.1013	1.29				
female	Female						
elder	Age Greater Than 65			0.6921	3.45		
nworker	Non-Worker	0.2332	2.60				
cleric	Clerical / Administrative Support	1.2027	5.51	1.3379	4.00	0.9574	4.08
mfg	Manufacturing, Construction, Maintenance, or Farming	-1.0630	-6.31	-1.0092	-3.52	-1.1829	-5.69
flexsche	Flexible Work Schedule			-0.5464	-3.08	-0.2099	-2.10

Vehicle Type Choice Affecting Distance: Vehicle Type Choice Model

The same multinomial logit model was built for the alternate interdependency and the results can be seen in Table 54. The estimation showed very similar results with a few exceptions. Females were shown to prefer vans to trucks and people living in household with more members prefer trucks to autos and SUVs to trucks. In addition, some variable that were previously significant, now were not.

Table 54 Multinomial Logit Model – Vehicle Type Choice Affecting Distance – Dallas

Variable	Description	Auto		Van		SUV	
		β	t	β	t	β	t
(Constant)		0.3832	3.53	0.7262	3.60	0.3610	3.61
trphhacc_mean	Number of People in Household	-0.1675	-2.51			0.3663	4.75
numtrips	Total Number of Trips During Day	-0.0396	-2.42				
disctr_i	Presence of a Disretionary Trip			0.3285	2.14		
maintr_i	Presence of Maintenance Trip					0.0999	1.03
veh_ava	Availability of Vehicles (vehicle count / household size)			-0.5787	-2.97		
highinc	Less Than $44,999			0.5926	3.50		
rural	Not Urban Area	-0.2189	-2.39				
degrecv	Person has at least a Bachelor's Degree	0.1151	1.45				
female	Female	0.5211	6.53				
elder	Age Greater Than 65			0.6685	3.32		
nworker	Non-Worker	0.1596	1.76				
cleric	Clerical / Administrative Support	0.9963	4.50	1.3309	3.97	0.9650	4.11
mfg	Manufacturing, Construction, Maintenance, or Farming	-0.9245	-5.41	-1.0443	-3.62	-1.2009	-5.77
flexsche	Flexible Work Schedule			-0.6325	-3.54	-0.2813	-2.80

Vehicle Type Choice Affecting Distance: Distance Model

Lastly, the independent linear regression model was built for the case in which vehicle type choice affects distance and the results are shown in Table 55. Again, there were many similarities between this model and the alternate interdependency, but there were some notable differences. Due to the directionality of the interrelationship, vehicle usage variables were used. All three type, autos, vans, and SUVs, had a negative relationship with distance. In addition, the vehicle age variable was significant in this model. Both variables, for vehicle that are less than 5 years old and those between 5 and 10 years of age, had a positive relationship with distance.

Table 55 Linear Regression Model – Vehicle Type Choice Affecting Distance - Dallas

Variable	Description	β	t
(Constant)		23.9418	4.46
autochoc	Auto Used	-5.2322	-1.49
vanchoc	Van Used	-9.8581	-1.97
suvchoc	SUV Used	-6.9848	-1.85
newvh	Age of vehicle <= 5 years	17.6255	4.97
oldvh	Age of vehicle 5 < and <= 10	11.0678	2.97
trphhacc_mean	Average Number of Occupants on Trips	10.2972	5.51
numtrips	Total Number of Trips During Day	1.9070	3.14
disctr_i	Presence of a Discretionary Trip	15.6657	5.61
maintr_i	Presence of Maintenance Trip	-10.2158	-3.39
veh_ava	Availability of Vehicles (vehicle count / household size)	9.9509	3.54
highinc	Less Than $44,999		
rural	Not Urban Area	6.3825	2.15
female	Female	-8.6618	-3.26
elder	Age Greater Than 65	-5.4302	-1.66

Latent Segmentation Model: Distance Affecting Vehicle Type Choice

The following subsections show the results for the latent segmentation model divided in sections. This first one describes the case in which distance affects vehicle type choice, the second describes the alternate case, and the third describes the summary and model fit data. The results for the segment in which distance is affecting vehicle type choice are shown in Table 56. In the vehicle type choice component of this interdependency, coefficient values were once again obtained with respect to truck. Persons that travel longer distances prefer truck over any other type. A higher number of household occupants and persons that engaged in maintenance trips showed preference for SUVs over trucks. Higher availability of vehicles showed a preference of trucks to vans. Persons living in households that are not in urban areas and those employed in manufacturing, construction, maintenance, or farming positions prefer trucks to autos. Persons that are unemployed or work in clerical or administrative positions prefer autos to trucks. And finally, persons with flexible work schedules prefer trucks to SUVs. The distance model component showed that persons with more household members, persons that engaged in a discretionary trip, and those with higher availability of vehicles have a positive relationship with distance.

Table 56 Model Segment Where Distance Affects Vehicle Type Choice

Vehicle Type Choice Model

	Auto		Van		SUV	
Variable Name	**β**	**t-stat**	**β**	**t-stat**	**β**	**t-stat**
Constant	0.4118	1.08	1.9496	2.505	1.0314	2.137
Total travel distance across all trips	-0.002	-1.31	-0.002	-1.46	-0.004	-2.82
Number of household occupants	—	—	—	—	0.6984	3.3
Presence of maintenance trip(s)	—	—	—	—	0.4569	1.25
Availability of vehicles	—	—	-0.786	-1.11	—	—
Not Urban Area	-0.367	-1.04	—	—	—	—
Non-worker	0.3811	1.16	—	—	—	—
Occupation - Clerical / Admin Support	0.8442	1.24	—	—	—	—
Occupation - Manufacturing/Construction	-0.969	-1.63	—	—	-1.266	-1.99
Work Flexibility	—	—	—	—	-0.64	-1.75

Distance Model

Variable Name	**β**	**t**
Constant	71.664	2.352
Number of household occupants	43.887	3.56
Presence of a discretionary trip(s)	39.065	1.98
Availability of vehicles	56.066	2.3

Latent Segmentation Model: Vehicle Type Choice Affecting Distance

The estimations results for the segment in which vehicle type choice affects distance can be seen in Table 57. Persons living in households with more members prefer trucks to autos and SUVs to trucks. Higher number of trips throughout the day showed a preference of trucks to autos. People that engaged in a discretionary trip, persons older than 65, and those that engaged in a discretionary trip prefer Vans to trucks. However, people with high availability of vehicles prefer vans to trucks. Females and unemployed persons prefer autos to trucks while people living in households that are in not in urban areas prefer trucks to autos. Persons that are employed in clerical and administrative support positions prefer any mode to truck and those employed in manufacturing, construction, maintenance, or farming positions prefer truck to any other type as has been seen before. And finally, persons with flexible work schedules prefer trucks to vans and SUVs. The distance model showed that people that used autos have a positive relationship with distance while people that used vans or SUVs have a negative relationship with distance. Vehicle less than 10 years old, a high number of trips, high availability of vehicles, and households in not in urban areas have a positive relationship with distance. On the contrary, people that engaged in maintenance trips and persons over 65 years old showed a negative relationship with distance.

Table 57 Model Segment Where Vehicle Type Choice Affects Distance

Vehicle Type Choice Model

Variable	Auto		Van		SUV	
	β	t	β	t	β	t
Constant	0.4543	4.258	0.5056	2.291	0.3878	4.506
Number of household occupants	-0.141	-1.9	—	—	0.3255	3.8
Total number of trips during the day	-0.035	-1.99	—	—	—	—
Presence of a discretionary trip(s)	—	—	0.353	2.09	—	—
Availability of vehicles	—	—	-0.368	-1.69	—	—
Income > 99,999	—	—	0.634	3.47	—	—
Household not in urban area	-0.223	-2.19	—	—	—	—
Female	0.5729	6.58	—	—	—	—
Age greater than equals 65	—	—	0.6155	2.78	—	—
Non-worker	0.1596	1.76	—	—	—	—
Occupation - Clerical / Admin Support	0.8925	3.69	1.2932	3.55	1.0579	4.08
Occupation - Manufacturing/Construction	-1.016	-5.51	-1.146	-3.58	-1.208	-5.12
Work Flexibility	—	—	-0.723	-3.69	-0.235	-2.19

Distance Model

Variable Name	β	t
Constant	17.723	10.138
Auto Used	1.7085	1.45
Van Used	-1.848	-1.1
SUV Used	-0.367	-0.29
Age of vehicle <= 5 years	5.4076	4.69
Age of vehicle is > 5 and <= 10	2.6815	2.23
Total number of trips during the day	3.9951	19.89
Presence of maintenance trip(s)	-7.51	-7.72
Availability of vehicles	1.5156	1.73
Household not in urban area	9.3443	9.25
Female	-5.913	-6.69
Age greater than equals 65	-5.715	-5.27

Latent Segmentation Model: Summary

Table 58 shows the results from the latent segmentation model and a summary of the data. The latent segmentation component, which represents a binary logit model, showed that 89.2 percent of individuals belong to the interdependency in which vehicle type choice affects distance and the remaining 10.8 percent belong to the alternate interdependency. It can also be seen that between the interdependency there is a different average distance and there are different vehicle usage distributions. Under the direction where vehicle type affects distance, the average distance traveled was 33.1 miles. As far as the vehicle type distribution, auto was the most used with 40.7 percent followed by SUV, truck, and then van. In the interdependency where vehicle distance affects vehicle type choice, SUVs were used the most with a 37.1 percent followed by auto, truck, and then van.

Table 59 shows the model fit statistics. To compare the three different models (each independent specification and the joint latent segmentation model, BIC values were use. It can be noted that the joint model had a BIC value that was lower than either of the independent specifications. This indicates that the joint model has a better goodness of fit of the data.

Table 58 Model Estimation Summary

Latent Segment Characteristics	
Share of Individuals belonging to the interdependency where Vehicle Type Choice affecting Distance	89.2%
Share of Individuals belonging to the interdependency where Distance affects Vehicle Type Choice	10.8%
Vehicle Type Choice affecting Distance	
Average distance	33.1
Share of Auto Vehicle Type	40.7%
Share of Van Vehicle Type	10.1%
Share of SUV Vehicle Type	28.4%
Share of Truck Vehicle Type	20.7%
Distance affects Vehicle Type Choice	
Average distance	163.8
Share of Auto Vehicle Type	31.8%
Share of Van Vehicle Type	13.0%
Share of SUV Vehicle Type	37.1%
Share of Truck Vehicle Type	18.1%

Table 59 Model Fit Statistics

Model Fit	Mean Log-likelihood	Number of Parameters	BIC
Independent Specification: Vehicle Type Choice affects Distance	-24577.4299	36	49451.5
Independent Specification: Distance affects Vehicle Type Choice	-24612.4116	33	49496.75
Joint Model Specification - Latent Segmentation Based Model of Vehicle Type Choice and Distance	-21463.5659	58	43405.06

E) Discussion

Within the shorter-term vehicle usage decisions, two important choice dimensions include the choice of vehicle from the household fleet and the distance traveled. There are interrelationships between the two choice dimensions and therefore any study of the choice dimensions needs to acknowledge the interplay between the choice variables. Two potential interrelationships exist between these choice dimensions namely, vehicle-type choice affects distance and distance affects vehicle-type choice. In most studies two approaches are commonly adopted to study the interrelationships between variables. In the first approach, the choices are assumed to be simultaneously made. However, the approach assumes that individuals process a relative large number of choices simultaneously and denies the possibility for sequential decision making. In the second approach, the choices are assumed to be made sequentially. However, in this approach a causal structure is fixed for the entire population and then models are estimated. The true causality is individual decision maker specific and alternative causalities may be required to accurately describe the behaviors of the entire population.

In this study a latent segmentation based model is proposed to study the interrelationships between the choice variables within a single framework. Data from the recent wave of the National Household Travel Survey (NHTS 2009) was used to study the interrelationship between choice of vehicle in households with multiple vehicle types and the daily distance traveled. The results point to the presence of alternative causalities with the causal structure where vehicle type choice affects distance explaining 89 percent of the behaviors and the causal structure where distance affects vehicle type choice explains the remaining 11 percent of the vehicle usage decisions. Additionally a host of socio-economic and demographic attributes were explored to explain the vehicle usage behaviors. The results are behaviorally plausible and have important implications for transport policy. Significant differences were observed in the model specifications of the vehicle type choice and distance under the two causalities and point to the need for employing modeling frameworks that recognize the presence of alternative causalities when explaining travel behaviors. The empirical exercise sheds light on the presence of alternative causal structures and highlights the need for employing modeling frameworks that can accommodate multiple causal structures within the same modeling framework.

Chapter 5 – CONCLUSIONS AND FUTURE RESEARCH

The study of vehicle ownership and usage decisions are of interest in the context of understanding the implications of such decisions on energy consumption, and greenhouse gas emissions. The literature on travel behavior is replete with examples of longer-term vehicle ownership and its associated choice dimensions namely, composition of vehicles in the household fleet, the evolution of household fleets from year-to-year and the usage of each vehicle in the household fleet on an annual basis. However, there is very limited research in the context of understanding the shorter-term vehicle usage decisions. The study of shorter-term vehicle usage decisions is all the more important in the context of households with multiple vehicles so that the usage of each vehicle can be accurately tracked. This research attempts to contribute to this gap in the literature on short-term vehicle choices.

To this end, in the first part of the thesis (Chapter 4) an exploration of the short-term vehicle choices of vehicle type choice an distance were conducted using data from the 2009 National Household Travel Survey. It was found that short-term vehicle choice dimensions are important to explore and that there are possible interrelationship between vehicle choice and distance. The study also explored possible interdependencies between the two choice dimensions by modeling the influence of one on the other by introducing them as explanatory variables. It was found that there are notable differences between the two interdependencies, and therefore, the direction of the interrelationship is important to explore. In addition to directly exploring this interrelationship, the focus of the first exploration was also to understand the differences in behavior across different regions in the United States with varying levels of automobile dependency and demographic differences. There were several explanatory variables that were used in the models and showed different values across the regions. This happened under both causalities indicating that there are significant spatial differences and that models are not transferable across regions.

In the second part of the thesis, this directionality is explored further. Due to the way that model are estimated, the two interrelationships can be modeled either simultaneously or sequentially. A simultaneous approach may be erroneous because it assume that both decisions are done at the same time when in reality there is small gap between the decisions. A sequential approach models one variable as a function of the other to capture conditionality. The latent segmentation approach captures both interdependencies to choose the best fit for the data. The results showed that 89% of the population chooses vehicle type first and then distance while the remaining 11% chooses distance and the vehicle type. These results indicate that both interdependencies hold true but for different subgroups of the population. Given the findings in this research, vehicle type choice and distance traveled should not be modeled simultaneously or sequentially while only considering one causality. It is important to use a latent segmentation approach that considers both scenarios to adequately model short-term vehicle choice decisions.

These findings are very insightful and contribute to our understanding of short-term vehicle choices. There are also some limitations of the current work opening avenues for future research and inquiry. First, the latent segmentation results were from the Dallas metropolitan region so more research needs to be done to understand shares of population belonging to different causalities in other regions. Given the spatial differences discovered in the first part of the thesis, the latent segmentation model should be applied to other areas to see how the spatial transferability holds when both interdependencies are accounted for. Second, a temporal analysis may be useful to find how these trends are changing with respect to time. An important part of transportation planning is to forecast for the future and by examining short-term vehicle usage decisions across different time periods in the past, the right predictions can be made. This allows for appropriate policy implementation that can potentially help shape our cities into more efficient and sustainable systems.

Third, the temporal scale of the shorter-term vehicle usage decision is still up for debate. In Konduri et al. (2011) a tour-level exploration of vehicle type choice and usage employing a discrete-continuous joint modeling framework provided significant results. On the other hand, in this empirical exercise, the choice dimensions modeled at a day-level also provided significant results. Therefore, it is not known if shorter-term vehicle usage is a tour-level, day-level or a multi-day level choice process. Therefore, additional data in the form of multi-day travel diaries and panel data over a longer term period may be needed to address this question. Fourth, the focus of this study was on capturing the variability in the systematic component by allowing for multiple causal structures. However, it does not accommodate the error correlations due to common unobserved attributes and endogeneity effects due to dependent variable on the right hand side. There is recent work on the inclusion of error correlations and endogeneity with the latent segmentation based modeling framework in the transportation safety arena (Xiong and Mannering 2013). The exploration of these statistical advances for the study of shorter-term vehicle usage decisions is left for a future exercise. Finally, the study is comprised of a person-level modeling of the vehicle type choice from the household fleet and the distance traveled. However, there are interactions between members of the household and the choice of vehicle type is likely a household-level decision process. Therefore, future studies should incorporate this consideration in the analysis.

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